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VMD-PMB-TCN: A Novel Model for Nonstationary Time Series Forecasting with an Application to Cryptocurrency Price Prediction

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Contents

1 Introduction **7**

2 Related Work **13**
2.1 Overview . . . 13
2.1.1 Aspects in Overview . . . 13
2.1.2 Structure of Overview . . . 14
2.1.3 Preliminary Observations . . . 15
2.1.4 Scope and Structure of Literature Review . . . 15
2.2 Statistical Time Series Models . . . 16
2.2.1 Statistical Time Series Models vs. Machine Learning-based Models . . . 16
2.3 Machine Learning Models . . . 16
2.3.1 Traditional Machine Learning Models . . . 17
2.3.2 Deep Learning Models . . . 17
2.3.3 Traditional Machine Learning Models vs. Deep Learning Models . . . 18
2.4 Hybrid Models . . . 18
2.4.1 Statisitical Time Series and Machine Learning Hybrid Models . . . 19
2.4.2 Traditional Machine Learning and Deep Learning Hybrid Models . . . 19
2.4.3 CNN-based Deep Learning Hybrid Models . . . 19
2.4.4 Sequence Model-based Deep Learning Hybrid Models . . . 22
2.4.5 Attention-based Deep Learning Hybrid Models . . . 24
2.4.6 Decomposition-based Deep Learning Hybrid Models . . . 25
2.4.7 Change Point Detection-based Deep Learning Hybrids . . . 26
2.5 Proposed Models . . . 27
2.5.1 Benchmark Study . . . 27
2.5.2 Proposed: VMD-PMB-TCN . . . 27
2.5.3 Proposed: VMD-PMB-CMHA-TCN . . . 29
2.5.4 Novelty . . . 29

3 Fundamentals **30**
3.1 Time Series . . . 30
3.1.1 Definitions . . . 30
3.1.2 Stationarity . . . 30
3.1.3 Handling Nonstationarity . . . 31
3.1.4 Detecting Nonstationarity . . . 32
3.1.5 Forecasting . . . 33
3.2 Variational Mode Decomposition (VMD) . . . 33
3.2.1 Description . . . 33
3.2.2 Parameters . . . 34
3.2.3 Time Series . . . 34
3.3 Temporal Convolutional Network (TCN) . . . 35
3.4 Self-Attention Mechanism . . . 37
3.4.1 Scaled Dot-Product Attention . . . 37
3.4.2 Multi-Head Attention . . . 38
3.5 Activation Functions . . . 39
3.6 Evaluation Metrics . . . 40

3.6.1 Regression Metrics . . . 40
3.6.2 Classification Metrics . . . 41
3.6.3 Important Metrics . . . 41

4 Methodology **42**
4.1 Models . . . 43
4.1.1 Benchmark: TCN . . . 43
4.1.2 Proposed: VMD-PMB-TCN . . . 45
4.1.3 Proposed: VMD-PMB-CMHA-TCN . . . 47
4.1.4 Ablation: CMHA-TCN . . . 49
4.2 Data Overview . . . 50
4.2.1 Description: Benchmark Dataset & Extended Dataset . . . 50
4.2.2 Primary Analysis: Benchmark Dataset & Extended Dataset . . . 51
4.2.3 Supplementary Analysis: Interrelationships . . . 55
4.3 Data Preprocessing . . . 56
4.3.1 Differencing . . . 57
4.3.2 Scaling . . . 57
4.3.3 Sliding Window . . . 58
4.3.4 VMD . . . 59

5 Experimental Setup **64**
5.1 Frameworks . . . 64
5.1.1 Benchmark Framework . . . 64
5.1.2 Revised Benchmark Framework . . . 65
5.1.3 Novel Framework . . . 66
5.2 Evaluation Strategy . . . 67
5.3 Benchmark Experiments . . . 68
5.3.1 Primary . . . 69
5.3.2 Ablation . . . 69
5.3.3 Variational Mode Decomposition with Data Leakage . . . 70
5.4 Extended Experiments . . . 70
5.5 Hyperparameter Tuning . . . 71
5.5.1 Tuning Process . . . 71
5.5.2 Hyperparameter Search Space . . . 72
5.6 Experimental Analysis . . . 73
5.6.1 Input Analysis . . . 74
5.6.2 Input Modes Analysis . . . 74
5.6.3 Expected Outputs Analysis . . . 75

6 Results **76**
6.1 Benchmark Framework . . . 76
6.2 Novel Framework . . . 77
6.2.1 Overall Results . . . 77
6.2.2 Monthly Results . . . 82

7 Conclusion and Future Work **84**
7.1 Future Work . . . 86

8 References **89**

A Reviewed Studies Overview **104**
A.1 Abbreviations in Overview . . . 104
A.1.1 Columns . . . 104
A.1.2 Cryptocurrencies . . . 105
A.1.3 Time Granularities . . . 105
A.1.4 Models . . . 106
A.2 Studies on Cryptocurrency Price Prediction . . . 109
A.2.1 Overview . . . 109
A.2.2 Overview Statistics . . . 133
A.3 Studies on Cryptocurrency Price Movement Prediction . . . 139
A.3.1 Overview . . . 139
A.3.2 Overview Statistics . . . 146

B Fundamentals **149**
B.1 Variational Mode Decomposition . . . 149
B.1.1 Mode Definition . . . 149
B.1.2 Formulation . . . 149
B.1.3 Optimization . . . 150
B.2 Temporal Convolutional Network . . . 152
B.2.1 Convolutional Layer . . . 152
B.2.2 Dilated Causal Convolutional Layer . . . 153

C Supplementary Data Analysis **157**
C.1 Dataset Statistics . . . 157
C.2 Price Visualization . . . 158
C.3 Returns Visualization . . . 160
C.4 Autocorrelation Visualization . . . 163
C.4.1 ACF Plots . . . 163
C.4.2 PACF Plots . . . 168
C.5 Interrelationships . . . 173
C.5.1 Pearson Correlation . . . 173
C.5.2 Spearman Correlation . . . 173
C.5.3 Granger Causality . . . 174

D Hyperparameters **179**
D.1 Benchmark Framework . . . 179
D.2 Novel Framework . . . 181

E Supplementary Benchmark Experimental Results **183**
E.1 *BTC/USD* Results . . . 183
E.2 *ETH/USD* Results . . . 184
E.3 *LTC/USD* Results . . . 185
E.4 *XMR/USD* Results . . . 186
E.5 *XRP/USD* Results . . . 187

F Supplementary Novel Experimental Results **188**
F.1 Overall Results . . . 188
F.1.1 DLVMD Results . . . 188
F.1.2 Overfitting . . . 189
F.2 Monthly Results . . . 190
F.2.1 *BTC/USD* . . . 190
F.2.2 *ETH/USD* . . . 199
F.2.3 *LTC/USD* . . . 208
F.2.4 *XMR/USD* . . . 217
F.2.5 *XRP/USD* . . . 226

G Supplementary Experimental Analysis **235**
G.1 Split Analysis: Default Input . . . 235
G.1.1 Benchmark Experiment . . . 235
G.1.2 Extended Experiment . . . 236
G.2 Split Analysis: EVMD Input Modes . . . 240
G.2.1 Benchmark Experiment . . . 240
G.2.2 Extended Experiment . . . 241
G.3 Split Analysis: SVMD Input Modes . . . 244
G.3.1 Benchmark Experiment . . . 244
G.3.2 Extended Experiment . . . 245
G.4 Split Analysis: Expected Outputs . . . 248
G.4.1 Benchmark Experiment . . . 248
G.4.2 Extended Experiment . . . 250

Abstract

Time series are ubiquitous in today's data-rich world, appearing in domains such as finance, transportation, and everyday activities. Time series forecasting focuses on predicting future values based on historical observations. This task can be relatively straightforward when the statistical properties of the time series remain stable over time, i.e., when the time series is stationary. However, this is rarely the case in practice, as most time series exhibit nonstationary behaviour, with their properties fluctuating over time due to factors such as trends and seasonality.

Examples of nonstationary time series are prevalent in the financial domain, particularly in cryptocurrency price data. The cryptocurrency market has experienced significant growth in popularity over the past decade. It has evolved from its initial purpose as a decentralized payment system into a class of assets resembling traditional financial instruments used for investment. As such, there is high demand for forecasting these time series, especially due to the high levels of volatility they exhibit.

In this paper, we propose two novel models for forecasting nonstationary time series, namely Temporal Convolutional Network with Variational Mode Decomposition and Parallel Mode Branches (VMD-PMB-TCN) and Causal Multi-Head Attention-enhanced Temporal Convolutional Network with Variational Mode Decomposition and Parallel Mode Branches (VMD-PMB-CMHA-TCN). The models are proposed after conducting extensive research into state-of-the-art models for forecasting cryptocurrency prices. The methodology leverages VMD to decompose the nonstationary close prices of cryptocurrencies into several more stationary modes that are modeled by separate branches, each consisting of a TCN in the case of VMD-PMB-TCN, and a TCN empowered by a causal multi-head attention mechanism in the case of VMD-PMB-CMHA-TCN. The outcomes of the separate branches are eventually summed to form the 1-step-ahead predictions of cryptocurrency prices.

The results show that the proposed models are competitive over multiple years and able to outperform several TCN-based benchmark models as well as models introduced as part of an ablation study in the daily forecasts of the close prices of *Bitcoin*, *Ethereum*, *Litecoin*, *Monero*, and *Ripple* with respect to specific months.

1 Introduction

In today's digital day and age, cryptocurrencies are widely recognized as one of the more prominent technological advancements in this digital era. Especially in the last few years, cryptocurrencies have become increasingly relevant, as signified by the rapid and large growth of the cryptocurrency market. In June 2025, the cryptocurrency market reached a market capitalization of 4.2 trillion dollars, constituting a growth of more than 500% compared to January 2015 [1]. Furthermore, according to a recent report, more than 741 million people worldwide own a form of cryptocurrency as of 2025, denoting an increase of 12.4% in cryptocurrency ownership compared to 2024 [2].

Cryptocurrencies

The world was introduced to cryptocurrencies for the first time in late 2008 when an individual under the pseudonym Satoshi Nakamoto wrote a paper on the creation of *Bitcoin* (*BTC*) [3]. Subsequently, in early 2009, *Bitcoin* was launched. The initial intention behind *Bitcoin* was to create a fully digital peer-to-peer currency that is decentralized [3]. In other words, online payments using a currency such as this do not involve a third party, such as a bank, nor does a central authority, such as a bank, control ownership and transactions involving this type of currency. Decentralization is achieved via the use of cryptographic proof instead of a trusted third party to protect a peer-to-peer transaction [3]. This has the added benefit of lower transaction costs whilst preventing fraud [3, 4].

The usage of cryptographic proof to achieve decentralization is facilitated by the application of a technology called blockchain, which is an essential building block of *Bitcoin* and the vast majority of other cryptocurrencies like *Ethereum* (*ETH*), *Litecoin* (*LTC*), and *Ripple* (*XRP*), for example [5]. The blockchain functions as a ledger, keeping track of all transactions involving a given cryptocurrency [3, 6]. This ledger is publicly available and kept track of by members of a blockchain network. Each member has a copy of this ledger, making it a public distributed ledger [3, 6]. As the name of the technology suggests, a blockchain is made out of a chain of blocks, with each block consisting of a multitude of transactions [6]. New blocks are added to this chain of blocks after the previous block has reached a maximum size. These blocks are only added to the blockchain after the transactions inside them have been validated, as well as the block itself through cryptographic methods and a consensus protocol [6]. A consensus protocol, in essence, is a protocol in which more than half of the members of a network need to agree on the ledger's state [7].

Various consensus protocols are applied in combination with blockchain technology [8]. *Bitcoin*, for example, makes use of the Proof of Work (PoW) protocol, whereas *Ethereum*, which made use of PoW previously, now makes use of the Proof of Stake (PoS) protocol [8, 9]. The PoW protocol involves a competition between members of a blockchain network, commonly referred to as miners, to be the fastest to solve a puzzle [8]. The more computational power a member has, the more likely said member is to win this competition. The member of the network that solves this puzzle first is the member that is allowed to create a new block and receives a reward, usually a certain amount of cryptocurrency [8]. This member subsequently broadcasts the new block to the rest of the network, which, once a majority of the network has validated the solution to the puzzle, is added to the blockchain [8]. The PoS protocol, on the other hand, consists of members of a blockchain network, also known as validators, who put an amount of cryptocurrency as collateral [8]. The more a member has at stake, the higher the chance said member is selected to validate and create a new block for which the member

is rewarded [8].
Although the initial intention behind cryptocurrencies was for them to be used as a means of payment, their use has also developed into stock-like financial assets utilized for investing and trading. This is further supported by the fact that cryptocurrencies are increasingly included in the portfolios and trading strategies of financial institutions [10]. The interest in cryptocurrencies as financial assets can be attributed to several unique characteristics that these assets possess [10]. First of all, cryptocurrencies are extremely volatile, meaning the prices of cryptocurrencies fluctuate frequently with relatively large swings [10]. According to *Forbes* in 2024, *Bitcoin*, for example, was stated as being the most volatile asset across the market, with it averaging a volatility of just under 50% over the last 10 years [11]. This high volatility is attractive to investors and traders as it provides ample opportunities to make a profit; however, the volatility also makes trading in cryptocurrencies a risky endeavor. Another interesting aspect of cryptocurrencies is that they can be traded at all times [10]. This is especially unique when one considers that stocks can only be traded during the day due to stock exchanges being closed during the night. Stock exchanges are normally also closed on the weekends and holidays. The decentralization of cryptocurrencies and the decreased necessity of identification whilst trading cryptocurrencies are additional attractive aspects of cryptocurrencies [10].

Cryptocurrency Price Prediction
The interest in trading and investing in cryptocurrencies means that methods that can predict the future prices of cryptocurrencies are in high demand. Given how volatile cryptocurrency prices are, it is important for the predictions that are produced to be highly accurate. This is a rather daunting task as the volatility of cryptocurrency prices could be attributed to a vast array of factors that one would potentially need to take into account to produce accurate predictions [12–15]. These factors include market sentiment, aspects of the blockchain underlying a cryptocurrency, macroeconomic factors such as the exchange rate of the *United States Dollar* (*USD*), prices of other cryptocurrencies, technological advances, and regulatory changes such as a government prohibiting the usage of cryptocurrencies [12–15].
The task of cryptocurrency price prediction is commonly considered a time series forecasting task among the literature on the topic [16–52]. Time series forecasting involves the use of what is known as time series data. This refers to data in which the data points are ordered temporally, with each data point recorded at a usually consistent time interval, for example, every minute. Time series forecasting leverages the inherent temporal structure of time series data, using past and present data points to predict future values [53].
The task of predicting the prices of cryptocurrencies is approached from two different angles, namely either as a regression or a classification task. The regression task involves predicting the exact price in the next unit of time, whereas the classification task merely involves predicting the movement of the price in the next unit of time, meaning whether the price increases, decreases, or remains the same. Some studies focus on both tasks [54, 55], whilst others focus on one of the two [16, 56]. Both the regression task and the classification task have been performed at varying time granularities. Certain studies focus on high-frequency price prediction involving the prediction of the price or price movement in the next second or minute [16, 57], and others on predicting the price or its movement for the next day(s) [58, 59]. In this study, we will mainly focus on the regression task.

Approaches

Over the past decade, a large number of methods have been applied to tackle the challenge of predicting the prices of cryptocurrencies [12–15, 60–66]. Initial approaches to address the task of predicting the prices of cryptocurrencies consist of the application of traditional machine learning (ML) models, such as Bayesian Regression (BR) [67], Linear Regression (LR) [68], and Support Vector Machines (SVM) [68]. Later approaches shifted towards more advanced ML models, such as deep learning (DL) models like Convolutional Neural Networks (CNNs) [69] and Recurrent Neural Networks (RNNs) [70]. Besides the application of these methods, statistical time series (STS) models such as Autoregressive Integrated Moving Average (ARIMA) [47] and Vector Autoregression (VAR) [52] have also been employed in an attempt to tackle this problem. On top of the previously listed models, several attempts at predicting the prices of cryptocurrencies include the usage of hybrid models that attempt to incorporate two or more individual methods to combine the strengths of these methods, such as in [40] and [71].

To gain an understanding of the state-of-the-art method(s) with respect to the prediction of cryptocurrency prices, we study several survey papers on the prediction of cryptocurrency prices [12–15, 60–66]. Recent survey papers point to advanced DL architectures and hybrid DL-based architectures as showcasing the most potential in being able to accurately predict cryptocurrency prices [12–14, 60, 63]. Although the survey papers point towards the general direction of the state-of-the-art, the papers do not conclusively state which precise methods can be considered as such; hence, we evaluated the relevant studies cited in the survey papers, as well as several studies outside of the survey papers, individually to facilitate a comparison in performance between the various studies. After evaluating the literature, we conclude that the field of cryptocurrency price prediction is scattered, as noted in [27], and therefore, even after evaluating the studies individually, it is not possible to compare their performance fairly. That the field of cryptocurrency price prediction is scattered can be concluded from a multitude of reasons. First of all, among the evaluated papers, the majority do not compare their results with those of previous research. Since there is no benchmark dataset for cryptocurrency price prediction, the papers make use of varying datasets; hence, it is often the case that the papers that do compare the obtained results to the results of previous research do it, for the most part, in an unfair manner by comparing models trained and tested using datasets that are different in several aspects. Some papers utilize datasets covering a different period in time [57, 72–79], or datasets in which the price of cryptocurrencies are expressed in a different currency [74], or datasets from a different source [57, 72, 73, 75–77, 80] in comparison to the dataset used by the paper the results are being compared to. Additionally, certain papers compare the obtained performance to the performance in a previous paper whilst performing a price prediction at a different time granularity [57, 78, 79], or compare the prediction accuracy of the price of a certain cryptocurrency with the prediction accuracy another paper achieved for a different cryptocurrency [74]. Further unfair comparisons to the results of previous research come in the form of comparing the accuracy obtained in terms of the regression task to that of results of the classification task [34, 79], and the comparison in terms of a certain metric, for example, the Root Mean Square Error (RMSE), in which said metric has been calculated using normalized data in one paper whilst the opposite is the case in the paper that the results are compared to [72]. When independently comparing the results of the existing research, the aforementioned differences between studies make the comparison difficult, on top of the fact that the studies tend to use varying methodologies for training and testing procedures, as well as different methods for preprocessing.

Benchmark Study

Due to the scattered field of cryptocurrency price prediction, the initial step that we take to propose a novel model to advance the field is to identify a study with publicly available source code and data to serve as a benchmark study over which the novel model can be built. Based on the necessary criteria, the study conducted by Murray et al. [27] is selected as the benchmark study.

In an attempt to address the aforementioned difficulties that come with the field of cryptocurrency price prediction being scattered, Murray et al. [27] propose a framework to predict the close prices of *Bitcoin* (*BTC*), *Ethereum* (*ETH*), *Litecoin* (*LTC*), *Ripple* (*XRP*), and *Monero* (*XMR*) in *United States Dollars* (*USD*) using the, according to them, most popular approaches, specifically ARIMA, Gated Recurrent Unit (GRU), k-Nearest Neighbours (KNN), Long Short-Term Memory (LSTM) with a convolutional layer (CNN-LSTM), Random Forest (RF), Support Vector Regression (SVR), Temporal Convolutional Network (TCN), Temporal Fusion Transformer (TFT), and a LSTM-GRU hybrid. In addition to applying several singular models, several ensembles using various combinations of these models are also applied [27]. The models are adopted to perform regression-based predictions of the daily close prices with respect to the mentioned cryptocurrencies. According to the findings of Murray et al. [27], the CNN-LSTM is the most accurate in predicting the daily prices in comparison to all other models, including the ensembles.

An inspection of the source code corresponding to the framework proposed by Murray et al. [27], however, reveals several flaws with the experiments that are conducted in [27], due to which the findings of Murray et al. [27] are unreliable, as we will further detail in Section 5.1.1. After addressing the flaws and rerunning the conducted experiments, the TCN model is actually shown to be more accurate overall.

Proposed Method

Due to the infeasibility of directly comparing most of the reviewed studies, we instead compare the performance of the methods evaluated within each study to identify promising directions for proposing a novel method. Based on this, we identify a promising direction that applies hybrid models that combine a signal decomposition technique with deep learning [25, 44, 81]. Specifically, the utilization of the signal decomposition technique Variational Mode Decomposition (VMD) is shown to achieve promising results when combined with deep learning models [82–94].

The time series of cryptocurrency prices are often of a nonstationary and nonlinear nature [81, 82, 84, 86, 87, 95]. Although deep learning models are adequate for processing data of this kind, they can struggle to fully extract and capture the underlying characteristics of such data [88, 96, 97]. Instead, VMD can be applied to decompose the time series into several more stationary subseries, thereby mitigating the nonlinearity and nonstationarity of the original time series [82, 97]. The subseries, referred to as *modes*, capture the characteristics underlying the time series at varying frequencies. Given that the modes are more stationary, the model's ability to capture the underlying characteristics of the time series can, in principle, be enhanced by extracting them from the individual modes.

Instead of using a single model, numerous studies that adopt VMD for forecasting time series have shown improved performance when using a decomposition-based ensemble [82–85, 92, 96–102]. The decomposition-based ensembles use separate models, each forecasting a specific mode. The produced forecasts are subsequently aggregated to form the forecast of the original time series.

The vast majority of the studied studies that report promising results when combining VMD with a machine learning model to forecast a time series, however, are limited in their approach. This is due to the fact that these studies apply VMD in a manner that leads to data leakage by decomposing the full time series before splitting the data in a training set, validation set, and a test set for evaluation [81–87, 89, 91–94, 98, 99, 101–109]. This results in the modes being determined based on future data as well, causing future data to leak into the model's training process. Due to this, the evaluation of the models yields inflated results that do not reflect the true capabilities of the models in a real-world setting, as we will further demonstrate in Section 6.

Based on the detailed strengths and limitations of the different methods, we propose Temporal Convolutional Network with Variational Mode Decomposition and Parallel Mode Branches (VMD-PMB-TCN) and Temporal Convolutional Network with Variational Mode Decomposition and Parallel Mode Branches (VMD-PMB-CMHA-TCN). VMD-PMB-TCN builds upon the efficacy shown by TCN after rerunning the experiments conducted by Murray et al. [27] without the original experimental flaws. VMD-PMB-TCN is composed of parallel branches, where each branch is composed of a TCN to process and forecast a specific mode. By aggregating the separate forecasts, the model produces a forecast for the original time series. As described, the TCNs are not separate models but rather separate components of the same model. This is because VMD is applied in a leakage-free manner by only decomposing the time steps preceding the target output. As a result, the value of each mode at the target time step is unknown, preventing the TCN branches from being trained as separate models to forecast each individual mode.

In an attempt to improve upon VMD-PMB-TCN, VMD-PMB-CMHA-TCN adds a causal multi-head attention mechanism to each branch after the TCN. The attention mechanism is used to emphasize the most important time steps with respect to each separate forecast. In studies that have adopted attention mechanisms, its addition to a model's architecture is shown to improve performance [82, 103, 110–130].

At the foundation of the proposed methods is a novel framework based on that of Murray et al. [27]. The framework consists of the same experiments as those in the framework proposed by Murray et al. [27] to benchmark the proposed method. To further achieve this, the TCN adopted by Murray et al. [27] and the TCN proposed by Bai et al. [131] are included in the framework as well, alongside the Causal Multi-Head Attention-enhanced Temporal Convolutional Network (CMHA-TCN) to facilitate an ablation study. The novel framework, furthermore, extends the original framework by incorporating additional experiments using an expanded dataset from 1 June 2017 to 31 May 2025 to produce forecasts in a more recent context.

Research Questions

In the course of this study, we attempt to answer the following research questions:

- How do the models adopted by Murray et al. [27] actually compare to one another?
- Can VMD-PMB-TCN and VMD-PMB-CMHA-TCN improve upon the selected benchmark models and the models included in the ablation study?
- How do VMD-PMB-TCN and VMD-PMB-CMHA-TCN compare to one another?
- What is the effect of applying VMD in a leakage-free manner? And, what is the effect of applying VMD in a manner that leads to data leakage?

Contributions
The study makes the following contributions:

- Performs an extensive review of the existing research on cryptocurrency price prediction.
- Builds upon the study conducted by Murray et al. [27], to address the scattered field of cryptocurrency price prediction.
- Addresses flaws in the experimentation conducted by Murray et al. [27].
- Addresses limitations of previous studies to have employed VMD for cryptocurrency price prediction and other time series forecasting tasks by applying it in a manner that prevents data-leakage [81–87, 89, 91–94, 98, 99, 101–109].
- Evaluation of the novel VMD-PMB-TCN and VMD-PMB-CMHA-TCN models for cryptocurrency price prediction.
- Evaluation of the efficacy of applying VMD in a leakage-free manner.
- Evaluation of the influence of data leakage when applying VMD to the time series prior to splitting it into a training, validation, and test set.
- Evaluation of the efficacy of applying VMD to a nonstationary and nonlinear time series in comparison to applying differencing and no transformation of that kind.

The remainder of this paper is structured as follows. In Section 2, the related work is reviewed. Section 3 provides fundamental theoretical background about important concepts at the center of the study. Section 4 describes the proposed methodology. Section 5 outlines the experimental setup. The results of the experiments are presented in Section 6. Finally, Section 7 concludes the paper and suggests directions for future work.

2 Related Work

For the current research on cryptocurrency price prediction, a total of 130 papers are initially studied, consisting of 11 survey papers and 115 individual papers. As argued in the Introduction, it is not possible to conclusively ascertain from the survey papers which methods are state-of-the-art when it comes to cryptocurrency price prediction. As a result, we conduct an individual evaluation of the results in the relevant studies cited in the survey papers, as well as in several studies outside these survey papers.

2.1 Overview

Upon the results of the studies having been evaluated, we make an overview consisting of the results of each study grouped based on the time granularity at which the cryptocurrency price prediction is performed, the considered cryptocurrency, and the type of task corresponding to the results, namely either (*exact*) *cryptocurrency price prediction* (regression) or *cryptocurrency price movement prediction* (classification). The results considered are those with respect to the most frequently discussed cryptocurrencies in the examined literature consisting of *Bitcoin* (*BTC*), *Ethereum* (*ETH*), *Litecoin* (*LTC*), *Monero* (*XMR*), *Ripple* (*XRP*), *Dogecoin* (*DOGE*), *Cardano* (*ADA*), *EOS.IO* (*EOS*), *Binance Cash* (*BCH*), *Binance Coin* (*BNB*), *Dash* (*DASH*), *Stellar* (*XLM*), *Polkadot* (*DOT*), *Solana* (*SOL*), *Tether* (*USDT*), *TRON* (*TRX*), *Zcash* (*ZEC*), *Amp* (*AMP*), *Cosmos* (*ATOM*), *Avalanche* (*AVAX*), *Chainlink* (*LINK*), *Terra* (*LUNA*), *Polygon* (*MATIC*), and *New Economy Market* (*NEM*).

2.1.1 Aspects in Overview

For each paper, the following aspects, other than the results, are noted in the overview:

- The time period that is covered by the adopted dataset.
- The number of observations that are used for evaluating the models.
- The type of data that is used as input to the models, either univariate or multivariate.
- The features that are used as input to the models.
- The time granularity of the prediction interval.
- The models that are applied.
- The top performing model(s) based on the reported metrics.
- The availability of the source code.
- The normalization of the results.

With respect to the results, the performance in terms of the most prominent metrics that are used across the papers concerning the type of task, either classification or regression, is reported. The metrics that are kept track of regarding the regression task, *cryptocurrency price prediction*, are:

- the Root Mean Squared Error (RMSE), given by (31).
- the Mean Absolute Percentage Error (MAPE), given by (35).
- the Mean Absolute Error (MAE), given by (33).
- the Regression Accuracy, given by (39).

On the other hand, the metrics that are kept track of regarding the classification task, *cryptocurrency price movement prediction*, are:

- the Classification Accuracy, given by (40).
- the Precision, given by (41).
- the Recall, given by (42).
- the F1 Score, given by (43).

2.1.2 Structure of Overview

The resulting overview can be found in Appendix A, where A is structured as follows:

- In A.1, the definitions of the abbreviations used in the overview can be found, where:
  - Table 8 contains the definitions of the abbreviations with respect to the columns of the overview.
  - Table 9 contains the definitions of the abbreviations with respect to the cryptocurrencies in the overview.
  - Table 10 contains the definitions of the abbreviations with respect to the time granularities of the time intervals in the overview.
  - Table 11 contains the definitions of the abbreviations with respect to the names of the models in the overview.
- A.2 is subdivided into A.2.1 and A.2.2, where:
  - A.2.1 contains the overview of the studies concerning *cryptocurrency price prediction*, including:
    - Table 12: the studies and the reported results at second-level intervals.
    - Table 13: the studies and the reported results at minute-level intervals.
    - Table 14: the studies and the reported results at hourly intervals.
    - Table 15: the studies and the reported results at daily intervals.
  - A.2.2 consists of the statistics with respect to the overview in A.2.1, where:
    - Table 16 shows the number of studies by applied model.
    - Table 17 shows the number of studies by forecasted cryptocurrency.
    - Table 18 shows the number of studies by data type.
    - Table 19 shows the number of studies by feature type.
    - Table 20 shows the number of studies with publicly available source code.

- A.3 is subdivided into A.3.1 and A.3.2, where:
  - A.3.1 contains the overview of the studies concerning *cryptocurrency price movement prediction*, comprising:
    * Table 21: the studies and the reported results at second-level intervals.
    * Table 22: the studies and the reported results at minute-level intervals.
    * Table 23: the studies and the reported results at hourly intervals.
    * Table 24: the studies and the reported results at daily intervals.
  - A.3.2 consists of the statistics with respect to the overview in A.3.1, where:
    * Table 25 shows the number of studies by applied model.
    * Table 26 shows the number of studies by forecasted cryptocurrency.
    * Table 27 shows the number of studies by data type.
    * Table 28 shows the number of studies by feature type.
    * Table 29 shows the number of studies with publicly available source code.

2.1.3 Preliminary Observations

As shown by Tables 16 and 25, respectively, Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), AutoRegressive Integrated Moving Average (ARIMA), and Support Vector Machine (SVM) are the most frequently applied models among the reviewed literature with respect to *cryptocurrency price prediction*, whereas SVM, LSTM, Random Forest (RF), and Convolutional Neural Network (CNN) are the most frequently applied models with respect to *cryptocurrency price movement prediction*. Furthermore, Tables 17 and 26 demonstrate that most reviewed studies focus on the prediction of the price or price movement of *BTC*, with the vast amount of said studies solely focusing on *BTC*. Besides *BTC*, the reviewed studies mostly focus on predicting the price or price movements of *ETH*, *LTC*, and *XRP*.
Based on Tables 18 and 27, the majority of studies use a multivariate approach to predict prices and price movements. Tables 19 and 28 display that the utilization of candlestick data, consisting of the open price, high price, low price, close price, and volume (OHLCV), and other historical market data as features are the most prominently adopted features followed by blockchain data, for example the hash rate of the blockchain network, technical indicators, such as Bollinger Bands, macroeconomic data, like the price of gold, historical market data of other cryptocurrencies, and *Twitter* / *X* data or sentiment.

2.1.4 Scope and Structure of Literature Review

The overview demonstrates that the range of methods that are used to predict cryptocurrency prices and price movements is vast. The applied models can be categorized into roughly three groups: Statistical Time Series (STS) models; Machine Learning (ML) models, including Traditional ML and Deep Learning (DL) models; and hybrid models. In the remainder of the Related Work, we discuss how these categories of models perform relative to one another, and how the models within each category fare in comparison to one another. The listed comparisons mainly focus on the studies in relation to the regression task, *cryptocurrency price prediction*, as that is the focus of this study. Although the initial intention was to perform these comparisons using the results reported by each study in the overview, we ultimately deemed this

approach infeasible due to the scattered nature of the field of cryptocurrency price prediction. For instance, differences in metric calculation, evaluation periods, and datasets across studies render direct comparisons of the reported results unreliable. As such, the approach taken focuses on in-study comparisons. The scattered nature of the field is further emphasized by the lack of publicly available source code and accompanying datasets, as highlighted in Tables 20 and 29. The Related Work will conclude with a justification of the proposed model.

2.2 Statistical Time Series Models

The STS models that are applied to *cryptocurrency price prediction* include AutoRegression (AR) [47], AutoRegressive Integrated Moving Average (ARIMA) [27, 30, 32, 38–40, 42, 44, 47, 48, 50–52, 60, 70, 78, 81, 132–136], Autoregressive Integrated Moving Average with Exogenous Variable (ARIMAX) [33, 44], Autoregressive Fractionally Integrated Moving Average (ARFIMA) [30], Bayesian Vector AutoRegression (BVAR) [52], FaceBook Prophet (FBProphet) [33, 38], Moving Average (MA) [47], Seasonal AutoRegressive Integrated Moving Average (SARIMA) [50], and Vector AutoRegression (VAR) [52]. Among the considered literature, ARIMA is the most frequently adopted STS model for *cryptocurrency price prediction*, with no other STS model adopted nearly as often.

2.2.1 Statistical Time Series Models vs. Machine Learning-based Models

The comparison in performance between the models that are applied within the individual papers that adopt STS models demonstrates that, regardless of the time interval of the predictions and time period over which the predictions are made, ML-based models tend to outperform STS models in *cryptocurrency price prediction* [27, 30, 32, 39, 40, 42, 42, 44, 48, 50, 60, 70, 78, 81, 132–134, 134–136]. In particular, DL-based sequence models, such as RNNs and TCNs, and hybrid models built on these architectures have been shown to yield significant improvements in recorded error metrics compared to STS models [39, 40, 70, 81, 132, 133]. For example, in [39] and [40], ML- and DL-based models produce a lower RMSE, MAE, and MAPE by at least 60–70%, in comparison to ARIMA, while in [132], an LSTM similarly produces a lower RMSE, MAE, and MAPE by 80–90%, relative to those produced by ARIMA.
The tendency of ML-based models to outperform STS models in *cryptocurrency price prediction* is consistent with the nature of cryptocurrency price data and the assumptions underlying STS models [12, 81, 83, 84, 87]. STS models assume and require that the data is linear and stationary in nature, as defined in Section 3.1.2. Given the high amount of volatility that cryptocurrency prices exhibit, cryptocurrency prices typically suffer from nonstationarity and are of a non-linear nature [81, 82, 84, 86, 87, 95]. ML-based models, particularly DL-based models, have been shown to perform well when applied to complex nonlinear data and are therefore better suited to *cryptocurrency price prediction* [137].

2.3 Machine Learning Models

The application of individual ML models is the most frequently adopted approach to *cryptocurrency price prediction* among the considered studies. These models can further be categorized as either traditional ML models or DL models.

2.3.1 Traditional Machine Learning Models

The traditional ML approaches comprise of AdaBoost [42, 72, 138], Bayesian Regression (BR) [52, 133], Bayesian Ridge Regression (BRR) [37, 139], CatBoost [19], Decision Trees (DT) [37, 138], Extra Trees (ET) [140], Gradient Boosted Trees (GBT) [34], Gradient Boosting (GB) [32, 37, 138, 141], Gradient Boosting Machine (GBM) [72], Gaussian Poisson Regression (GPR) [17], Huber Regression (HR) [142], k-Nearest Neighbours (KNN) [17, 27, 34, 37, 138, 143], Lasso [37, 138], Least-Squares Support Vector Regression (LSSVR) [135], Light Gradient Boosting Machine (LGBM) [42, 138], Linear Regression (LR) [22, 31, 32, 37, 81, 138–141, 143–145], Ordinary Least Squares (OLS) [146], Random Forest (RF) [19, 27, 31, 32, 37, 39, 40, 138, 140, 141, 147, 148], Regression Trees (RT) [17], Ridge [37, 138], Support Vector Machine (SVM) / Support Vector Regression (SVR) [17, 27, 28, 32, 37–40, 54, 55, 81, 133, 135, 136, 138–140, 144–146, 149], Theil-Sen Regression (TSR) [139, 142], Twin Support Vector Regression (TWSVR) [135], and eXtreme Gradient Boosting (XGBoost) [19, 33, 39, 40, 72, 78, 138, 140]. Among traditional ML models, SVM is the most frequently applied for *cryptocurrency price prediction* in the considered studies, by a significant margin, followed by LR and RF.

2.3.2 Deep Learning Models

In terms of individual ML models, the models that are applied the most in the considered literature are DL models, namely Backpropagation Neural Network (BPNN) [23, 28], Bayesian Neural Network (BNN) [44, 144, 150], Bayesian Regularization Neural Network (BRNN) [17], Bidirectional Gated Recurrent Unit (BiGRU) [151, 152], Bidirectional Long Short-Term Memory (BiLSTM) [26, 35, 38, 58, 60, 78, 80, 81, 151–155], Convolutional Neural Network (CNN) [19, 23, 35, 39, 40, 44, 55, 60, 69, 72, 136, 138, 143, 147, 155–157], DLinear [43], Deep Neural Network (DNN) [16, 34, 37, 54, 55, 138, 140, 158], Feedforward Neural Network (FFNN) [17, 18, 72, 136, 150], Gated Recurrent Unit (GRU) [14, 16, 19, 26, 27, 35, 39, 40, 42, 49, 57, 58, 69, 72, 78–80, 142, 151–153, 155, 158–163], Generalized Regression Neural Network (GRNN) [36], ITransformer [43], Long Short-Term Memory (LSTM) [14, 16, 19, 22–26, 29, 31, 35, 36, 38–40, 42–45, 48–50, 55, 57, 58, 60, 69–71, 73, 78–80, 95, 132–134, 136, 139–142, 147–152, 155–160, 162–168], LSTMNet [43], ModernTCN [43], Multilayer Perceptron (MLP) [39, 40, 42–44, 60, 134, 146, 149, 157, 165], NeuralProphet [45], PatchTST [43], Probablistic BiGRU (P-BiGRU) [151], Probablistic BiLSTM (P-BiLSTM) [151], Probablistic GRU (P-GRU) [151], Probablistic LSTM (P-LSTM) [151], Radial Basis Function Neural Network (RBFNN) [17], Recurrent Neural Network (RNN) [35, 42, 44, 54, 70, 78], Residual Neural Network (ResNet) [55], SegRNN [43], State-Frequency Memory Recurrent Neural Network (SFM) [44], Stacked Denoising Autoencoder (SDAE) [28], Stochastic LSTM [165], Stochastic MLP [165], Temporal Convolutional Network (TCN) [27, 43, 149, 162], Temporal Fusion Transformer (TFT) [27, 45], Time Distributed BiGRU (TD-BiGRU) [151], Time Distributed BiLSTM (TD-BiLSTM) [151], Time Distributed GRU (TD-GRU) [151], Time Distributed LSTM (TD-LSTM) [151], TimeMixer [43], and Transformer [43, 60, 74, 149, 164], where certain studies used the mentioned individual models in tandem through ensembles [27, 34, 55, 57, 146, 162]. LSTM is the most widely applied DL model for *cryptocurrency price prediction* across the considered studies, by a substantial margin, followed by GRU and CNN.

2.3.3 Traditional Machine Learning Models vs. Deep Learning Models

Similar to the findings in Section 2.2.1, among studies that apply both traditional ML and DL-based models, the latter tend to be more accurate in predicting cryptocurrency prices, regardless of the time interval of the predictions or the period over which the predictions are conducted [17, 19, 27, 28, 31, 38, 39, 42, 55, 72, 81, 133, 136, 139, 140, 142–144, 147, 149]. For example, in [19], DL models produce a lower RMSE and MAE by at least 80–90% in comparison to several traditional ML models. Similarly, in [139], an LSTM produces a lower RMSE and MAE by 60–90% compared to several traditional ML models. The efficacy of DL-based models relative to traditional ML models in *cryptocurrency price prediction* is particularly evident in DL-based sequence models and hybrid models built on these architectures [19, 27, 31, 38, 39, 55, 72, 81, 133, 139, 140, 142, 147, 149]. DL-based models have been demonstrated to possess an enhanced ability to process complex nonlinear data, capture nonlinear temporal dependencies and complex patterns, and exhibit greater robustness to noise [27, 40, 43]. Among DL-based models, sequence models are particularly proficient at capturing temporal dependencies [169]. Given the nonlinear, nonstationary, and consequently complex nature of cryptocurrency price data, the tendency of DL-based models to outperform traditional ML models is consistent with their characteristics.

Among the DL-based models, LSTM- and GRU-based models are generally more accurate than other DL-based models applied within the individual papers with respect to *cryptocurrency price prediction* [16, 23, 27, 35, 36, 39, 40, 44, 54, 60, 69, 72, 78, 134, 136, 140, 155–158]. It is important to note, however, that these models are among the most extensively studied in the considered literature. In contrast, other sequence models, such as TCN- and Transformer-based models, are relatively under-explored and have been shown to be capable of achieving a performance that is competitive with, and in some cases superior to, that of LSTM- and GRU-based models [43, 44, 162, 164].

2.4 Hybrid Models

Following the application of numerous individual models, efforts were made to further improve *cryptocurrency price prediction* by proposing hybrid models that combine 2 or more methods, incorporating the strengths of the individual methods while mitigating their inherent limitations. The hybrid models that are applied to *cryptocurrency price prediction* in the considered studies consist of AE-GRU [170], AE-LSTM [170], ARIMA-CNN [136], ARIMA-FFNN [136], ARIMA-LSTM [42, 136], ARIMA-MLP [42], ARIMA-SVR [136], BiLSTM with Variational Mode Decomposition (VMD-BiLSTM) [81], Binary Autoregressive Tree (BART) [30], CNN-BiLSTM [20, 21], CNN-GRU [39, 40, 78], CNN-LSTM [20, 21, 23, 27, 39–41, 45, 46, 55, 78, 156, 157], CNN-LSTM with Attention Mechanism (CNN-LSTM-AM) [46], CNN-RNN [55], Convolutional LSTM (ConvLSTM) [60, 156], Deep Learning Linear Support Vector Regression (DSVR) [59], Deep Neural Decision Trees (DNDT) [59], Deep Recurrent Convolutional Neural Network (DRCNN) [59], DNN-LSTM [171], GRU-TCN [162], LSTM-AR [24], LSTM-GRU [14, 27, 49, 71, 162, 163, 172], LSTM-RNN [39, 160], LSTM-TCN [162], LSTM with Attention Mechanism (LSTM-AM) [171], LSTM with Change Point Detection (LSTM-CPD) [95, 168], LSTM with Attention Mechanism and Change Point Detection (LSTM-AM-CPD) [95], LSTM with Dual Attention Mechanism (DAM-LSTM) [45], Long Short-Term Memory with Empirical Mode Decomposition (EMD-LSTM) [81], Long Short-Term Memory with Empirical Wavelet Transform (EWT-LSTM) [25], LSTM with Empirical Wavelet Transform and Cuckoo Search (EWT-LSTM-CS) [25], Multi-Input CNN-LSTM (MI-

CNN-LSTM) [41], Multi-Scale Residual CNN-LSTM (MRC-LSTM) [157], Support Vector Regression with Principal Component Analysis (PCA-SVR) [28], Self-Attention based Multiple LSTM (SAM-LSTM) [95], SAM-LSTM with Change Point Detection (SAM-LSTM-CPD) [95], SVR-BNN [150], SVR-FFNN [150], SVR-LSTM [150], Weighted and Attentive Memory channels (WAMC) [40], and Causal Multi-Head Attention Temporal Convolutional Network with Wavelet Transform (WT-CATCN) [44].

2.4.1 Statisitical Time Series and Machine Learning Hybrid Models

In an attempt to further improve the accuracy of *cryptocurrency price prediction*, Wu et al. [24], Nguyen et al. [136], and Bouteska et al. [42] apply hybrid models that combine STS models with ML models and compare the performance to that of several individual models.

Improved Results after Hybridization
In [24] and [136], the application of these hybrid models results in minor improvements of the prediction accuracy compared to the individual models. In [24], Wu et al. proposes an LSTM-AR model for the daily price prediction of *BTC*, which improves predictive performance by approximately 3–5% in terms of the reported RMSE, MAE, and MAPE compared to an individual LSTM. Even smaller gains in predictive performance are reported in [136], where Nguyen et al. introduces the hybrid models ARIMA-FFNN, ARIMA-CNN, ARIMA-LSTM, and ARIMA-SVR for the daily close price prediction of *BTC*. Compared to the individual ARIMA, FFNN, CNN, LSTM, and SVR models, these hybrids achieve only marginal improvements, reducing RMSE and MAPE by approximately 0–1%.

Inferior Results after Hybridization
In [42], on the other hand, the adopted STS-ML hybrid models, ARIMA-MLP and ARIMA-LSTM, are generally outperformed by several individual ML- and DL-based models, including MLP, LSTM, AdaBoost, LightGBM, RNN, and GRU, in the price prediction of *BTC*, *ETH*, *LTC*, and *XRP*. In terms of the reported RMSE, MAE, and MAPE, the STS–ML hybrid models are on occasion more than 20% less effective than the strongest individual models.

2.4.2 Traditional Machine Learning and Deep Learning Hybrid Models

Improved Results after Hybridization
Instead of STS-ML hybrid models, Cocco et al. [150] compare the performance of the individual DL models BNN, FFNN, and LSTM with that of the hybrid traditional ML-DL models SVR-BNN, SVR-FFNN, and SVR-LSTM for the daily price prediction of *BTC* and *ETH*. The results indicate that SVR-FFNN and SVR-LSTM significantly improve upon FFNN and LSTM, respectively, reducing MAPE by approximately 40–50%. On the contrary, SVR-BNN is shown to be less accurate than its individual counterpart, BNN, producing a significantly lower MAPE. Overall, the individual BNN achieved the lowest MAPE among all considered models.

2.4.3 CNN-based Deep Learning Hybrid Models

Most of the considered studies that adopt hybrid models use CNN-based DL hybrid models [20, 21, 23, 27, 39–41, 45, 46, 55, 60, 78, 156, 157]. The performance of CNN-based DL hybrid models, compared with individual models, varies considerably across studies [23, 27, 39, 40, 45, 55, 60, 78, 156, 157], where certain studies report substantial improvements when

applying CNN-based DL hybrid models [39, 40, 60, 157], and others report no improvements whatsoever [45, 55].

Improved Results after Hybridization

The studies conducted by Guo et al. [157], Murray et al. [27], Wu et al. [60], Nasirtafreshi [39], and Zhang et al. [40] demonstrate that CNN-based deep learning hybrid models achieve a higher predictive performance compared to individual models. In [157], Guo et al. propose a hybrid CNN-based model entitled Multi-scale Residual CNN and LSTM (MRC-LSTM) to predict the daily close price of *BTC*, *ETH*, and *LTC*. The MRC-LSTM's architecture consists of a 1-dimensional convolutional layer, a so-called "Multi-Scale Residual Block", an LSTM, and an MLP. The block consists of three 1-dimensional convolutional layers with varying kernel sizes for feature extraction at varying time scales, a 2-dimensional convolutional layer to which the concatenated output of the three 1-dimensional convolutional kernels is fed, allowing for cross-channel fusion, and a skip connection that leads into the concatenation operation from the layer before the block, equipping the block with residual learning. Besides MRC-LSTM, Guo et al. [157] also apply MLP, LSTM, CNN, and CNN-LSTM for the daily close price predictions. The results of the study demonstrate that MRC-LSTM achieves an approximately 3–6%, 9–12%, and 30–51% lower RMSE, MAE, and MAPE in the daily close price prediction of *BTC*, *ETH*, and *LTC*, respectively, compared to the second-best performing model. The CNN-LSTM improves upon the error metrics of the individual models by approximately 6–8% and 3–16% with respect to *BTC* and *LTC*, however, produces 1–8% worse error metrics with respect to *LTC*.

Furthermore, and as previously described in the Introduction, Murray et al. [27] adopt the hybrid models CNN-LSTM and LSTM-GRU as well as ARIMA, GRU, KNN, RF, SVR, TCN, TFT, and several ensembles for the daily close price prediction with respect to *BTC*, *ETH*, *LTC*, *XRP*, and *XMR*. According to the results reported by Murray et al. [27], the CNN-LSTM is the most accurate, with an RMSE, MAE, and MAPE 3% lower than those of the GRU, which has the second-lowest reported error metrics. The model with the third-lowest reported error metrics is the other hybrid model, LSTM-GRU.

Additionally, in [60], Wu et al. not only conduct a survey on cryptocurrency price prediction, but also employ ARIMA, MLP, CNN, LSTM, BiLSTM, ConvLSTM, and Transformer to predict the daily close price of *BTC*, *ETH*, *LTC*, and *DOGE*. Overall, the results of the experiments conducted by Wu et al. [60] demonstrate the ConvLSTM to be the more accurate model based on reducing the reported RMSE by approximately 5—30% relative to the second most accurate model based on these same metrics.

On the other hand, in [39], Nasirtafreshi proposes an LSTM-RNN hybrid to predict the daily close price of *ETH*. In addition to the LSTM-RNN hybrid, Nasirtafreshi [39] applies individual models ARIMA, SVR, RF, XGB, MLP, LSTM, GRU, and CNN as well as hybrid models CNN-LSTM and CNN-GRU. According to the resulting RMSE, MAE, and MAPE, the LSTM-RNN is the most accurate model, with error metrics approximately 30–40% lower than those of the CNN-GRU. The CNN-LSTM is shown to be the third-most-accurate model, with error metrics that are 8–12% higher than those of the CNN-GRU. The CNN-LSTM, in turn, outperforms the most accurate individual model, CNN, by 5–9% across the recorded error metrics.

Lastly, in [40], Zhang et al. propose the hybrid model Weighted and Attentive Memory channels (WAMC), consisting of an attentive memory module, a channel-wise weighting module, and a convolution and pooling module, to predict the daily close prices of *ETH* and *BCH*. The WAMC model is a multi-input model, with each input channel corresponding to the time

series of the price of a specific cryptocurrency, including one channel containing the price of the target cryptocurrency. The goal of multiple input channels is to leverage the inherent correlations among cryptocurrency prices to enhance the prediction accuracy. The attentive memory module comprises a GRU and an MLP with one hidden layer that serves as a self-attention mechanism for each input channel. The goal of the module is to identify the most important time steps for cryptocurrency price forecasting. The channel-wise weighting module comprises a GRU per channel, with each GRU producing an encoding. The encodings are combined and further processed by several dense layers to determine the weights per channel. The weights indicate the importance of each channel with respect to the prediction. Finally, the output of the attentive memory module and the weights determined by the channel-wise weighting module are combined and fed to the convolution and pooling module. The convolution and pooling module comprises a 2-dimensional CNN with convolutional layers followed by max-pooling. The role of the CNN is to learn local features. Based on the learned features, the price of the target cryptocurrency is predicted. Alongside the proposed hybrid model, the hybrid models CNN-LSTM and CNN-GRU are applied, as well as the individual models ARIMA, SVR, RF, XGBoost, MLP, LSTM, GRU, and CNN. Compared with the RMSE, MAE, and MAPE produced by the other models, WAMC is shown to be 10–30% more accurate. Based on the same error metrics, CNN-GRU is the second-most accurate model, followed by CNN-LSTM, which produces approximately 3–20% lower error metrics than the most accurate individual model, CNN.

Mixed Results after Hybridization

In contrast to the previously discussed studies, the findings reported by Kilimci et al. [156], Li and Dai [23], and Kang et al. [78] are mixed regarding whether CNN-based deep learning hybrid models are more accurate than individual models. In [156], Kilimci et al. apply hybrid models ConvLSTM and CNN-LSTM alongside individual models LSTM and CNN to forecast the hourly price of *BTC*. Based on the recorded RMSE, MAE, and MAPE, ConvLSTM is the most accurate model, reducing the error metrics of the other models by approximately 30–60Furthermore, in [23], Li and Dai propose a CNN-LSTM hybrid model for the daily price prediction of *BTC*, with the CNN serving as an extractor of the important characteristics that affect the price of *BTC* and the LSTM forecasts the price based on these extracted characteristics. In addition to the proposed model, Li and Dai [23] apply individual models: DNN, CNN, and LSTM. The results of the experiment show that CNN-LSTM yields the lowest RMSE and MAE by 1–2%, whereas the CNN produces the lowest MAPE by approximately 15% compared to CNN-LSTM.

Finally, in [78], Kang et al. propose a CNN-GRU hybrid model for the price prediction of cryptocurrencies. The proposed CNN-GRU consists of a 1-dimensional convolutional layer stacked on top of 2 GRUs, followed by a dense layer. The intuition behind the proposed model's architecture is that the convolutional layer extracts salient features and suppresses noise, whilst the GRUs capture long-term dependencies. To assess the efficacy of the proposed model, it, alongside ARIMA, RNN, FBProphet, GRU, LSTM, CNN-LSTM, BiLSTM, and XGBoost, is utilized to predict the close price of *BTC*, *ETH*, and *XRP* at a 1-minute interval. Based on the results reported by Kang et al. [78], the proposed CNN-GRU hybrid is shown to be more accurate than all other models by a small margin at predicting the 1-minute close prices of *BTC*, *ETH*, and *XRP*. The CNN-LSTM, on the other hand, is shown to be less accurate than a multitude of individual models.

Inferior Results after Hybridization

The research conducted by Ji et al. [55] and Fu et al. [45] appears to demonstrate that individual models are more accurate than CNN-based hybrid DL models. In [55], Ji et al. apply the hybrid model CNN-LSTM alongside DNN, LSTM, CNN, SVM, ResNet, and an ensemble model for the daily price prediction of *BTC*. According to the findings of Ji et al. [55], the LSTM was shown to be slightly more accurate than the other models.
Additionally, in [45], Fu et al. propose DAM-LSTM, which combines an LSTM with a novel dual-attention mechanism (DAM) for forecasting cryptocurrency prices using multimodal data. DAM consists of two unimodal attention modules applied to different data modalities. Subsequently, the outputs of both attention modules are combined to enable data fusion. The architecture, as described, allows DAM to capture cross-modal and intra-modal information. For evaluation, DAM-LSTM as well as CNN-LSTM and individual models LSTM, NeuralProphet, and TFT are utilized to predict the daily price of *BTC*. The results of the evaluation show DAM-LSTM to be more accurate 10-20% in terms of MAE and MAPE compared to the second-most accurate model, LSTM, which outperforms CNN-LSTM by 5–10%.

2.4.4 Sequence Model-based Deep Learning Hybrid Models

The second-most-adopted type of hybrid model in the considered literature is the DL hybrid model, which combines different sequence models [14, 27, 39, 49, 71, 160, 162, 163, 172]. Similar to the performance of CNN-based DL hybrid models, the reported performance of sequence model-based DL hybrid models varies across the relevant studies in comparison to the performance of individual models [14, 27, 39, 49, 71, 162, 163, 172], with certain studies reporting significant reductions of the recorded error metrics when applying sequence model-based DL hybrid models [39, 49, 71], and other studies reporting increased error metrics when doing so [14, 27].

Improved Results after Hybridization
As previously discussed in Section 2.4.3, the results reported by Nasirtafreshi [39] demonstrate an LSTM-RNN hybrid to be more accurate than all other models adopted by Nasirtafreshi [39] in terms of the daily close price prediction of *ETH* by an approximate margin of 30-40%. In comparison to the individual models, the LSTM-RNN is shown to be more accurate by an approximate margin of 40-50%.
In addition to the study conducted by Nasirtafreshi [39], the research performed by Tanwar et al. [163], Patel et al. [71], and Girsang and Stanley [49] show sequence model-based DL hybrid models to be more accurate than individual models in terms of *cryptocurrency price prediction*. In [163], Tanwar et al. propose an LSTM-GRU hybrid model for the daily price prediction of *LTC* and *ZEC*. The proposed LSTM-GRU is based on the existing interdependencies between a cryptocurrency and its parent cryptocurrency and on how leveraging these interdependencies could improve price prediction accuracy. With respect to *LTC* and *ZEC*, *BTC* serves as their parent cryptocurrency, as both were created from *BTC*. To incorporate this interdependency, the price movement of *BTC* serves as input to the respective model, alongside the price data of *LTC* or *ZEC*, depending on the current target cryptocurrency. The LSTM-GRU proposed by Tanwar et al. [163] has a unique architecture in that it uses multiple input channels. The price data of the target cryptocurrency serves as input to the LSTM-GRU through 2 different channels. The price data serves as input to an LSTM stacked upon a GRU, followed by a dense layer, whilst also serving as input to an LSTM, followed by a dense layer. The direction of *BTC* is separately fed to two dense layers. Finally, the outputs of all channels are concatenated and

used to produce the prediction. To validate the proposed model, its results are compared with those of the individual LSTM and GRU models. The results demonstrate that the proposed LSTM-GRU is slightly more accurate overall for the price prediction of *LTC* as well as *ZEC*, based on the reported RMSE.

Similar to Tanwar et al. [163], Patel et al. [71] also propose an LSTM-GRU hybrid for the daily price prediction of *LTC* and *XMR*. Based on the efficacy of LSTMs and GRUs in tasks involving sequential data and their resilience to the vanishing gradient problem, Patel et al. [71] propose combining LSTM and GRU to capitalize on the strengths of each model individually. The architecture of the proposed model is a 2-input model, in which the price data for a cryptocurrency is passed to both input channels. The first input channel consists of an LSTM followed by another LSTM and a dense layer. The other input channel consists of a single GRU, followed by a dense layer. The outputs of each channel are combined with another dense layer, after which the model produces a prediction of the respective cryptocurrency's price. Alongside the proposed model, Patel et al. [71] apply an individual LSTM. The evaluation of both models shows the LSTM-GRU to be more accurate by a significant margin, with the LSTM-GRU producing an RMSE, MAE, and MAPE that are at times lower by approximately 60–90%.

In line with both Tanwar et al. [163] and Patel et al. [71], Girsang and Stanley [49] propose an LSTM-GRU hybrid model as well for predicting the daily close price of *ETH* and *SOL*. The idea behind combining an LSTM and a GRU into a single model is to strike a balance between memory capacity and complexity, tackle exploding and vanishing gradients, and aid in controlling the gradient and information flow. The architecture of the LSTM-GRU consists of feeding the data separately to two channels: one with two LSTMs followed by a dense layer, and the other with a GRU followed by a dense layer. The outputs of both channels serve as input to a dense layer to make the final prediction. Besides the LSTM-GRU hybrid, Girsang and Stanley [49] apply the individual counterparts LSTM and GRU. The results of the study indicate that LSTM-GRU is 20–30% more accurate than LSTM and GRU, based on the reported RMSE, MAE, and MAPE.

Mixed Results after Hybridization

Politis et al. [162] report mixed results with respect to sequence model-based DL hybrid models being more effective than individual models. In [162], Politis et al. apply several sequence model-based hybrid models to predict the price of *ETH*, namely LSTM-GRU, LSTM-TCN, and GRU-TCN. In addition to the hybrid models, Politis et al. [162] also apply LSTM, GRU, TCN, and an ensemble. Based on the recorded error metrics, the LSTM-GRU is shown to be the most accurate model for daily price prediction of *ETH*, with an accuracy improvement of 3–6%. The RMSE and MAPE recorded for the LSTM-GRU are also 10–15% lower than those of the most accurate individual model, GRU. According to the same results, the other hybrid models, LSTM-TCN and GRU-TCN, are both less accurate than GRU in predicting the daily *ETH* price. The TCN, on the other hand, is shown to be the most accurate model when it comes to the weekly price prediction of *ETH*.

Inferior Results after Hybridization

Finally, the results reported by Patel et al. [14] do not support the claim that sequence model-based DL hybrid models outperform individual models. In [14], Patel et al., besides conducting a survey on cryptocurrency price prediction, propose an LSTM-GRU hybrid model based on the interdependencies that exist between cryptocurrencies. Patel et al. [14] adopt the pro-

posed LSTM-GRU, alongside LSTM and GRU, to predict the price of *DASH*. To incorporate interdependencies among cryptocurrencies in the proposed model, the prices of the target cryptocurrency, *DASH*, and *BTC* and *LTC* serve as inputs to the model. This is based on the fact that *LTC* was created based on *BTC* and *DASH* based on *LTC*. Similarly to the study conducted by Tanwar et al. [163], Patel et al. [14] propose a unique architecture that makes use of multiple input channels, where the price of *BTC*, *LTC*, and *DASH* serve as separate inputs to a block consisting of an LSTM stacked upon a GRU, followed by 2 dense layers. The outputs of the blocks are concatenated, and the concatenated output is used to produce the price prediction. Evaluation of the proposed model, as well as the individual models, demonstrates that the LSTM-GRU is less accurate than the LSTM and GRU, producing slightly higher error metrics than both. The findings of Patel et al. [14] are in line with the findings of Murray et al. [27], which, as previously denoted in Section 2.4.3, show a GRU to be more accurate than an LSTM-GRU with respect to the daily price prediction of *BTC*, *ETH*, *LTC*, *XMR*, and *XRP*.

2.4.5 Attention-based Deep Learning Hybrid Models

Another relatively frequent type of model that is used in the considered literature is a DL-based architecture that includes an attention mechanism [40, 44–46, 95, 171]. Based on studies that apply models with attention mechanisms, the addition of an attention mechanism to a model's architecture generally results in an improved forecasting accuracy compared to otherwise similar architectures without attention mechanisms [40, 44–46, 95, 171].

Improved Results after Hybridization

As one might recall from Section 2.4.3, Zhang et al. [40] propose WAMC, which consists of an attention mechanism that measures the importance of the various time steps in the input data. The results reported by Zhang et al. [40] demonstrate that WAMC is 10–30% more accurate than any other model. Similarly, in [45], the dual attention mechanism (DAM) that Fu et al. propose in combination with an LSTM, DAM-LSTM, increases the accuracy by 10-20% in comparison to an individual LSTM.

The effectiveness of attention mechanisms is further demonstrated in the studies conducted by Ladhari and Boubaker [171], Kim et al. [95], Guo et al. [44], and Livieris [46]. In [171], Ladhari and Boubaker apply a DNN-LSTM hybrid and an LSTM with an attention mechanism (LSTM-AM) for the hourly price prediction of *BTC*. Based on the evaluation of both models, LSTM-AM is more accurate than the DNN-LSTM, reducing RMSE, MAE, and MAPE by approximately 40%.

Furthermore, in [95], Kim et al. propose a novel hybrid model entitled Self-Attention based Multiple LSTM with Change Point Detection (SAM-LSTM-CPD) for the daily price prediction of *BTC*. The model can be divided into two parts, namely, the application of change point detection (CPD) and the self-attention-based multiple LSTM (SAM-LSTM). The SAM-LSTM is a multi-input model in which each input channel corresponds to a separate feature category. Each channel consists of an LSTM followed by an attention mechanism that focuses on the important parts of the input within the channel. The outputs of the channels are combined using an MLP to predict the price. According to Kim et al. [95], the architecture as proposed is beneficial for several reasons, namely, the model is encouraged to learn optimal price dynamics by inputting the features separately based on domain knowledge, and the application of multiple attention mechanisms, one for each feature group, allows for the extraction of diverse and

richer timely information. The SAM-LSTM model is only one part of the proposed method; the other, as stated earlier, is the application of CPD. CPD is a method that allows for the detection of points in a time series corresponding to a significant change in the data. In [95], CPD is mainly applied for the normalization of the data to allow for a more stable price prediction. By applying the CPD algorithm Pruned Exact Linear Time (PELT), the identified change points are used to segment the time series into several parts. Subsequently, each segment is normalized using solely the characteristics of the data belonging to that segment. To assess the efficacy of the proposed method, the performance of the proposed model is compared with an LSTM without an attention mechanism and CPD normalization (LSTM), an LSTM with CPD normalization (LSTM-CPD), and an LSTM with both an attention mechanism and CPD normalization (LSTM-AM-CPD). The results reported by Kim et al. [95] show the SAM-LSTM-CPD to reduce RMSE, MAE, and MAPE by 2–14% compared to the other models.
Additionally, in [44], Guo et al. introduce a novel model for predicting the daily price of *BTC* entitled Wavelet Transform Causal Multi-Head Attention Temporal Convolutional Network (WT-CATCN) that combines Wavelet Transform and Causal Multi-Head Attention with a Temporal Convolutional Network (TCN). The proposed model, WT-CATCN, first applies wavelet decomposition using the Discrete Wavelet Transform to the input data to handle its nonstationarity and non-linearity. The components produced by decomposition are passed to separate stacks of CATCN blocks. Each CATCN block starts with a causal multi-head attention layer followed by a TCN. The causal multi-head attention layer is applied to emphasize the most important parts of the input data whilst maintaining the data's causal nature. Ultimately, WT-CATCN produces wavelet-decomposed components corresponding to the next timestep, which, after wavelet reconstruction, yield the predicted price. In addition to WT-CATCN, Guo et al. [44] apply ARIMA, ARIMAX, CNN, MLP, LSTM, Sequence-to-Sequence RNN (Seq2Seq RNN), Bayesian Neural Networks (BNNs), and State-Frequency Memory Recurrent Neural Network (SFM). The results of the evaluation conducted by Guo et al. [44] demonstrate that the WT-CATCN is more accurate than any other model, recording a lower RMSE and MAE by approximately 15–40%. Guo et al. [44] furthermore conducted an ablation study demonstrating that applying the multi-head attention mechanism on top of wavelet decomposition results in a 15–35% decrease in error metrics. Additionally, when the multi-head attention mechanism is made causal, the error metrics decrease by an additional 12–28%.
Finally, in [46], Livieris proposes a framework to handle nonstationarity in multivariate time series through the application of several transformations. According to Livieris, these transformations are necessary for multivariate time series data to be suitable and of an appropriate quality for training a model. To validate the proposed approach, Livieris used a CNN-LSTM and a CNN-LSTM with an attention mechanism (CNN-LSTM-AM) to forecast the daily prices of several financial assets, including *BTC*. The results of the study demonstrate that CNN-LSTM-AM slightly outperforms the CNN-LSTM.

2.4.6 Decomposition-based Deep Learning Hybrid Models

Another class of hybrid models applied in the considered literature combines signal decomposition techniques with DL models [25, 44, 81]. Based on results from studies employing these models, decomposition-based DL hybrids generally yield substantial improvements in forecasting accuracy with respect to *cryptocurrency price prediction*.

Improved Results after Hybridization

In [44], as described in Section 2.4.5, Guo et al. propose WT-CATCN, a model that combines the decomposition of the input using the discrete wavelet transform with TCN and causal multi-head attention. Guo et al. [44] employ wavelet decomposition to address the nonstationarity and nonlinearity of the input data. The results reported by Guo et al. [44] show the WT-CATCN to be more accurate than any other model by 15–40% based on the recorded error metrics. The ablation study conducted by Guo et al. [44] furthermore shows the application of wavelet decomposition to lower the error metrics by 7–30% compared to when wavelet decomposition is not applied.
Furthermore, in [81], Li et al. propose a novel hybrid model entitled BiLSTM with Variational Mode Decomposition (VMD-BiLSTM) for the prediction of the daily close price of *BTC*. The model combines the signal decomposition technique VMD with a BiLSTM. Similar to Guo et al. [44], VMD is applied to handle the nonstationarity of cryptocurrency prices by decomposing the original time series into several more stationary time series with different frequencies that represent the intrinsic factors of the original time series. Besides, the proposed model, VMD-BiLSTM, Li et al. [81] apply an LSTM in combination with Empirical Mode Decomposition (EMD-LSTM), BiLSTM, ARIMA, LR, and SVR. The evaluation of the models shows that the VMD-BiLSTM yields RMSE, MAE, and MAPE values approximately 50–70% lower. Based on the error metrics, EMD-LSTM is shown to be less accurate than several individual models, including ARIMA, BiLSTM, and at times LR.
Lastly, in [25], Altan et al. propose an LSTM-based hybrid method that combines decomposition based on Empirical Wavelet Transform (EWT), an LSTM, and Cuckoo Search (CS) (EWT-LSTM-CS). In the EWT-LSTM-CS, the cryptocurrency price time series is first decomposed using EWT into 11 intrinsic mode functions (IMFs) to address volatility and noise. Subsequently, each IMF serves as input to a separate LSTM to forecast each respective IMF. Finally, the forecasts of the IMFs are combined using weighted coefficients to construct the predicted value of the price, where CS is used to optimize said weighted coefficients to achieve maximal accuracy. To assess the effectiveness of EWT-LSTM-CS, the proposed model, alongside LSTM and EWT-LSTM, is applied to predict the daily prices of *BTC*, *LTC*, *XRP*, and *DASH*. Compared with the other models, the EWT-LSTM-CS achieves significantly lower RMSE, MAE, and MAPE. In particular, compared to the individual LSTM, the error metrics produced by the EWT-LSTM-CS tend to be lower by 60–90%.

2.4.7 Change Point Detection-based Deep Learning Hybrids

A final type of hybrid model applied in the considered literature combines change point detection (CPD) with DL-based models [95, 168]. Overall, the integration of CPD with deep learning models is shown to improve forecasting accuracy.

Improved Results after Hybridization
As detailed in Section 2.4.5, Kim et al. [95] propose SAM-LSTM-CPD for the daily price prediction of *BTC*. Based on the results reported by Kim et al. [95], the application of CPD leads to substantial improvements in the recorded error metrics.
Moreover, in [168], Akila et al. propose a similar model, namely a hybrid method that combines an LSTM with CPD using the PELT algorithm (LSTM-CPD). Akila et al. [168] apply CPD to govern the way the LSTM is trained by training the LSTM using data before and after the points detected by CPD separately to allow the LSTM to adjust to sudden changes in the data. To assess the effectiveness of the LSTM-CPD method, both the proposed method

and an individual LSTM are used to forecast the daily price of *BTC*. The application of CPD is shown to lead to significantly more accurate results, as the resulting RMSE and MAE are lowered by 20-45%.

2.5 Proposed Models

Due to the scattered nature of the research into *cryptocurrency price prediction*, previously highlighted in the Introduction and Section 2.1.4, the initial approach adopted for proposing a novel model is to build upon an existing study among the initially reviewed literature with publicly available source code and data that enable the reproduction of the experiments conducted in the original study. This facilitates a reliable and fair comparison between the proposed models and the model from the original study that serves as a benchmark, while also contributing to greater reproducibility and comparability within the field, helping mitigate its scattered nature.

2.5.1 Benchmark Study

Based on the approach as outlined, the study conducted by Murray et al. [27] is selected as an appropriate foundation upon which to propose a novel model due to several factors:

- Murray et al. [27] evaluate a diverse range of models, including at least one model from each of the previously discussed model groups that are applied to *cryptocurrency price prediction*:
  - **STS**: ARIMA.
  - **Traditional ML**: KNN, RF, and SVR.
  - **DL**: GRU, TCN, and TFT.
  - **Hybrid**: CNN-LSTM and LSTM-GRU.
- The dataset and source code used by Murray et al. [27] are publicly available and sufficiently complete to allow reproduction of the experiments conducted by Murray et al. [27].

According to the findings of Murray et al. [27], CNN-LSTM is the most accurate model in predicting the daily close price of *BTC*, *ETH*, *LTC*, *XRP*, and *XMR*; however, a review of the source code reveals several flaws in relation to the conducted experiments that render the results reported by Murray et al. [27] unreliable. As such, steps are taken to address these flaws, further described in Section 5.1.1. Once the flaws have been addressed, the experiments conducted by Murray et al. [27] are repeated. The results of rerunning the experiments, further discussed in Section 6.1, demonstrate that the TCN is overall the most accurate model among those evaluated by Murray et al. [27].

2.5.2 Proposed: VMD-PMB-TCN

Based on the conducted research, we propose Temporal Convolutional Network with Variational Mode Decomposition and Parallel Mode Branches (VMD-PMB-TCN), which combines the following components:

- **TCN**: The most accurate model overall among those applied by Murray et al. [27] according to the revised results of the conducted experiments. As such, the proposed models adopt the TCN architecture introduced by Bai et al. [131] as their foundation to improve predictive performance further.
- **VMD**: Hybrid models that combine a signal decomposition technique, such as VMD, with a DL-based model are shown to be particularly effective, with the combination resulting in significant improvements in terms of predictive performance, as highlighted in Section 2.4.4. The efficacy of combining VMD with DL-based models is further supported by numerous studies beyond the initially reviewed literature, not all of which focus on *cryptocurrency price prediction*, that report significant performance improvements when applying VMD to forecast non-stationary time series such as cryptocurrency prices [82–94, 96, 97, 99–109, 173–176].

VMD-PMB-TCN forecasts a time series according to the following principles:

1. Applies VMD to the input time series in a leakage-free manner, which:
    - **Mitigates the effects of nonlinearity and non-stationarity by decomposing the relevant time series into several relatively simpler, more stationary, and smoother modes** [82, 97]: Due to the modes being simpler, smoother, and more stationary than the original time series, the model's efficacy in capturing the patterns and characteristics underlying the time series can be enhanced and lead to an improved predictive performance [82, 92].
    - **Addresses limitations of previous research by applying VMD in a leakage-free manner** [81–87, 89, 91–94, 98, 99, 101–109]: The vast majority of the reviewed studies that apply VMD to forecast time series do so by applying it to the complete time series prior to splitting the time series into training, validation, and test sets. This leads to data leakage whereby information from future observations leaks into the model's training process, resulting in inflated performance and an unreliable assessment of the model's efficacy.
2. Forecasts each mode resultant of the decomposition with separate TCNs, where:
    - **Each TCN captures the temporal dependencies associated with a specific mode and generates the associated forecast based on the learned temporal dependencies:** This follows a common approach in the literature that can yield substantial improvements by using a decomposition-based ensemble, where instead of using a single model, the time series corresponding to the modes produced by the decomposition are forecasted individually by separate models with the resulting forecasts being aggregated to forecast the original time series [82–85, 92, 96–102].
3. The individual mode forecasts are summed to reconstruct the forecast of the original time series consistent with the reconstruction constraint of VMD, further detailed in Section 3.2.

It is important to note that, unlike the ensemble approach applied in previous research [82–85, 92, 96–102], VMD-PMB-TCN is not an ensemble in the traditional sense. The separate TCNs in VMD-PMB-TCN are not separate models, but rather separate branches of a single

architecture. This results from applying VMD in a leakage-free manner, so there are no ground-truth values against which the forecasts of the individual modes can be evaluated, preventing the training of separate models for each mode.

2.5.3 Proposed: VMD-PMB-CMHA-TCN

In addition to VMD-PMB-TCN, we propose Causal Multi-Head Attention-enhanced Temporal Convolutional Network with Variational Mode Decomposition and Parallel Mode Branches (VMD-PMB-CMHA-TCN), which attempts to improve on VMD-PMB-TCN by adding another component:

- **Attention Mechanism**: Incorporating attention mechanisms into a model's architecture, similar to the application of VMD, has been shown to substantially improve predictive performance, as highlighted in Section 2.4.5. Besides the studies mentioned in Section 2.4.5, the efficacy of utilizing attention mechanisms as part of a model's architecture to forecast time series is supported by several studies beyond the initially reviewed literature [82, 103, 110–130].

VMD-PMB-CMHA-TCN largely follows the same principles described in the Section 2.5.2. However, rather than consisting solely of a TCN, each branch of VMD-PMB-CMHA-TCN incorporates a TCN followed by an attention mechanism. The role of the TCN in each branch is to generate an embedding corresponding to the captured temporal dependencies. The attention mechanism then enhances this embedding by emphasizing the most important time steps with respect to the prediction. The enhanced embedding within each branch is subsequently used to forecast the respective mode. The attention mechanism incorporated into the architecture is the multi-head attention mechanism proposed by Vaswani et al. [177] as part of the Transformer architecture. Given the importance of preserving causality in time series forecasting tasks, the specific variant employed is the causal multi-head attention.

2.5.4 Novelty

To the best of our knowledge, both VMD-PMB-TCN and VMD-PMB-CMHA-TCN are novel models that have not been previously proposed and applied. No previously proposed model employs separate TCN branches to model the modes produced by a decomposition technique within a single end-to-end architecture, with the branch outputs subsequently aggregated through summation to generate the final forecast. Similarly, no previously proposed model incorporates an attention mechanism after a TCN in the separate branches within such an architecture.

3 Fundamentals

3.1 Time Series

3.1.1 Definitions

Time series are a specific type of data, namely data consisting of observations, i.e., instances, captured at regular or irregular time intervals, f.e, a minute; hence, a time series $\mathbf{X}$ consisting of T timesteps can be denoted as:

$$\mathbf{X} = \{\mathbf{X}_t\}_{t=0}^{T-1} = \{\mathbf{X}_0, \mathbf{X}_1, \ldots, \mathbf{X}_{T-1}\} \tag{1}$$

A time series can be categorized as either univariate or multivariate. This categorization depends on the number of variables captured at each observation, where a univariate time series X can be defined as:

$$X = \{X_t\}_{t=0}^{T-1}, \quad X_t \in \mathbb{R} \tag{2}$$

and a multivariate time series $\mathbf{X}$ with F variables as:

$$\mathbf{X} = \{\mathbf{X}_t\}_{t=0}^{T-1}, \quad \mathbf{X}_t = \begin{bmatrix} X_{t,1} \\ X_{t,2} \\ \vdots \\ X_{t,F} \end{bmatrix} \in \mathbb{R}^F, \quad F > 1. \tag{3}$$

3.1.2 Stationarity

A time series can furthermore be distinguished as either being stationary or nonstationary. As specified in [178], for a time series to be considered (weakly) stationary, it needs to meet certain conditions, namely:

(1) $\boldsymbol{\mu}_{\mathbf{X}_t}$ is time-invariant, i.e., does not depend on t

(2) $\boldsymbol{\sigma}_{\mathbf{X}_t}$ is time-invariant

(3) $\boldsymbol{\gamma}_{\mathbf{X}_t\mathbf{X}_{t+s}}$ is time-invariant for every s

where $\boldsymbol{\mu}_{\mathbf{X}_t}$ denotes the mean function of a time series $\mathbf{X}$, $\boldsymbol{\sigma}_{\mathbf{X}_t}$ denotes the variance function of $\mathbf{X}$, and $\boldsymbol{\gamma}_{\mathbf{X}_t\mathbf{X}_{t+s}}$ the autocovariance function of $\mathbf{X}$ for a time shift, i.e., lag of s according to the following definitions if $\mathbf{X}$ is univariate:

$$\boldsymbol{\mu}_{\mathbf{X}_t} = \mathbb{E}[X_t] \tag{4}$$

$$\boldsymbol{\sigma}_{\mathbf{X}_t} = \mathbb{E}[(X_t - \boldsymbol{\mu}_{X_t})^2] \tag{5}$$

$$\boldsymbol{\gamma}_{\mathbf{X}_t\mathbf{X}_{t+s}} = \mathbb{E}[(X_t - \boldsymbol{\mu}_{X_t})(X_{t+s} - \boldsymbol{\mu}_{X_{t+s}})], \quad s \in \mathbb{Z} \tag{6}$$

and according to these definitions if $\mathbf{X}$ is multivariate:

$$\boldsymbol{\mu}_{\mathbf{X}_t} = \begin{bmatrix} \mathbb{E}[X_{1,t}] \\ \mathbb{E}[X_{2,t}] \\ \vdots \\ \mathbb{E}[X_{F,t}] \end{bmatrix} \tag{7}$$

$$\boldsymbol{\sigma}_{\mathbf{X}_t} = \begin{bmatrix} \mathbb{E}[(X_{1,t} - \boldsymbol{\mu}_{X_{1,t}})^2] & \cdots & \mathbb{E}[(X_{1,t} - \boldsymbol{\mu}_{X_{1,t}})(X_{F,t} - \boldsymbol{\mu}_{X_{F,t}})] \\ \vdots & \ddots & \vdots \\ \mathbb{E}[(X_{F,t} - \boldsymbol{\mu}_{X_{F,t}})(X_{1,t} - \boldsymbol{\mu}_{X_{1,t}})] & \cdots & \mathbb{E}[(X_{F,t} - \boldsymbol{\mu}_{X_{F,t}})^2] \end{bmatrix} \tag{8}$$

$$\boldsymbol{\gamma}_{\mathbf{X}_t\mathbf{X}_{t+s}} = \begin{bmatrix} \mathbb{E}[(X_{1,t} - \boldsymbol{\mu}_{X_{1,t}})(X_{1,t+s} - \boldsymbol{\mu}_{X_{1,t+s}})] & \cdots & \mathbb{E}[(X_{1,t} - \boldsymbol{\mu}_{X_{1,t}})(X_{F,t+s} - \boldsymbol{\mu}_{X_{F,t+s}})] \\ \vdots & \ddots & \vdots \\ \mathbb{E}[(X_{F,t} - \boldsymbol{\mu}_{X_{F,t}})(X_{1,t+s} - \boldsymbol{\mu}_{X_{1,t+s}})] & \cdots & \mathbb{E}[(X_{F,t} - \boldsymbol{\mu}_{X_{F,t}})(X_{F,t+s} - \boldsymbol{\mu}_{X_{F,t+s}})] \end{bmatrix}, \quad s \in \mathbb{Z} \tag{9}$$

A stationary time series can additionally be referred to as a strictly stationary time series if the following holds for every timeshift s regardless of $t_1, t_2, \ldots, t_i$:

$$(\mathbf{X}_{t_0}, \mathbf{X}_{t_1}, \ldots, \mathbf{X}_{t_i}) \overset{D}{=} (\mathbf{X}_{t_0+s}, \mathbf{X}_{t_1+s}, \ldots, \mathbf{X}_{t_i+s}), \quad s \in \mathbb{Z}, \;\; i > 0 \tag{10}$$

In other words, if $(\mathbf{X}_{t_0}, \mathbf{X}_{t_1}, \ldots, \mathbf{X}_{t_i})$ shares an identical joint distribution with $(\mathbf{X}_{t_0+s}, \mathbf{X}_{t_1+s}, \ldots, \mathbf{X}_{t_i+s})$ for every s and regardless of $t_0, t_1, \ldots, t_i$, $\mathbf{X}$ is considered to be a strictly stationary time series [178].
The majority of time series observed in practice, however, are nonstationary [179], i.e., at least one of $\boldsymbol{\mu}_{\mathbf{X}_t}$, $\boldsymbol{\sigma}_{\mathbf{X}_t}$, and $\boldsymbol{\gamma}_{\mathbf{X}_t\mathbf{X}_{t+s}}$ is time-invariant. The nonstationarity of a time series can arise from a variety of sources. Two fundamental sources of nonstationarity, in particular, are the existence of seasonality or a trend within the time series, where seasonality refers to the existence of a cyclic pattern within the time series that repeats over a certain interval. A trend refers to the existence of a tendency for the level of the time series to increase or decrease in the long-term [179].

3.1.3 Handling Nonstationarity

Due to the fact that the mean, variance, and autocovariance of a time series $\mathbf{X}$ remain constant over time if $\mathbf{X}$ is stationary, $\mathbf{X}$ tends to be modeled more reliably, as its parameters can be estimated consistently. Consequently, if $\mathbf{X}$ is nonstationary, it is common practice in time series analysis to transform $\mathbf{X}$ to become stationary [178]. This practice is further justified by the fact that models commonly used in time series analysis, such as ARIMA and VAR, assume that $\mathbf{X}$ is stationary.
There exist several techniques for transforming a nonstationary time series $\mathbf{X}$ into a stationary one. Widely adopted methods for achieving this transformation are based on the removal of trend and/or seasonal components from $\mathbf{X}$, under the assumption that $\mathbf{X}$ is expressed using one of the following classical decompositions:

$$\mathbf{X}_t = \mathbf{H}_t + \mathbf{S}_t + \mathbf{R}_t \quad \text{or} \quad \mathbf{X}_t = \mathbf{H}_t \times \mathbf{S}_t \times \mathbf{R}_t \tag{11}$$

$$\mathbf{X}_t = \mathbf{S}_t + \mathbf{R}_t \quad \text{or} \quad \mathbf{X}_t = \mathbf{S}_t \times \mathbf{R}_t \tag{12}$$

$$\mathbf{X}_t = \mathbf{H}_t + \mathbf{R}_t \quad \text{or} \quad \mathbf{X}_t = \mathbf{H}_t \times \mathbf{R}_t \tag{13}$$

with $\mathbf{H}_t$ denoting the trend component, $\mathbf{S}_t$ the seasonal component, and $\mathbf{R}_t$ the stationary residual component [178]. According to these classical decompositions, stationarity of $\mathbf{X}_t$ can be attained by removing $\mathbf{H}_t$ and/or $\mathbf{S}_t$, such that $\mathbf{X}_t$ is expressed as $\mathbf{X}_t = \mathbf{R}_t$. In practice, this can be achieved by estimating $\mathbf{H}_t$ and $\mathbf{S}_t$ and then subtracting one or both from $\mathbf{X}_t$.
Another common method for removing trend and/or seasonal components from $\mathbf{X}$ is differencing. This transformation is defined as:

$$\mathbf{X}'_t = \mathbf{X}_t - \mathbf{X}_{t-s}, \quad s \in \mathbb{Z}^+, \;\; t = s, \ldots, T-1 \tag{14}$$

where s denotes the time shift [178]. For trend removal, a first-order difference, $s = 1$, is typically employed, whereas for the removal of a seasonal component, s is set equal to the period of said component [178].

3.1.4 Detecting Nonstationarity

Prior to applying transformations to a time series $\mathbf{X}$ with the goal of making it stationary, it is essential first to determine if $\mathbf{X}$ is in fact nonstationary. This determination can be made by inspecting visualizations pertaining to $\mathbf{X}$, such as plotting $\mathbf{X}$ itself, the mean and variance of $\mathbf{X}$ over time, or the autocorrelation function (ACF) and partial autocorrelation function (PACF) of $\mathbf{X}$. The ACF, $\rho_{\mathbf{X}_t\mathbf{X}_{t+s}}$, of $\mathbf{X}$ for a timeshift s can be defined as follows:

$$\rho_{\mathbf{X}_t\mathbf{X}_{t+s}} = \frac{\boldsymbol{\gamma}_{\mathbf{X}_t\mathbf{X}_{t+s}}}{\boldsymbol{\sigma}_{\mathbf{X}_t}}, \quad s \in \mathbb{Z} \tag{15}$$

where $\boldsymbol{\gamma}_{\mathbf{X}_t\mathbf{X}_{t+s}}$ denotes the autocovariance function of $\mathbf{X}$ defined in (6) and (9), and $\boldsymbol{\sigma}_{\mathbf{X}_t}$ denotes the variance of $\mathbf{X}$ as defined in (5) and (8). The ACF gives an insight into the dependencies within $\mathbf{X}$ as it captures the overall dependency between $\mathbf{X}_t$ and $\mathbf{X}_{t+s}$ [178]. This includes the direct dependency on timeshifts s and indirect dependencies pertaining to intermediate timeshifts. The PACF, on the other hand, measures the direct dependency between $\mathbf{X}_t$ and $\mathbf{X}_{t+s}$ after removing the dependencies related to the intermediate timeshifts. Although visualizations related to $\mathbf{X}$ can shed light on whether $\mathbf{X}$ is stationary or nonstationary, a more rigorous approach is to perform statistical tests, such as the Augmented Dickey-Fuller (ADF) test [180] or the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test [181].
The ADF test is based on the following hypotheses:

- $\mathbf{H}_0$: $\mathbf{X}$ contains a unit root, i.e., $\mathbf{X}$ is non-stationary.
- $\mathbf{H}_A$: $\mathbf{X}$ does not contain a unit root, i.e., $\mathbf{X}$ is stationary.

where a unit root is a non-stationary characteristic, $\mathbf{H}_0$ is the null hypothesis, and $\mathbf{H}_A$ is the alternative hypothesis, i.e., the hypothesis supported when the null hypothesis $\mathbf{H}_0$ is rejected. In contrast to the hypotheses of the ADF test, the null and alternative hypotheses of the KPSS test are reversed:

- $\mathbf{H}_0$: $\mathbf{X}$ is stationary.

- $\mathbf{H}_A$: $\mathbf{X}$ is non-stationary.

Both tests produce a value p and a test statistic, which, in combination with a chosen significance level α, e.g., 0.05 (5%), can be used to make a decision regarding $\mathbf{H}_0$. This decision can be made by comparing the produced test statistic to critical values at different significance levels and comparing the p-value to the chosen significance level α. Here, α represents the threshold for the evidence required to reject $\mathbf{H}_0$. For both the ADF test and the KPSS test, the following rules are adopted:

- If $p \leq \alpha$, there is sufficient evidence to reject $\mathbf{H}_0$ in favor of $\mathbf{H}_A$.
- If $p > \alpha$, one fails to reject $\mathbf{H}_0$, i.e., there is insufficient evidence against $\mathbf{H}_0$.

3.1.5 Forecasting

Time series forecasting is a specific type of time series analysis that uses past and present values of a time series, $\mathbf{X}$, to predict its future values. The process of forecasting $\mathbf{X}$ can be expressed as follows:

$$\hat{\mathbf{X}}_{T+1}, \hat{\mathbf{X}}_{T+2}, \ldots, \hat{\mathbf{X}}_{T+H} = f(\mathbf{X}_0, \mathbf{X}_1, \ldots, \mathbf{X}_T) \tag{16}$$

where $\hat{\mathbf{X}}_{T+1}, \hat{\mathbf{X}}_{T+2}, \ldots, \hat{\mathbf{X}}_{T+H}$ are the predicted future values of $\mathbf{X}$, H is the forecasting horizon, i.e., the number of future values of $\mathbf{X}$ that are predicted, f is the forecasting function or model, and $\mathbf{X}_0, \mathbf{X}_1, \ldots, \mathbf{X}_T$ are the observed past values.

3.2 Variational Mode Decomposition (VMD)

3.2.1 Description

In 2013, Dragomiretskiy and Zosso [182] introduced Variational Mode Decomposition (VMD), a novel signal processing technique. VMD decomposes a signal into K sub-signals called modes, where K is a user-defined parameter [82]. Each mode u_k is a narrowband signal centered around a corresponding central frequency ω_k. The central frequencies are typically distinct, as VMD encourages separation of the modes in the spectral domain [88]. In other words, each mode tends to capture distinct frequency components of the original signal, with the first mode capturing the lowest frequencies and the Kth mode capturing the highest.
VMD can be described as a variational optimization problem that minimizes the bandwidth of each mode around its corresponding central frequency, whilst ensuring that the original signal is reconstructed by the sum of the modes [81, 182]. The optimization problem is further described in Section B.1.2.
To attain the optimal solution to the variational optimization problem, VMD employs the alternating direction method of multipliers (ADMM) [81, 82], further described in Section B.1.3. ADMM iteratively solves optimization problems when the objective functions are divisible with respect to the variables by decomposing them into simpler subproblems [183]. At each iteration, the variables are updated alternately, with the others held fixed, followed by a dual update that enforces the constraint [183]. The ADMM algorithm iterates until the change in each mode between successive iterations falls below a user-defined convergence tolerance ϵ.
VMD was proposed as an improvement over existing decomposition methods, such as Empirical Mode Decomposition (EMD) and wavelet decomposition. Unlike EMD, it is based on

a well-defined mathematical framework [89, 182]. Moreover, Dragomiretskiy and Zosso [182] demonstrated that VMD is more robust to noise and less prone to mode mixing, meaning that the modes extracted by VMD are less likely to overlap [86].

3.2.2 Parameters

In this study, several parameters are considered with respect to VMD:

- K: the number of modes into which VMD decomposes an input.
- α: a penalty factor that controls the bandwidth of the modes. Larger values of α enforce narrower bandwidth modes at the risk of inaccurate center frequency estimation, whereas smaller values allow wider bandwidth modes that may be more susceptible to noise [182, 184]. Moreover, the value of α also indirectly influences reconstruction accuracy by directly affecting the quality of the estimated modes [185].
- τ: a step size parameter that influences the convergence of the ADMM algorithm and its sensitivity to noise [186]. An appropriate choice of τ can improve ADMM convergence: larger values increase sensitivity to noise, while smaller values reduce this sensitivity and typically result in more stable but slower convergence [183, 186].
- ϵ: the convergence threshold of the ADMM algorithm.

3.2.3 Time Series

In the context of time series, VMD decomposes a univariate time series $X \in \mathbb{R}^{T\times 1}$ into K subseries (modes), resulting in a multivariate time series $\mathbf{X} \in \mathbb{R}^{T\times K}$. The individual subseries in $\mathbf{X}$ capture features and underlying components of X across multiple scales [81, 82]. The resulting subseries tend to be simpler and more stationary than X [82]. VMD can therefore be used to suppress nonstationarity when the original time series is nonstationary.

3.3 Temporal Convolutional Network (TCN)

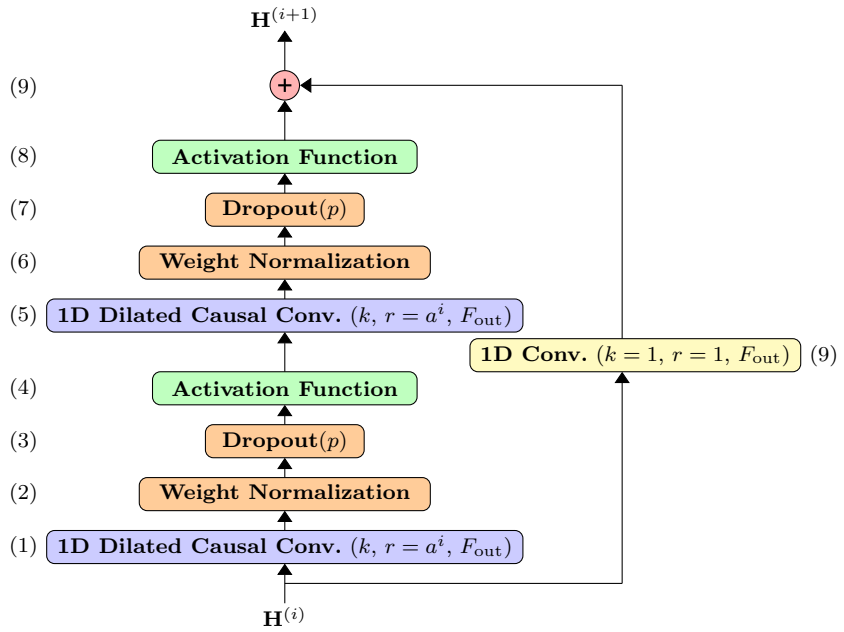


Figure 1: The architecture of the residual block central to the architecture of the TCN proposed by Bai et al. [131] with a kernel size k, a dilation rate $r = a^i$, a number of output features, i.e., a number of applied kernels F_{out}, and a dropout rate p applied to intermediate representation $\mathbf{H}^{(i-1)}$ resulting in $\mathbf{H}^{(i)}$, where a is the dilation base and i the index of the residual block.

The concept of Temporal Convolutional Networks (TCNs) was formally introduced for the first time by Lea et al. [187]. Nevertheless, the architecture widely associated with TCNs was later proposed by Bai et al. [131]. TCNs are specialized variants of Convolutional Neural Networks (CNNs) tailored for modeling sequences, such as time series. Each TCN layer part of the architecture introduced by Bai et al. [131] is implemented as a residual block, shown in Figure 1. Each residual block is composed of special 1D convolutional layers, further described in Section B.2.1 of Appendix B, referred to as 1D dilated causal convolutional layer, discussed in Section B.2.2. 1D dilated causal convolutional layers ensure that the sequences are processed in a manner that respect the causality in the data, ensure that the corresponding sequence length is retained throughout processing the sequences, and utilize dilation. By combining these layers with a skip connection to enable residual learning and stacking multiple residual blocks, TCNs can be constructed as deep networks capable of capturing large receptive fields and, consequently, long-term dependencies.

Residual Block: Concept

The concept of a residual block was first formalized by He [188], who introduced residual networks (ResNet). Each residual block includes a branch parallel to the transformation $\mathcal{F}$, known as a skip connection, which adds the input $\mathbf{X}$ of $\mathcal{F}$ to its output resulting in $\hat{\mathbf{Y}}$. This can be formalized as:

$$\hat{\mathbf{Y}} = \mathcal{F}(\mathbf{X}) + \mathbf{X} \tag{17}$$

This is referred to as residual learning, where instead of learning a full transformation of the input, the layers learn modifications to the input [131, 188]. The skip connection facilitates an identity mapping, meaning that the input is passed through without transformation, and is therefore denoted as $\mathbf{X}$ in (17). Residual learning was introduced to improve the performance of deep neural networks [188]. As demonstrated by He et al. [188], residual learning mitigates performance degradation in deeper networks and makes them easier to optimize by enabling the network's layers to learn a residual mapping. Residual learning is important for stabilizing deeper TCNs [131].

Residual Block: Details
Given time series input $\mathbf{H}^{(i)} \in \mathbb{R}^{B \times T \times F}$ if $\mathbf{H}^{(i)}$ is the initial input or $\mathbf{H}^{(i)} \in \mathbb{R}^{B \times F \times T}$ if $\mathbf{H}^{(i)}$ is an intermediate input, where B denotes the batch size, T the number of time steps, and F the number of variables, i.e., features. In case $\mathbf{H}^{(i)}$ is the initial input, it is first reshaped to $\mathbf{H}^{(i)} \in \mathbb{R}^{B \times F \times T}$ to satisfy the required input shape of convolutional layers, described in Section B.2.1. Each residual block processes $\mathbf{H}^{(i)}$ as follows:

(1) First, the residual block applies a 1D dilated causal convolutional layer, depicted in Figure 14, with a kernel size k, a dilation rate $r = a^i$, and the number of output features, i.e., the number of kernels F_{out} with a denoting the dilation base, and i the index of the corresponding TCN layer resulting in $\mathbf{H}^{(i)} \in \mathbb{R}^{B \times T \times F}$ becoming $\mathbf{H}^{(i)} \in \mathbb{R}^{B \times T \times F_{\text{out}}}$.

(2) Subsequently, the weights of the layer are normalized using weight normalization.

(3) Next, a dropout layer randomly sets a tunable fraction p of the layer's output to zero for regularization.

(4) After that, nonlinearity is introduced by applying a nonlinear activation function. The original architecture proposed by Bai et al. [131] uses the Rectified Linear Unit (ReLU), defined in (29), as the activation function. In this study, the activation function is a tunable hyperparameter. Therefore, the activation function is not specified in Figure 1.

(5) Identical to (1)

(6) Identical to (2)

(7) Identical to (3)

(8) Identical to (4)

(9) Lastly, residual learning is incorporated through a skip connection. This connection adds the initial input of the block, $\mathbf{H}^{(i-1)} \in \mathbb{R}^{B \times T \times F}$, after passing it through a default 1D convolutional layer, shown in Figure 13, with kernel size $k = 1$, dilation rate $r = 1$, and F_{out} output features to the output of (8). This results in $\mathbf{H}^{(i)} \in \mathbb{R}^{B \times T \times F_{\text{out}}}$. The 1D convolutional layer ensures that the initial input and the output of the last activation function have the same shape, accounting for possible differences in feature dimension.

Based on the given architecture and (77), with $a = 2$, the receptive field R of the TCN can be expressed as:

$$R = 1 + 2(k-1)(2^D - 1) \tag{18}$$

where D denotes the number of residual blocks of which the TCN is composed. The illustrated architecture allows the receptive field size to be flexibly adjusted by varying the depth D, the dilation base a, or the kernel size k [131].

3.4 Self-Attention Mechanism

A self-attention mechanism assigns weights to the various positions in an input sequence, enabling the modeling of dependencies regardless of their distance [177]. The weight assignment results in a weighted representation of the input in which the more relevant dependencies are assigned larger weights [177]. This allows a self-attention mechanism to essentially emphasize the important information within the original input [44]. The specific attention mechanism adopted in this paper is the scaled dot-product attention mechanism introduced by Vaswani et al. [177] as part of the Transformer architecture.

3.4.1 Scaled Dot-Product Attention

Vaswani et al. [177] define an attention mechanism as a function that computes an output from a query and a number of key-value pairs, where the output is given by a weighted sum of the values. Each value has a corresponding weight that is determined by the similarity between a query and a corresponding key [177]. Based on this definition, the output matrix $\mathbf{Z}$ of a scaled dot-product attention mechanism is given by:

$$\mathbf{Z} = \text{Softmax}(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d_k}})\mathbf{V} \tag{19}$$

with $\mathbf{Q}$ denoting a matrix consisting of the query vectors, $\mathbf{K}$ a matrix consisting of the key vectors, and $\mathbf{V}$ a matrix consisting of the value vectors. Each query and key vector has a dimensionality d_k, whereas each value vector has a dimensionality d_v. In other words, to calculate the similarities between the queries and the keys, a matrix product is computed between $\mathbf{Q}$ and $\mathbf{K}$, which effectively computes a dot product between the individual queries and keys simultaneously. Subsequently, the outcome of this is scaled by $\sqrt{d_k}$ to prevent the dot products from becoming too large as d_k increases. After which, a softmax function is applied to compute the attention weights, yielding an attention weight matrix $\mathbf{A}$, which is then multiplied by the value matrix $\mathbf{V}$. To capture the dependencies between the time steps in an original input $\mathbf{X} \in \mathbb{R}^{B\times T\times F}$, the query, key, and value matrices $\mathbf{Q} \in \mathbb{R}^{B\times T\times d_k}$, $\mathbf{K} \in \mathbb{R}^{B\times T\times d_k}$, and $\mathbf{V} \in \mathbb{R}^{B\times T\times d_v}$ are defined as:

$$\begin{aligned}\mathbf{Q} &= \mathbf{X}\mathbf{W}^Q + \mathbf{b}^Q \\ \mathbf{K} &= \mathbf{X}\mathbf{W}^K + \mathbf{b}^K \\ \mathbf{V} &= \mathbf{X}\mathbf{W}^V + \mathbf{b}^V\end{aligned} \tag{20}$$

where $\mathbf{W}^Q \in \mathbb{R}_{F\times d_k}$, $\mathbf{W}^K \in \mathbb{R}^{F\times d_k}$, and $\mathbf{W}^V \in \mathbb{R}^{F\times d_v}$ denote learnable weights and $\mathbf{b}^Q \in \mathbb{R}^{d_k}$, $\mathbf{b}^K \in \mathbb{R}^{d_k}$, and $\mathbf{b}^V \in \mathbb{R}^{d_v}$ learnable biases corresponding to a linear layer that projects $\mathbf{X}$ to $\mathbf{Q}$, $\mathbf{K}$, and $\mathbf{V}$, respectively. The attention weights $\mathbf{A}$ and the output of the scaled dot-product attention mechanism $\mathbf{Z}$ are therefore given by $\mathbf{A} \in \mathbb{R}^{B\times T\times T}$ and $\mathbf{Z} \in \mathbb{R}^{B\times T\times d_v}$, respectively. The attention mechanism, as defined, does not inherently enforce causality. As certain sequence modeling tasks demand causality, one can apply a mask $\mathbf{M} \in \mathbb{R}^{T\times T}$. By

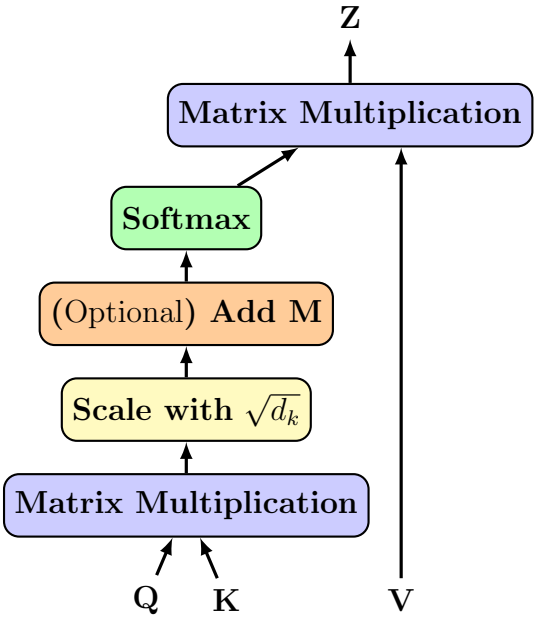
adding this mask to the scaled matrix product before applying the softmax, the attention mechanism is forced to respect the input's causal structure. This mask is defined as follows:

$$\mathbf{M} = \begin{cases} \mathbf{M}_{i,j} = 0, & \text{if } j \leq i \\ \mathbf{M}_{i,j} = -\infty, & \text{if } j > i \end{cases} \tag{21}$$

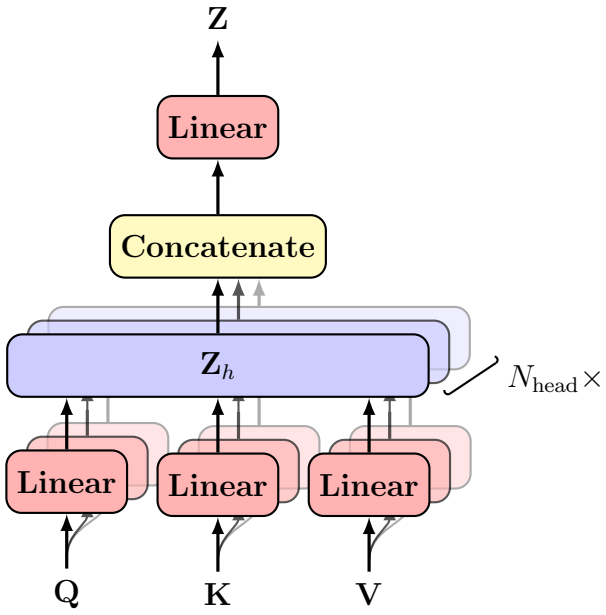
with i and j denoting the time step indices corresponding to the first and second dimensions, respectively. By adding $\mathbf{M}$ to the attention scores, dependencies on future time steps are nullified, as the addition of $-\infty$ results in attention weights of zero after the softmax operation. Causal scaled dot-product attention can be formalized as:

$$\mathbf{Z} = \text{Softmax}(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d_k}} + \mathbf{M})\mathbf{V} \tag{22}$$

The process of applying a scaled dot-product attention mechanism as described is illustrated in Figure 2a.



(a) The application of scaled dot-product attention using the query matrix $\mathbf{Q} \in \mathbb{R}^{B\times T\times d_k}$, the key matrix $\mathbf{K} \in \mathbb{R}^{B\times T\times d_k}$, the value matrix $\mathbf{V} \in \mathbb{R}^{B\times T\times d_v}$, and optionally a causal mask $\mathbf{M} \in \mathbb{R}^{T\times T}$ resulting in an output $\mathbf{Z} \in \mathbb{R}^{B\times T\times d_v}$.



(b) The application of multi-head attention resulting in an output $\mathbf{Z} \in \mathbb{R}^{B\times T\times F}$, where $\mathbf{Z}_h \in \mathbb{R}^{B\times T\times \frac{F}{N_{\text{head}}}}$ denotes the output produced by a single head using $\mathbf{Q}_h \in \mathbb{R}^{B\times T\times \frac{F}{N_{\text{head}}}}$, $\mathbf{K}_h \in \mathbb{R}^{B\times T\times \frac{F}{N_{\text{head}}}}$, and $\mathbf{V}_h \in \mathbb{R}^{B\times T\times \frac{F}{N_{\text{head}}}}$, and N_{head} the number of attention heads.

Figure 2: Scaled Dot-Product Attention

3.4.2 Multi-Head Attention

Instead of employing scaled dot-product attention on its own, as shown in Figure 2a, Vaswani et al. [177] used a modified version referred to as multi-head attention, as part of the Transformer

architecture. Multi-head attention applies scaled dot-product attention N_{head} times in parallel, where N_{head} is the number of attention heads. Each head applies scaled dot-product attention using distinct learnable linear projections of $\mathbf{Q}$, $\mathbf{K}$, and $\mathbf{V}$. Thus, the query, key, and value matrix of a head h are defined as:

$$\begin{aligned}\mathbf{Q}_h &= \mathbf{X}\mathbf{W}_h^Q + \mathbf{b}_h^Q \\ \mathbf{K}_h &= \mathbf{X}\mathbf{W}_h^K + \mathbf{b}_h^K \\ \mathbf{V}_h &= \mathbf{X}\mathbf{W}_h^V + \mathbf{W}_h^V\end{aligned} \tag{23}$$

where $\mathbf{Q}_h \in \mathbb{R}^{B\times T\times \frac{F}{N_{\text{head}}}}$, $\mathbf{K}_h \in \mathbb{R}^{B\times T\times \frac{F}{N_{\text{head}}}}$, and $\mathbf{V}_h \in \mathbb{R}^{B\times T\times \frac{F}{N_{\text{head}}}}$, with $d_k = d_v = \frac{F}{N_{\text{head}}}$. The output of head h, $\mathbf{Z}_h \in \mathbb{R}^{B\times T\times \frac{F}{N_{\text{head}}}}$, is therefore defined as:

$$\mathbf{Z}_h = \text{Softmax}(\frac{\mathbf{Q}_h\mathbf{K}_h^\top}{\sqrt{d_k}})\mathbf{V_h} \tag{24}$$

In the case of causal multi-head attention, $\mathbf{Z}_h$ is defined as:

$$\mathbf{Z}_h = \text{Softmax}(\frac{\mathbf{Q}_h\mathbf{K}_h^\top}{\sqrt{d_k}} + \mathbf{M})\mathbf{V_h} \tag{25}$$

To determine the final output $\mathbf{Z}$, the outputs of the individual heads are concatenated. Subsequently, $\mathbf{Z}$ is given as a learnable projection of the concatenated outputs to $\mathbf{Z}$. This can be formalized as follows:

$$\mathbf{Z} = \text{Concatenate}(\mathbf{Z}_0, \ldots, \mathbf{Z}_{N_{\text{head}}-1})\mathbf{W}^Z + \mathbf{b}^Z \tag{26}$$

where $\mathbf{W}^Z \in \mathbb{R}^{F\times F}$ denotes the learnable weights and $\mathbf{b}^Z \in \mathbb{R}^F$ the learnable biases of the linear projection of the concatenated outputs to $\mathbf{Z} \in \mathbb{R}^{B\times T\times F}$. Multi-head attention facilitates the capture of dependencies between time steps across multiple distinct representation subspaces [177]. The number of attention heads N_{head} is a tunable parameter of a multi-head attention mechanism. Another tunable parameter considered in this study is the dropout rate p_{mha} of the dropout layer applied to $\mathbf{A}_h$. Although not reflected in the provided formulation, the layer randomly zeroes out a part of $\mathbf{A}_h$ before the matrix multiplication with $\mathbf{V}_h$. In Figure 2b, the application of a multi-head attention is depicted.

3.5 Activation Functions

Throughout this study, several activation functions are employed in the architectures of the models. These activation functions consist of the Exponential Linear Unit (ELU) [189], the Rectified Linear Unit (ReLU) [190], the Gaussian Error Linear Unit (GELU) [191], and the Sigmoid Linear Unit (SiLU) [192]. Each activation function is defined as follows:

$$\text{ELU}(x) = \begin{cases} x, & x > 0 \\ \alpha\left(e^x - 1\right), & x \leq 0 \end{cases} \tag{27}$$

$$\text{GELU}(x) = x\Phi(x) \approx 0.5x\left(1 + \tanh\left(\sqrt{\frac{2}{\pi}}\left(x + 0.044715x^3\right)\right)\right) \tag{28}$$

$$\mathrm{ReLU}(x) = \begin{cases} x, & x > 0 \\ 0, & x \leq 0 \end{cases} \tag{29}$$

$$\mathrm{SiLU}(x) = x \cdot \sigma(x) = x \cdot \frac{1}{1 + e^{-x}} \tag{30}$$

where α is a parameter of ELU set to 1.0 by default, Φ denotes the cumulative distribution function of the standard Gaussian distribution, and σ denotes the sigmoid function.

3.6 Evaluation Metrics

In the course of this study, several evaluation metrics are adopted and reported in relation to *cryptocurrency price prediction* (regression) and *cryptocurrency price movement prediction* (classification).

3.6.1 Regression Metrics

The metrics that are adopted and reported include several regression-based metrics defined as follows:

$$\text{Root Mean Squared Error (RMSE)} = \sqrt{\frac{1}{T}\sum_{t=0}^{T-1}(y_t - \hat{y}_t)^2} \tag{31}$$

$$\text{Normalized RMSE (NRMSE)} = \sqrt{\frac{1}{T}\sum_{t=0}^{T-1}(y_t^{\text{norm}} - \hat{y}_t^{\text{norm}})^2} \tag{32}$$

$$\text{Mean Absolute Error (MAE)} = \frac{1}{T}\sum_{t=0}^{T-1}|y_t - \hat{y}_t| \tag{33}$$

$$\text{Normalized MAE (NMAE)} = \frac{1}{T}\sum_{t=0}^{T-1}|y_t^{\text{norm}} - \hat{y}_t^{\text{norm}}| \tag{34}$$

$$\text{Mean Absolute Percentage Error (MAPE)} = \frac{100\%}{T}\sum_{t=0}^{T-1}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{35}$$

$$\text{Normalized MAPE (NMAPE)} = \frac{100\%}{T}\sum_{t=0}^{T-1}\left|\frac{y_t^{\text{norm}} - \hat{y}_t^{\text{norm}}}{y_t^{\text{norm}}}\right| \tag{36}$$

$$\text{Coefficient of Determination } (R^2) = 1 - \frac{\sum_{t=0}^{T-1}(y_t - \hat{y}_t)^2}{\sum_{t=0}^{T-1}(y_t - \bar{y})^2} \tag{37}$$

$$\text{Directional Accuracy (DA)} = \frac{100}{T}\sum_{t=0}^{T-1}\mathbf{1}\left(\text{sign}(y_t - y_{t-1}) = \text{sign}(\hat{y}_t - y_{t-1})\right) \tag{38}$$

$$\text{Regression Accuracy (RA)} = 1 - \frac{\sum_{t=0}^{T-1}|y_t - \hat{y}_t|}{\sum_{t=0}^{T-1}|y_t - \bar{y}|} \tag{39}$$

where y_t is the predicted value at time step t, $\hat{y}_t$ is the expected value at time step t, y_t^{norm} is the predicted normalized value at time step t, $\hat{y}_t^{\text{norm}}$ is the expected normalized value at time step t, and T is the amount of instances, i.e., time steps. For all the described metrics, except R^2, RA, and DA, lower values indicate better performance.

3.6.2 Classification Metrics

The adopted and reported evaluation metrics also include several classification-based metrics formulated as follows:

$$\text{Classification Accuracy} = \frac{T_{\text{correct}}}{T} \cdot 100\% \tag{40}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{41}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{42}$$

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{43}$$

where T_{correct} is the number of correctly classified time steps, TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives. In the context of *cryptocurrency price movement prediction*, true positives are the number of time steps correctly classified as an increase in price, true negatives are the number of time steps correctly classified as a decrease in price, false positives are the number of time steps incorrectly classified as an increase in price, and false negatives are the number of time steps incorrectly classified as a decrease in price.

3.6.3 Important Metrics

Given that this study primarily focuses on the regression task of *cryptocurrency price prediction*, the most important evaluation metrics are RMSE, MAE, MAPE, and R^2. These metrics are adopted to evaluate the models we apply, as they are the most commonly used performance measures in *cryptocurrency price prediction*, as highlighted by the overview in A.2.1, as well as other regression tasks for assessing the best-performing model. In addition to RMSE, MAE, MAPE, and R^2, DA is included as an important evaluation metric to assess how well a model captures the direction of cryptocurrency price movements, in addition to the closeness of its predictions.

4 Methodology

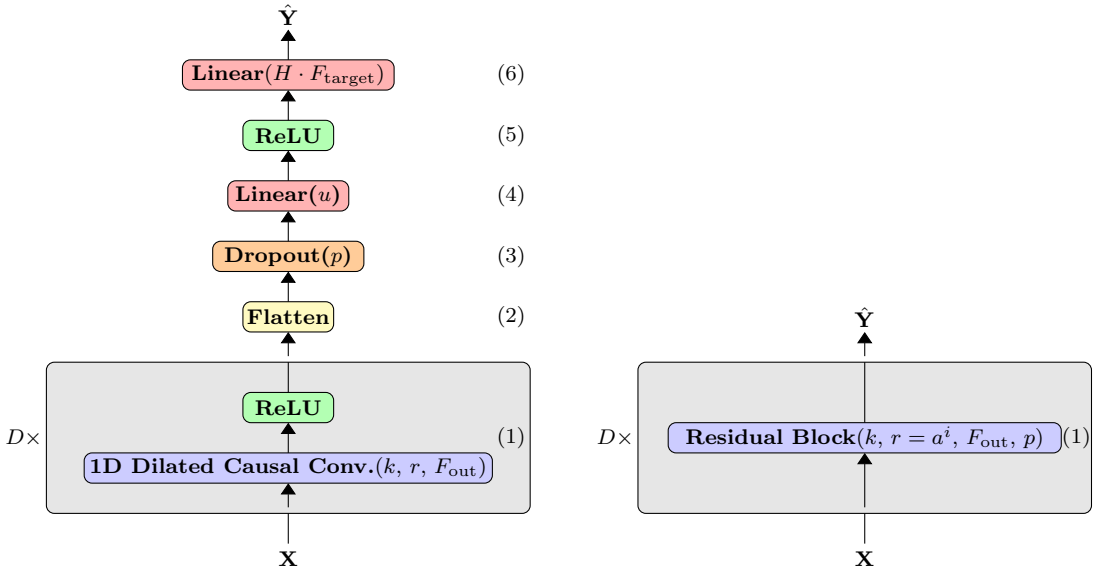
The proposed methodology builds upon the methodology proposed by Murray et al. [27] by incorporating the Temporal Convolutional Network (TCN) proposed in their study as a benchmark. Besides the TCN proposed by Murray et al. [27], the TCN proposed by Bai et al. [131] is included as an additional benchmark, as its architecture is more commonly associated with TCNs in the literature. The TCN as proposed by Bai et al. [131] serves as the foundation for the models proposed in this study:

- Temporal Convolutional Network with Variational Mode Decomposition and Parallel Mode Branches (VMD-PMB-TCN)
- Causal Multi-Head Attention-enhanced Temporal Convolutional Network with Variational Mode Decomposition and Parallel Mode Branches (VMD-PMB-CMHA-TCN)

Besides the benchmark and proposed models, the methodology adds Causal Multi-Head Attention-enhanced Temporal Convolutional Network (CMHA-TCN) to facilitate an ablation study. In line with the methodology proposed by Murray et al. [27], the proposed methodology also adopts the same dataset and a similar preprocessing procedure.

4.1 Models

4.1.1 Benchmark: TCN



(a) Architecture of the TCN adopted by Murray et al. [27] applied to an input $\mathbf{X}$ resulting in an output $\hat{\mathbf{Y}}$. The architecture corresponds to D blocks that sequentially apply a 1D dilated causal convolutional layer with F_{out} kernels, kernel size k, dilation rate r and ReLU. The blocks are followed by a flatten layer, a dropout layer with dropout rate p, a linear layer with u units, ReLU, and a final layer with $H \cdot F_{\text{target}}$ units, where H is the horizon and F_{target} the number of target variables.

(b) Architecture of the TCN proposed by Bai et al. [131] applied to an input $\mathbf{X}$ resulting in an output $\hat{\mathbf{Y}}$. The architecture corresponds to D residual blocks, according to the structure in Figure 1, with kernel size k, F_{out} kernels, dilation rate $r = a^i$, dilation base a, block index i, and dropout rate p.

Figure 3: Benchmark Models

As described in Section 3.3, TCNs are CNNs specifically designed for modeling sequences, such as time series. To achieve this, TCNs employ 1-dimensional (1D) dilated causal convolutional layers, illustrated in Figure 14 and defined in Section B.2.2. These layers ensure that the input sequence is processed in a manner that preserves causality while maintaining the sequence length throughout layer application. Through dilation, TCNs can capture long-term temporal dependencies in parallel, in contrast to RNNs, which process sequences sequentially [131]. This study incorporates two different TCN architectures: the TCN proposed by Murray et al. [27], and the TCN proposed by Bai et al. [27], depicted in Figure 3. Both serve as benchmark models in this study.

TCN: Murray et al. [27]
In Figure 3a, the architecture of the TCN part of the methodology proposed by Murray et al. [27] is depicted. The core of the proposed architecture is D stacked blocks, with each

containing a 1D dilated causal convolution layer that applies F_{out} kernels with a kernel size k and a dilation rate r, followed by the nonlinear activation function Rectified Linear Unit (ReLU), defined in (29).
Given an initial time series input $\mathbf{X} \in \mathbb{R}^{B \times T \times F}$ where B denotes the batch size, T the number of time steps, and F the number of variables, i.e., features, the TCN proposed by Murray et al. [27] processes $\mathbf{X}$ as follows:

(1) (a) First, $\mathbf{X}$ is reshaped to $\mathbf{X} \in \mathbb{R}^{B \times F \times T}$ to match the expected input shape of 1D convolutional layers described in Section B.2.1.

(b) Subsequently, $\mathbf{X}$ is processed by the D stacked blocks, where each block's output is defined as $\mathbf{H} \in \mathbb{R}^{B \times F_{\text{out}} \times T}$.

(2) Next, $\mathbf{H}$ is passed to a flattening layer that transforms $\mathbf{H}$ from $\mathbf{H} \in \mathbb{R}^{B \times F_{\text{out}} \times T}$ into $\mathbf{H} \in \mathbb{R}^{B \times (F_{\text{out}} \cdot T)}$.

(3) Following the flattening layer, $\mathbf{H}$ is forwarded to a dropout layer which randomly sets a fraction p of the flattened output to zero.

(4) The output of the dropout layer is then fed to a linear layer with u units that projects the corresponding output from $\mathbf{H} \in \mathbb{R}^{B \times (F_{\text{out}} \cdot T)}$ to $\mathbf{H} \in \mathbb{R}^{B \times u}$.

(5) Afterward, ReLU is applied to $\mathbf{H}$.

(6) Finally, another linear layer with $(H \cdot F_{\text{target}})$ units projects the output to the forecast of the time series $\hat{\mathbf{Y}} \in \mathbb{R}^{B \times (H \cdot F_{\text{target}})}$, where F_{target} is the number of target variables that are forecasted and H is the number of time steps that are forecasted, i.e., the horizon. To match the shape of the initial input, $\hat{\mathbf{Y}}$ is reshaped from $\hat{\mathbf{Y}} \in \mathbb{R}^{B \times (H \cdot F_{\text{target}})}$ to $\hat{\mathbf{Y}} \in \mathbb{R}^{B \times H \times F_{\text{target}}}$.

TCN: Bai et al. [27]
The architecture of the TCN introduced by Bai et al. [131] is illustrated in Figure 3b. The architecture consists of a stack of D residual blocks, the structure of which is described in Section 3.3 and depicted in Figure 1. Each residual block applies F_{out} kernels with a kernel size k, and an exponentially increasing dilation rate $r = a^i$, where a denotes the dilation base and i denotes the block index, through its 1D dilated causal convolutional layers. Each block, furthermore, adopts a dropout rate p through its dropout layers.
When processing $\mathbf{X}$ using the architecture shown in Figure 3b, $\mathbf{X}$ is first reshaped from $\mathbf{X} \in \mathbb{R}^{B \times T \times F}$ to $\mathbf{X} \in \mathbb{R}^{B \times F \times T}$. Considering each residual block employs dilated causal convolutional layers that apply F_{out} kernels and retain the sequence length of $\mathbf{X}$, the outputs of all residual blocks, excluding the final block, are given by $\mathbf{H} \in \mathbb{R}^{B \times F_{\text{out}} \times T}$. The final residual block produces the forecast of F_{target} time series $\hat{\mathbf{Y}} \in \mathbb{R}^{B \times F_{\text{target}} \times T}$ by applying F_{target} kernels in the second dilated causal convolutional layer instead of F_{out} kernels. $\hat{\mathbf{Y}}$ is subsequently reshaped to $\hat{\mathbf{Y}} \in \mathbb{R}^{B \times T \times F_{\text{target}}}$ in accorddance with the original input shape and processed only to include the final H timesteps in line with the chosen horizon H resulting in $\hat{\mathbf{Y}} \in \mathbb{R}^{B \times H \times F_{\text{target}}}$.

4.1.2 Proposed: VMD-PMB-TCN

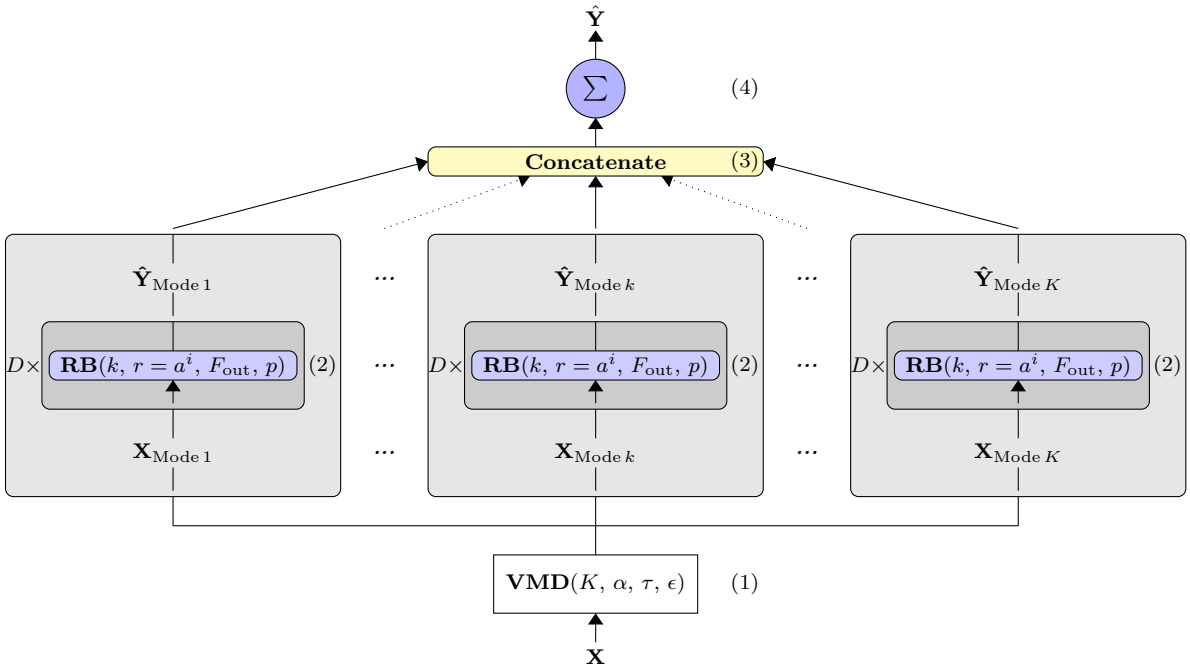


Figure 4: Architecture of the proposed model VMD-PMB-TCN applied to a univariate input $\mathbf{X}$, resulting in a univariate output $\hat{\mathbf{Y}}$. $\mathbf{X}$ is first decomposed through VMD into K modes denoted as $\mathbf{X}_{\text{Mode }1}, \ldots, \mathbf{X}_{\text{Mode }k}, \ldots, \mathbf{X}_{\text{Mode }K}$. The modes are subsequently modeled and forecasted separately by a TCN consisting of D residual blocks (RB), according to the structure in Figure 1, with kernel size k, F_{out} kernels, dilation rate $r = a^i$, dilation base a, block index i, and dropout rate p. The forecasts of the modes are subsequently concatenated and summed to form the final output $\hat{\mathbf{Y}}$.

In Figure 4, the proposed Temporal Convolutional Network with Variational Mode Decomposition and Parallel Mode Branches (VMD-PMB-TCN) is displayed. Fundamental to the architecture of VMD-PMB-TCN is the application of VMD, a signal decomposition technique that decomposes the univariate time series serving as input into K modes further described in Section 3.2. The intuition behind the application of VMD is twofold:

- The modes produced as a result of the decomposition tend to be simpler and more stationary than the original univariate time series. As such, applying VMD mitigates the nonstationarity and noise in the original time series.
- Each mode captures the underlying dynamics of the original univariate time series across different frequency ranges, where mode 1 captures characteristics at low frequencies, such as long-term trends, and mode K captures characteristics at high frequencies, such as short-term fluctuations. Because each individual mode tends to be simpler and more stationary than the original univariate time series, the model's ability to extract these dynamics with respect to the original time series should be enhanced by extracting them from the individual modes.

The decomposition of the original univariate time series through VMD is constrained such that the modes can reconstruct the original input through summation, as given by (63). Based

on this, and to further enhance the suppression of nonstationarity and the extraction of the dynamics of the original time series, VMD-PMB-TCN processes and forecasts the time series of the individual modes using separate TCNs according to the architecture proposed by Bai et al. [131], shown in Figure 3b and described in Section 4.1.1, before forecasting the initial univariate time series by summing the individual forecasts. It is important to note that the separate TCNs are not separate models, but separate branches part of the VMD-PMB-TCN model. This is because VMD is applied in a leakage-free manner, meaning there is no ground truth to compare the individual forecasts to. As such, the individual forecasts are merely intermediate outputs of VMD-PMB-TCN before producing the final output.

VMD-PMB-TCN: Details
As illustrated in Figure 4 and given a univariate time series input $\mathbf{X} \in \mathbb{R}^{B \times T \times 1}$, VMD-PMB-TCN processes $\mathbf{X}$ as follows:

(1) First, VMD decomposes $\mathbf{X}$ into a multivariate time series input $\mathbf{X} \in \mathbb{R}^{B \times T \times K}$ corresponding to K modes, i.e., subseries.

(2) (a) Next, the modes $\mathbf{X}_{\text{Mode }1} \in \mathbb{R}^{B \times T \times 1}$, ..., $\mathbf{X}_{\text{Mode }k} \in \mathbb{R}^{B \times T \times 1}$, ..., $\mathbf{X}_{\text{Mode }K} \in \mathbb{R}^{B \times T \times 1}$ that make up the multivariate time series after decomposition serve as input to separate TCNs. Before serving as input, however, each mode is first reshaped to $\mathbf{X}_{\text{Mode }1} \in \mathbb{R}^{B \times 1 \times T}$, ..., $\mathbf{X}_{\text{Mode }k} \in \mathbb{R}^{B \times 1 \times T}$, ..., $\mathbf{X}_{\text{Mode }K} \in \mathbb{R}^{B \times 1 \times T}$ in accordance with the expected shape of inputs of a TCN.

(b) Considering that each TCN applies F_{out} kernels and preserves the length of the time series input, the outputs of the D residual blocks that the TCNs consist of, ignoring the final residual block, are of shape $\mathbf{H}_{\text{Mode }1} \in \mathbb{R}^{B \times F_{\text{out}} \times T}$, ..., $\mathbf{H}_{\text{Mode }k} \in \mathbb{R}^{B \times F_{\text{out}} \times T}$, ..., $\mathbf{H}_{\text{Mode }K} \in \mathbb{R}^{B \times F_{\text{out}} \times T}$.

(c) The final residual block in each branch produces the forecast of the individual modes given by $\hat{\mathbf{Y}}_{\text{Mode }1} \in \mathbb{R}^{B \times 1 \times T}$, ..., $\hat{\mathbf{Y}}_{\text{Mode }k} \in \mathbb{R}^{B \times 1 \times T}$, ..., $\hat{\mathbf{Y}}_{\text{Mode }K} \in \mathbb{R}^{B \times 1 \times T}$ through the application of 1 kernel in the second dilated causal convolutional layer instead of F_{out} kernels. The forecasts of the modes are subsequently reshaped to $\hat{\mathbf{Y}}_{\text{Mode }1} \in \mathbb{R}^{B \times T \times 1}$, ..., $\hat{\mathbf{Y}}_{\text{Mode }k} \in \mathbb{R}^{B \times T \times 1}$, ..., $\hat{\mathbf{Y}}_{\text{Mode }K} \in \mathbb{R}^{B \times T \times 1}$.

(3) Once the individual forecasts have been determined and processed, they are concatenated along the mode, i.e., the feature dimension, resulting in $\hat{\mathbf{Y}}_{\text{Concat}} \in \mathbb{R}^{B \times T \times K}$.

(4) Afterward, a sum is performed across the mode dimension, defined as:

$$\hat{\mathbf{Y}} = \sum_{k=1}^{K} \hat{\mathbf{Y}}_{\text{Mode }k} \tag{44}$$

where $\hat{\mathbf{Y}} \in \mathbb{R}^{B \times T \times 1}$ denotes the forecast of the initial time series. Finally, $\hat{\mathbf{Y}}$ is processed to only contain the forecasts pertaining to the last H time steps in line with the chosen horizon, thus $\hat{\mathbf{Y}} \in \mathbb{R}^{B \times H \times 1}$.

4.1.3 Proposed: VMD-PMB-CMHA-TCN

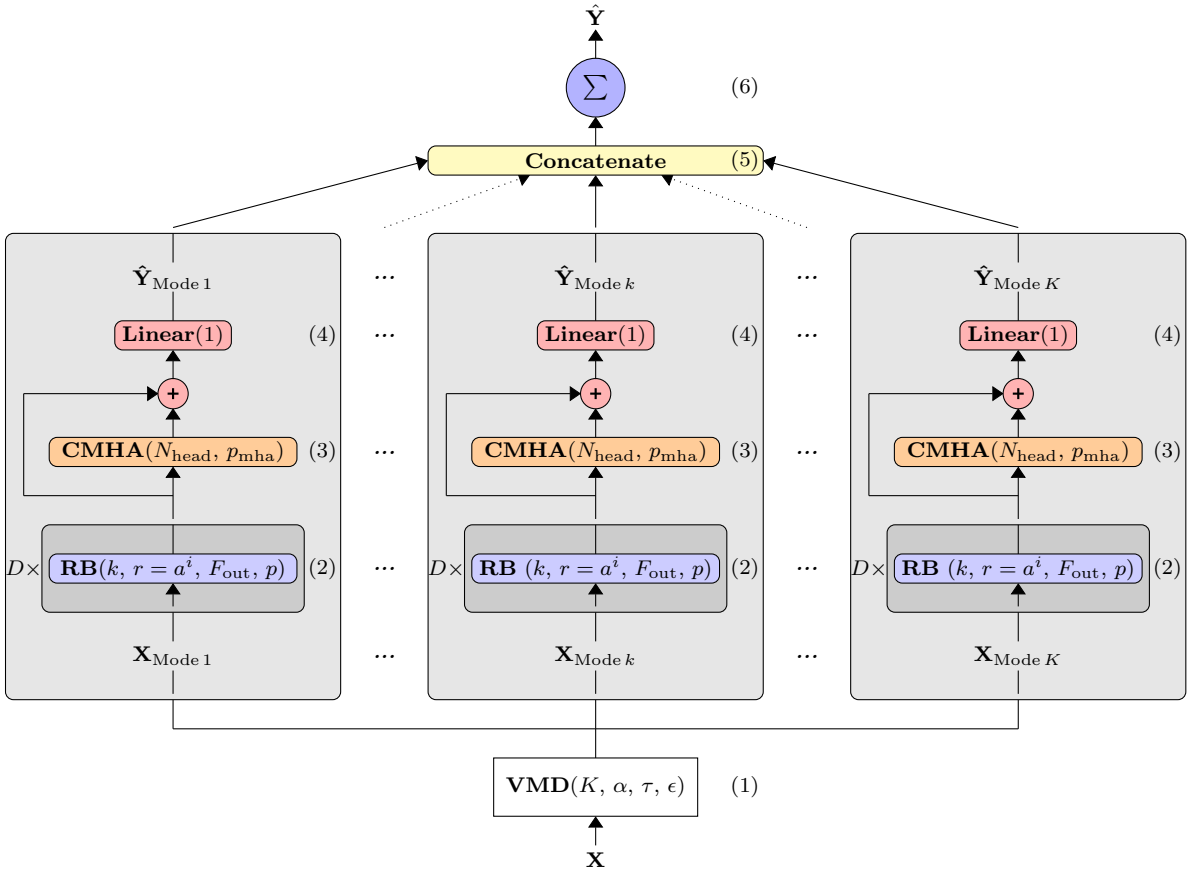


Figure 5: Architecture of the proposed model VMD-PMB-CMHA-TCN applied to a univariate input $\mathbf{X}$, resulting in a univariate output $\hat{\mathbf{Y}}$. $\mathbf{X}$ is first decomposed through VMD into K modes denoted as $\mathbf{X}_{\text{Mode }1}, \ldots, \mathbf{X}_{\text{Mode }k}, \ldots, \mathbf{X}_{\text{Mode }K}$. The modes are subsequently modeled separately by a TCN consisting of D residual blocks (RB), according to the structure in Figure 1, with kernel size k, F_{out} kernels, dilation rate $r = a^i$, dilation base a, block index i, and dropout rate p. The separate embeddings produced as a result of the TCNs are subsequently enhanced through the application of a CMHA layer with N_{head} attention heads and a dropout rate p_{mha} corresponding to a dropout layer part of the CMHA layer applied to the attention weights produced by each head. By using a skip connection, the output of the CMHA layer is added to the embedding produced by the corresponding TCN in a residual manner. Afterward, a linear layer with a single unit produces the forecast of the corresponding mode. The mode forecasts are subsequently concatenated and summed to form the final output $\hat{\mathbf{Y}}$.

The proposed Causal Multi-Head Attention-enhanced Temporal Convolutional Network with Variational Mode Decomposition and Parallel Mode Branches (VMD-PMB-CMHA-TCN) is shown in Figure 5. As depicted, the model's architecture closely resembles the architecture of VMD-PMB-CMHA-TCN, shown in Figure 4, with the notable difference that the architecture adds a causal multi-head attention mechanism (CMHA), described in Section 3.4.2 and depicted in Figure 2, and a linear layer after the TCN in the separate branches.
In each branch, the TCN is utilized to produce an embedding corresponding to the captured

temporal dependencies, and the multi-head attention mechanism is employed to enhance the quality of this embedding by emphasizing the dependencies most relevant to the forecast and suppressing the dependencies least relevant to the corresponding forecast.
Considering that preserving causality is important when forecasting time series, the employed attention mechanism is a causal multi-head attention mechanism. A causal multi-head attention mechanism preserves causality by applying a causal mask, which nullifies attention weights corresponding to dependencies on future time steps. The causal multi-head attention mechanism is followed by a linear layer that projects the resulting enhanced embedding to the individual forecast of the corresponding mode.

VMD-PMB-CMHA-TCN: Details
As depicted in Figure 5 and given a univariate time series input $\mathbf{X} \in \mathbb{R}^{B\times T\times 1}$, VMD-PMB-CMHA-TCN processes $\mathbf{X}$ in a manner that closely resembles VMD-PMB-TCN:

(1) Identical to (1) in VMD-PMB-TCN.

(2) (a) Identical to (2a) in VMD-PMB-TCN.

(b) Identical to (2b) in VMD-PMB-TCN, with the exception that the outputs of **all** residual blocks are given by $\mathbf{H}_{\text{Mode}\,1} \in \mathbb{R}^{B\times F_{\text{out}}\times T}$, ..., $\mathbf{H}_{\text{Mode}\,k} \in \mathbb{R}^{B\times F_{\text{out}}\times T}$, ..., $\mathbf{H}_{\text{Mode}\,K} \in \mathbb{R}^{B\times F_{\text{out}}\times T}$.

(c) The outputs of the residual blocks are subsequently reshaped to $\mathbf{H}_{\text{Mode}\,1} \in \mathbb{R}^{B\times T\times F_{\text{out}}}$, ..., $\mathbf{H}_{\text{Mode}\,k} \in \mathbb{R}^{B\times T\times F_{\text{out}}}$, ..., $\mathbf{H}_{\text{Mode}\,K} \in \mathbb{R}^{B\times T\times F_{\text{out}}}$ to match the required shape of the CMHA layer.

(3) (a) Once reshaped, the outputs of the residual blocks serve as input to a CMHA layer with N_{head} attention heads and a dropout rate p_{mha} corresponding to a dropout layer applied to the attention weights produced by each head.

(b) Given the output of the final residual block, the query, key, and value matrices, defined in (23), corresponding to the scaled dot-product attention applied by a single attention head in each branch are given by $\mathbf{Q}_h \in \mathbb{R}^{B\times T\times \frac{F_{\text{out}}}{H}}$, $\mathbf{K}_h \in \mathbb{R}^{B\times T\times \frac{F_{\text{out}}}{N_{\text{head}}}}$, and $\mathbf{V}_h \in \mathbb{R}^{B\times T\times \frac{F_{\text{out}}}{N_{\text{head}}}}$. The weighted representation produced from these matrices using a causal mask $\mathbf{M} \in \mathbb{R}^{T\times T}$ by a single head, according to (24), is thus given by $\mathbf{Z}_h \in \mathbb{R}^{B\times T\times \frac{F_{\text{out}}}{N_{\text{head}}}}$.

(c) Based on the weighted representation produced by a single head and the formulation in (26), the final outputs of the CMHA layers in the separate branches are therefore denoted as $\mathbf{Z}_{\text{Mode}\,1} \in \mathbb{R}^{B\times T\times F_{\text{out}}}, \ldots, \mathbf{Z}_{\text{Mode}\,k} \in \mathbb{R}^{B\times T\times F_{\text{out}}}, \ldots, \mathbf{Z}_{\text{Mode}\,K} \in \mathbb{R}^{B\times T\times F_{\text{out}}}$.

(d) To enhance the embeddings produced by the TCN in each branch, the output of the corresponding CMHA layer is added to the output of the final residual block through a skip connection. This is in line with how multi-head attention layers are applied in the Transformer architecture proposed by Vaswani et al. [177]. The enhanced embeddings produced in each branch are thus defined as:

$$\mathbf{H}'_{\text{Mode}\,k} = \mathbf{H}_{\text{Mode}\,k} + \mathbf{Z}_{\text{Mode}\,k}, \quad k = 1, \ldots, K, \quad \mathbf{H}'_{\text{Mode}\,k} \in \mathbb{R}^{B\times T\times F_{\text{out}}} \tag{45}$$

(4) Following this, the enhanced embeddings are fed into a corresponding linear layer with a 1 unit that projects the enhanced embeddings to the forecast of the separate modes given by $\hat{\mathbf{Y}}_{\text{Mode}\,1} \in \mathbb{R}^{B\times T\times 1}, \ldots, \hat{\mathbf{Y}}_{\text{Mode}\,k} \in \mathbb{R}^{B\times T\times 1}, \ldots, \hat{\mathbf{Y}}_{\text{Mode}\,K} \in \mathbb{R}^{B\times T\times 1}$.

(5) Identical to (3) in VMD-PMB-TCN

(6) Identical to (4) in VMD-PMB-TCN.

4.1.4 Ablation: CMHA-TCN

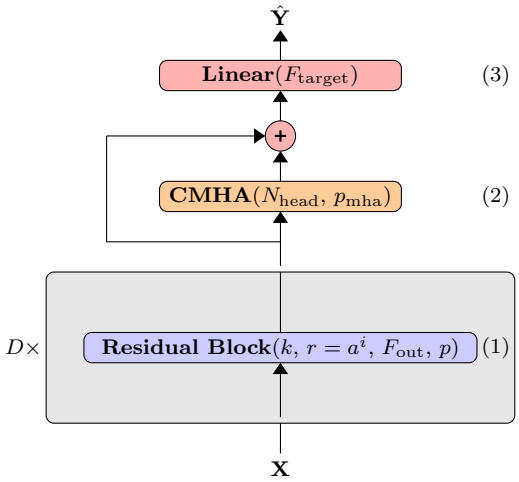


Figure 6: Architecture of CMHA-TCN applied to an input $\mathbf{X}$ resulting in an output $\hat{\mathbf{Y}}$. The architecture first applies a TCN consisting of D residual blocks, according to the structure in Figure 1, with kernel size k, F_{out} kernels, dilation rate $r = a^i$, dilation base a, block index i, and dropout rate p. The embedding produced by the TCN is subsequently enhanced through the application of a CMHA layer with N_{head} attention heads and a dropout rate p_{mha} corresponding to a dropout layer part of the CMHA layer applied to the attention weights produced by each head. By using a skip connection, the output of the CMHA layer is added to the embedding produced by the TCN in a residual manner. Afterward, a linear layer with F_{target} units forms the final output $\hat{\mathbf{Y}}$, where F_{target} denotes the number of target variables.

To facilitate an ablation study of VMD-PMB-CMHA-TCN, the Causal Multi-Head Attention-enhanced Temporal Convolutional Network (CMHA-TCN), as depicted in Figure 6, is adopted as part of the methodology. When comparing the architecture depicted in Figure 6 to the architecture of VMD-PMB-CMHA-TCN shown in Figure 5, it can be observed that the architecture is essentially identical to the one adopted in the separate branches of VMD-PMB-CMHA-TCN. In CMHA-TCN, as described in Section 4.1.3, the TCN is adopted to produce an embedding corresponding to the captured temporal dependencies, and the multi-head attention mechanism is applied to enhance the quality of this embedding by emphasizing the dependencies most relevant to the forecast and suppressing the dependencies least relevant to the corresponding forecast.
As can be seen in Figure 6 and given an initial time series input $\mathbf{X} \in \mathbb{R}^{B\times T\times F}$, $\mathbf{X}$ is processed by CMHA-TCN in the following steps:

(1) (a) Initially, $\mathbf{X}$ is reshaped to $\mathbf{X} \in \mathbb{R}^{B\times F\times T}$.

(b) Subsequently, $\mathbf{X}$ serves as input to a stack of D residual blocks with F_{out} kernels of size k, dilation rate $r = a^i$, where a is the dilation base and i the block index,

and dropout rate p resulting in the output $\mathbf{H} \in \mathbb{R}^{B \times F_{\text{out}} \times T}$, which is subsequently reshaped to $\mathbf{H} \in \mathbb{R}^{B \times T \times F_{\text{out}}}$.

(2) (a) Following that, the output of the final residual block is passed to a CMHA layer with N_{head} attention heads and a dropout rate p_{mha} corresponding to a dropout layer part of the CMHA layer applied to the attention weights produced by each head.

(b) As detailed in Section 4.1.3, the CMHA layer produces a weighted representation $\mathbf{Z} \in \mathbb{R}^{B \times T \times F_{\text{out}}}$, which is added to the embedding produced by the last residual block $\mathbf{H}$ in a residual manner by making use of a skip connection. This results in the enhanced embedding $\mathbf{H}' \in \mathbb{R}^{B \times T \times F_{\text{out}}}$, thus defined as:

$$\mathbf{H}' = \mathbf{H} + \mathbf{Z} \tag{46}$$

(3) Lastly, the enhanced embedding serves as input to a linear layer with F_{target} units which project the embedding to the forecast of F_{target} time series $\hat{\mathbf{Y}} \in \mathbb{R}^{B \times T \times F_{\text{target}}}$, which is in turn processed to only include the final H timesteps in accordance with the horizon, thus $\hat{\mathbf{Y}} \in \mathbb{R}^{B \times H \times F_{\text{target}}}$.

4.2 Data Overview

In this study, we adopt two datasets: the *benchmark dataset* and the *extended dataset*. The *benchmark dataset* is the same dataset utilized in the benchmark study by Murray et al. [27]. Its use is essential to conduct experiments identical to those conducted by Murray et al. [27]. The *extended dataset* is an extension of the *benchmark dataset* to be able to conduct experiments in a more recent context. Both datasets consist of a multivariate time series $\mathbf{S} \in \mathbb{R}^{T \times F}$, in accordance with the provided definition in (3), for each of *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD*. Each multivariate time series comprises several variables related to the prices of the respective cryptocurrencies.

4.2.1 Description: Benchmark Dataset & Extended Dataset

The multivariate time series corresponding to *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* in both the *benchmark dataset* and the *extended dataset* consist of the following price-related features:

- $\mathbf{S}_{\text{Open}} \in \mathbb{R}^{T \times 1}$: The open price in *USD*, the price of a cryptocurrency at the start of a unit of time, f.e, a day.
- $\mathbf{S}_{\text{High}} \in \mathbb{R}^{T \times 1}$: The high price in *USD*, the highest price of a cryptocurrency reached during a unit of time.
- $\mathbf{S}_{\text{Low}} \in \mathbb{R}^{T \times 1}$: The low price in *USD*, the lowest price of a cryptocurrency reached during a unit of time.
- $\mathbf{S}_{\text{Close}} \in \mathbb{R}^{T \times 1}$: The close price in *USD*, the price of a cryptocurrency at the end of a unit of time.

In the *benchmark dataset*, the described features are recorded at a daily frequency from 1 June 2017 to 31 May 2022 and were collected by Murray et al. [27] from two different sources:

- *Binance* [193] via the *Binance* API: The largest cryptocurrency exchange based on both market share and trading volume [194, 195].

- *Investing.com* [196]: An online platform that provides market data, analysis, news, and information on numerous financial assets, including stocks and cryptocurrencies.

In constructing the *benchmark dataset*, Murray et al. [27] relied primarily on *Binance* as the principal data source, with *Investing.com* used exclusively to fill missing values.
Given that 2022 is several years in the past, the data in the *benchmark dataset* for the mentioned features is extended beyond 31 May 2022 to form the *extended dataset*. To achieve this, the same sources used by Murray et al. [27] are employed to collect additional data from 1 June 2022 to 31 May 2025. Consequently, the *extended dataset* comprises data pertaining to the same features from 1 June 2017 to 31 May 2025 at a daily frequency.

4.2.2 Primary Analysis: Benchmark Dataset & Extended Dataset

To gain insight into the *benchmark dataset* and the *extended dataset*, we conduct an analysis with a particular focus on $\mathbf{S}_{\text{Close}}$ as its decomposition using VMD, according to the description in Section 4.1.2, is a central component of the proposed methodology. The main findings of the primary analysis are as follows:

- The statistics of the *benchmark dataset* and the *extended dataset*, presented in Tables 30 and 31, in combination with the visualizations of $\mathbf{S}_{\text{Close}}$ and $\mathbf{S}$ in general, such as those shown in Figure 7 and Figures 16 to 20, demonstrate that the prices of *BTC*/*USD*, *ETH*/*USD*, *LTC*/*USD*, *XMR*/*USD*, and *XRP*/*USD* in the *benchmark dataset* and the *extended dataset* tend to be highly volatile and nonstationary as evident from the large fluctuations, high standard deviation, and the time varying variance.

- The nonstationarity of the prices with respect to *BTC*/*USD*, *ETH*/*USD*, *LTC*/*USD*, *XMR*/*USD*, and *XRP*/*USD* is further evidenced by the results of the stationarity tests conducted on the *benchmark dataset* and the *extended dataset*, presented in Tables 1 and 2. The results demonstrate that $\mathbf{S}_{\text{Close}}$ for each cryptocurrency, with the exception of *LTC*/*USD* in the *extended dataset*, is identified as nonstationary by at least one of the performed stationarity tests when using a significance level of $\alpha = 0.05$ (5%).

Statistics and Visualizations
In line with the conditions provided in Section 3.1.2, the statistics and graphs in relation to the *benchmark dataset* and the *extended dataset* with regard to $\mathbf{S}_{\text{Open}}$, $\mathbf{S}_{\text{High}}$, $\mathbf{S}_{\text{Low}}$, and $\mathbf{S}_{\text{Close}}$ appear to confirm that the prices of *BTC*/*USD*, *ETH*/*USD*, *LTC*/*USD*, *XMR*/*USD*, and *XRP*/*USD* are indeed of a nonstationary nature and that the prices suffer from severe volatility.
The statistics with respect to the *benchmark dataset* and the *extended dataset* in Tables 30 and 31, part of Appendix C, highlight that the distribution of $\mathbf{S}_{\text{Open}}$, $\mathbf{S}_{\text{High}}$, $\mathbf{S}_{\text{Low}}$, and $\mathbf{S}_{\text{Close}}$ has a substantial dispersion and a pronounced positive skewness irrespective of the particular cryptocurrency. Additionally, the distributions of each time series exhibit relatively high standard deviations, suggesting substantial volatility.
This is further illustrated with respect to $\mathbf{S}_{\text{Close}}$ in Figure 7, where the time series for each cryptocurrency exhibits pronounced short- and long-term trends, with no clear evidence of seasonality, suggesting $\mathbf{S}_{\text{Close}}$ is nonstationary. Furthermore, Figure 7 highlights numerous abrupt

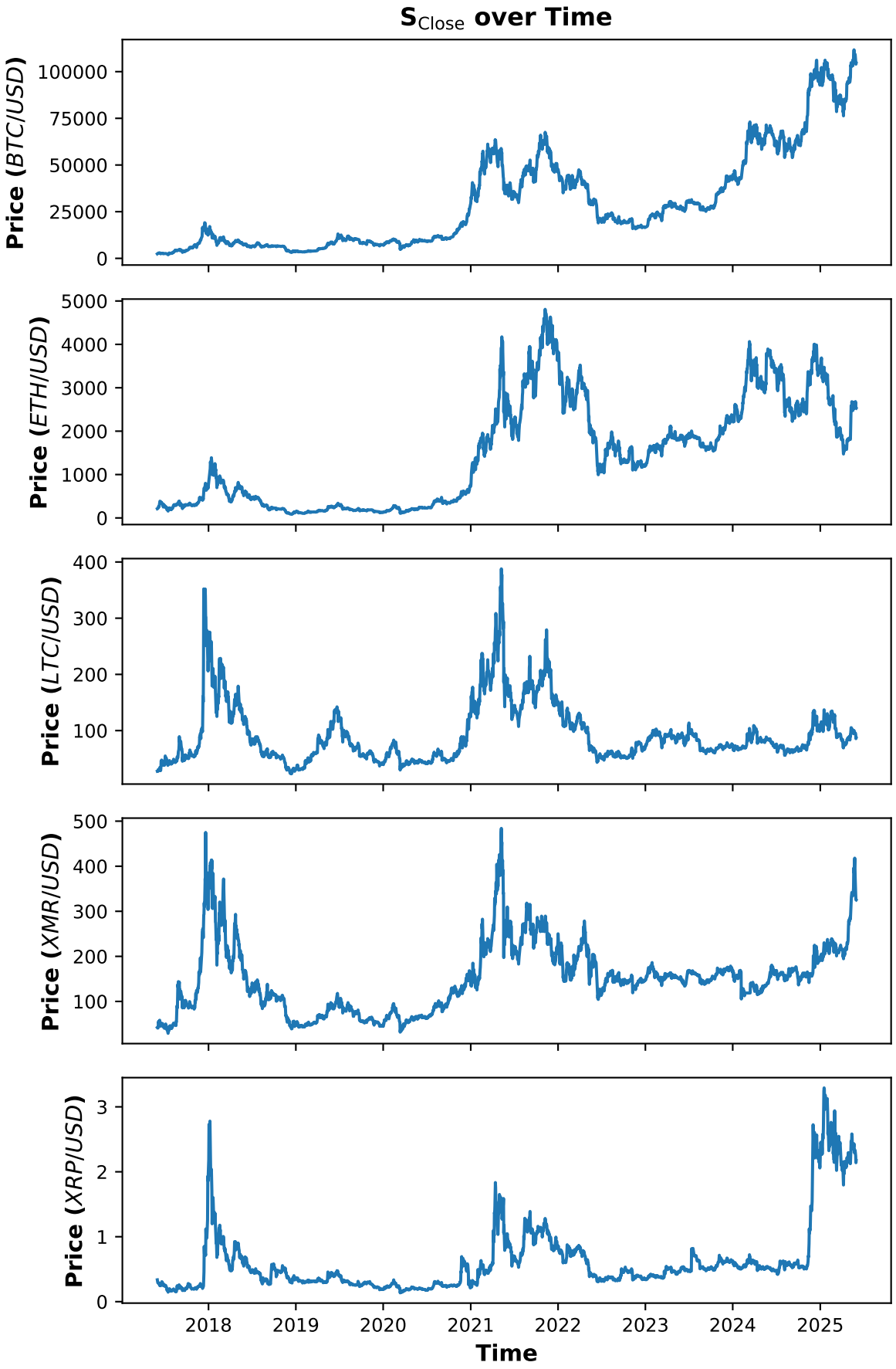


Figure 7: S_{Close} with respect to BTC/USD, ETH/USD, LTC/USD, XMR/USD, and XRP/USD from 1 June 2017 to 31 May 2025

changes in $\mathbf{S}_{\text{Close}}$ over short time intervals, indicating a high degree of volatility.
The high volatility of the prices of the respective cryptocurrencies is further emphasized by Figures 16 to 20 in Appendix C, where the difference between $\mathbf{S}_{\text{High}}$ and $\mathbf{S}_{\text{Low}}$ on the same day is often considerable. This is especially apparent in mid-2021, for example. Figures 21 to 25 in Appendix C, similarly, highlight the pronounced volatility in $\mathbf{S}_{\text{Close}}$, where the returns of $\mathbf{S}_{\text{Close}}$ are defined as the change in percentage of $\mathbf{S}_{\text{Close}}$ from one day to the next and the volatility as the standard deviation of the logarithmic returns in percentages [197]. In other words, the return of $\mathbf{S}_{\text{Close}}$ at time step t, $r_{t,\text{Close}}$, can be defined as follows:

$$r_{t,\text{Close}} = \left(\frac{\mathbf{S}_{t,\text{Close}} - \mathbf{S}_{t-1,\text{Close}}}{\mathbf{S}_{t-1,\text{Close}}} \right) \cdot 100\% \tag{47}$$

whereas the logarithmic return of $\mathbf{S}_{\text{Close}}$ at time step t, $r^{\log}_{t,\text{Close}}$, is given by:

$$r^{\log}_{t,\text{Close}} = \ln \left(\frac{\mathbf{S}_{t,\text{Close}}}{\mathbf{S}_{t-1,\text{Close}}} \right) \tag{48}$$

As depicted, $\mathbf{S}_{\text{Close}}$ exhibits significant volatility, particularly during early 2018, early 2020, and mid-2021. Moreover, these figures clearly indicate that $\mathbf{S}_{\text{Close}}$ suffers from volatility clustering, whereby periods of high volatility have a tendency to be followed by high volatility, and periods of low volatility have a tendency to be followed by low volatility.
The suggestion that $\mathbf{S}_{\text{Close}}$ is nonstationary is further supported by the plots of the autocorrelation function (ACF) and the partial autocorrelation function (PACF), as defined in Section 3.1.4, of $\mathbf{S}_{\text{Close}}$ in Appendix C displayed by Figures 26 to 35 and Figures 36 to 45, corresponding to both the *benchmark dataset* as well as the *extended dataset*. The ACF plots of $\mathbf{S}_{\text{Close}}$ for each cryptocurrency exhibit a slow decay as the lag increases, which may indicate the presence of a unit root, i.e., a nonstationary characteristic, and suggests the existence of a trend in $\mathbf{S}_{\text{Close}}$ [198]. If $\mathbf{S}_{\text{Close}}$ contains a unit root, the ACF behaviour described above is typically accompanied by PACF plots that exhibit significant partial autocorrelation at lags 0 and 1, while partial autocorrelations at higher lags are negligible [198]. Figures 36 to 45 show that the PACF plots of $\mathbf{S}_{\text{Close}}$ for the various cryptocurrencies generally follow this pattern, particularly for *BTC*. However, the PACF plots for *LTC* and *XMR*, for example, do exhibit relatively significant partial autocorrelations at additional lags.

Stationarity Tests
While the previously discussed statistical and graphical analyses suggest that $\mathbf{S}_{\text{Close}}$ and the prices of *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* in general are nonstationary, formal stationarity tests, namely the ADF and KPSS tests, described in Section 3.1.4, are conducted to corroborate these findings. In [27], Murray et al. claimed to have performed the ADF test on the *benchmark dataset* in relation to $\mathbf{S}_{\text{Close}}$, which demonstrated that $\mathbf{S}_{\text{Close}}$ with respect to each cryptocurrency, apart from *XRP/USD*, was shown to be nonstationary. Murray et al. [27], however, did not provide the test results to support these claims. As such, the ADF test is conducted again in this study alongside the KPSS test. The tests are conducted on both the *benchmark dataset* and the *extended dataset*.
As highlighted by Table 1, the results of the ADF test performed on the *benchmark dataset* are consistent with the findings of Murray et al. [27], with $\mathbf{S}_{\text{Close}}$ being found to be nonstationary for most cryptocurrencies, as the corresponding p-values exceed the chosen significance level α, except with respect to *XRP/USD*, where the p-value is significantly lower than α,

Crypto	Test Type	Test Stat.	p	Critical Val. (1%)	Critical Val. (5%)	Critical Val. (10%)	Determination
BTC/USD	ADF	-1.315	0.623	-3.434	-2.863	-2.568	Nonstationary
	KPSS	4.519	0.010	0.739	0.463	0.347	Nonstationary
ETH/USD	ADF	-1.204	0.672	-3.434	-2.863	-2.568	Nonstationary
	KPSS	3.920	0.010	0.739	0.463	0.347	Nonstationary
LTC/USD	ADF	-2.818	0.056	-3.434	-2.863	-2.568	Nonstationary
	KPSS	1.146	0.010	0.739	0.463	0.347	Nonstationary
XMR/USD	ADF	-2.564	0.101	-3.434	-2.863	-2.568	Nonstationary
	KPSS	1.395	0.010	0.739	0.463	0.347	Nonstationary
XRP/USD	ADF	-3.830	0.003	-3.434	-2.863	-2.568	Stationary
	KPSS	1.055	0.010	0.739	0.463	0.347	Nonstationary

Table 1: Results of the ADF and KPSS stationarity tests on the *benchmark dataset* with significance level $a = 0.5$ in relation to $\mathbf{S}_{\text{Close}}$ with respect *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD*.

indicating stationarity. In contrast, in relation to *BTC/USD* and *ETH/USD*, the p-values are significantly greater than α, providing a strong indication that $\mathbf{S}_{\text{Close}}$ is nonstationary. This indication is significantly weaker for *LTC/USD* and *XMR/USD*, as the p-values are closer to α. In particular, the p-value produced for $\mathbf{S}_{\text{Close}}$ in terms of *LTC/USD* narrowly exceeds the value of α, whilst for *XMR/USD*, $\mathbf{S}_{\text{Close}}$ is narrowly indicated to be nonstationary at a significance level of 0.1 (10%). The results of the KPSS test conducted on the *benchmark dataset* with respect to $\mathbf{S}_{\text{Close}}$ are largely consistent with the ADF test findings, except for *XRP/USD*. The KPSS test suggests $\mathbf{S}_{\text{Close}}$ to be nonstationary for all considered cryptocurrencies, as the associated p-values are below the chosen significance level α. Moreover, the test statistics significantly exceed the critical values at the lowest reported significance level, strongly suggesting that $\mathbf{S}_{\text{Close}}$ is nonstationary.

The results in Table 2 of the ADF and KPSS tests conducted on the *extended dataset* are, for the most part, in accordance with the results of those performed on the *benchmark dataset*. The results for *BTC/USD* and *XRP/USD* provide a stronger indication of $\mathbf{S}_{\text{Close}}$ being nonstationary with respect to the *extended dataset*, as reflected by the higher p-values with respect to the ADF test and the larger KPSS test statistics compared to those obtained in relation to the *benchmark dataset*. In contrast to the ADF test performed on the *benchmark dataset*, *XRP/USD* is indicated as being nonstationary by the ADF test, with the produced p-value being larger than α by a significant margin. Similarly to the KPSS test results of *BTC/USD*, the KPSS test results with respect to *ETH/USD* provide a stronger suggestion of $\mathbf{S}_{\text{Close}}$ being nonstationary. The p-value produced by the ADF test, on the other hand, is lower than the one produced in relation to the *benchmark dataset*. The p-value does, however, remain well above the chosen significance level α, therefore still suggesting $\mathbf{S}_{\text{Close}}$ to be nonstationary. The main difference between the results of the ADF and KPSS tests performed on the *benchmark dataset* and those performed on the *extended dataset* can be observed for *LTC/USD*. According to both the ADF and KPSS tests, $\mathbf{S}_{\text{Close}}$ with respect to *LTC/USD* is stationary at the chosen significance level α. The ADF test produces a p-value that is significantly below α, indicating that the null hypothesis of $\mathbf{S}_{\text{Close}}$ being nonstationary can be rejected. Similarly, the KPSS test statistic is slightly lower than the critical value at the significance level 0.1 (10%),

Crypto	Test Type	Test Stat.	p	Critical Val. (1%)	Critical Val. (5%)	Critical Val. (10%)	Determination
BTC/USD	ADF	-0.180	0.941	-3.433	-2.863	-2.567	Non-Stationary
	KPSS	6.009	0.010	0.739	0.463	0.347	Non-Stationary
ETH/USD	ADF	-1.691	0.436	-3.433	-2.863	-2.567	Non-Stationary
	KPSS	5.590	0.010	0.739	0.463	0.347	Non-Stationary
LTC/USD	ADF	-3.494	0.008	-3.433	-2.863	-2.567	Stationary
	KPSS	0.339	0.100	0.739	0.463	0.347	Stationary
XMR/USD	ADF	-2.944	0.040	-3.433	-2.863	-2.567	Stationary
	KPSS	1.362	0.010	0.739	0.463	0.347	Non-Stationary
XRP/USD	ADF	-2.124	0.235	-3.433	-2.863	-2.567	Non-Stationary
	KPSS	2.002	0.010	0.739	0.463	0.347	Non-Stationary

Table 2: Results of the ADF and KPSS stationarity tests on the *extended dataset* with significance level $a = 0.5$ in relation to $\mathbf{S}_{\text{Close}}$ with respect *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD*.

indicating that the null hypothesis of stationarity cannot be rejected at significance level α. The test results with respect to *XMR/USD* demonstrate another apparent difference between the test results on the *benchmark dataset* and the *extended dataset*. Instead of the ADF test suggesting $\mathbf{S}_{\text{Close}}$ to be nonstationary with respect to *XMR/USD*, it suggests $\mathbf{S}_{\text{Close}}$ to be stationary according to significance level α. The KPSS test, however, contradicts the result of the ADF test, as according to its results, $\mathbf{S}_{\text{Close}}$ is still pointed out as being nonstationary, albeit with a slightly lower test statistic compared to the test statistic produced with respect to the *benchmark dataset*.

4.2.3 Supplementary Analysis: Interrelationships

Motivated by the interrelationships and interdependencies between cryptocurrencies documented by Tanwar et al. [163] and Wu [143], particularly between dominant cryptocurrencies such as *BTC* and other cryptocurrencies, e.g., *LTC*, we conduct a supplementary analysis that examines the relationships between the considered cryptocurrencies using Pearson and Spearman correlation, alongside Granger causality tests up to a lag of 30, based on $\mathbf{S}_{\text{Close}}$ and the returns of $\mathbf{S}_{\text{Close}}$ in the *extended dataset*. As the relationships between $\mathbf{S}_{\text{Close}}$ of the relevant cryptocurrencies can be spurious, i.e., misleading, due to shared trends and the nonstationarity of $\mathbf{S}_{\text{Close}}$, the more stationary returns of $\mathbf{S}_{\text{Close}}$ are adopted as part of this analysis as they likely provide a more reliable basis for analyzing the correlation and causality between the cryptocurrencies rather than solely using $\mathbf{S}_{\text{Close}}$ [199]. The main findings of the supplementary analysis are as follows:

- The Pearson and Spearman correlations, in particular the latter, with respect to $\mathbf{S}_{\text{Close}}$ and the returns of $\mathbf{S}_{\text{Close}}$ demonstrate significant correlations between almost all pairs of the considered cryptocurrencies.
- The Granger causality tests demonstrate that not all of the considered cryptocurrencies share a causal relationship. Instead, evidence of causality is generally only observed between particular pairs of cryptocurrencies with respect to $\mathbf{S}_{\text{Close}}$ or the corresponding

returns. The results with respect to *BTC/USD* appear to be consistent with the lead-lag relationship and overall dominant role that *BTC* exhibits in the cryptocurrency market according to previous research [40, 143, 163].

Pearson and Spearman Correlation
The Pearson correlation measures the direction and strength of the linear dependence between two time series, while the Spearman correlation captures the direction and strength of their monotonic relationship [200]. As highlighted by Tables 32 to 35, there are significant correlations between almost all pairs of cryptocurrencies in relation to $\mathbf{S}_{\text{Close}}$ and the returns of $\mathbf{S}_{\text{Close}}$. The significant correlations are particularly evident from the measured Spearman correlation, which likely provides the most reliable correlation measure given that $\mathbf{S}_{\text{Close}}$ and the returns of $\mathbf{S}_{\text{Close}}$ are not of a linear nature. The Spearman correlation results for $\mathbf{S}_{\text{Close}}$ indicate strong dependencies among most cryptocurrencies. An exception is observed for *LTC/USD*, which exhibits weaker correlations with *BTC/USD* and *ETH/USD*, while still maintaining notable correlations with *XMR/USD* and *XRP/USD*. In contrast, the Spearman correlation results for the returns of $\mathbf{S}_{\text{Close}}$ indicate particularly strong correlations among *BTC/*USD, *ETH/USD*, and *LTC/USD*, as well as with other cryptocurrencies.

Granger Causality
The Granger causality tests assess whether one time series is predictive of another [201]. The results of the Granger causality tests provide various insights into the predictive relationships between the cryptocurrencies under consideration. As indicated in Tables 36 and 37, the other cryptocurrencies do not exhibit significant predictive power for *BTC/USD*. This result is consistent with the observed lead-lag relationship in cryptocurrency markets in previous studies, where *BTC* tends to lead, and other cryptocurrencies follow its price dynamics [40]. With respect to *ETH/USD*, Table 38 demonstrates that all other cryptocurrencies, except for *BTC/USD*, exhibit significant predictive power for $\mathbf{S}_{\text{Close}}$ at lags of up to 10. In terms of the returns of $\mathbf{S}_{\text{Close}}$, *BTC/USD*, *LTC/USD*, and *XMR/USD* demonstrate significant predictive power for *ETH/USD* at lower lags, whereas *XMR/USD* exhibits significant predictive power at higher lags, as shown in Table 39. The Granger causality test results for *LTC/USD*, based on $\mathbf{S}_{\text{Close}}$, as presented in Table 40, suggest that other cryptocurrencies, particularly *ETH/USD*, exhibit significant Granger-causal relationships with *LTC/USD* at lags of up to 3. In contrast, for the returns of $\mathbf{S}_{\text{Close}}$, Table 41 indicates that only *BTC/USD* exhibits significant Granger-causal relationships with *LTC*. Furthermore, the Granger causality test results for *XMR/USD*, based on $\mathbf{S}_{\text{Close}}$, shown in Table 42, only indicate *ETH/USD* to contain substantial predictive information for *XMR/USD* at low to moderate lags. The results based on the returns of $\mathbf{S}_{\text{Close}}$ demonstrate that especially *BTC/USD* and *ETH/USD* provide significant predictive information for *XMR/USD* across all examined lags. The results pertaining to *XRP/USD* only demonstrate significant Granger causality at lag 1 with respect to $\mathbf{S}_{\text{Close}}$ between *XRP/USD* and all other cryptocurrencies except *BTC/USD*. For the returns of $\mathbf{S}_{\text{Close}}$, none of the other cryptocurrencies exhibits any significant degree of predictive power at any lag.

4.3 Data Preprocessing

.
This study incorporates three distinct preprocessing pipelines that are utilized to preprocess the time series $\mathbf{S}$, defined in Section 4.2, with respect to *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* in the *benchmark dataset* and the *extended dataset*:

1. **Default**: Feature scaling followed by the application of a sliding window to create the windowed time series $\mathbf{S}^{\text{Windowed}}$. This preprocessing pipeline is incorporated to assess the efficacy of the transformations, differencing, and VMD in the other preprocessing pipelines. This addresses a limitation of Murray et al. [27], who did not assess the efficacy of differencing by comparing its performance with that of a preprocessing pipeline in which no transformation other than feature scaling was applied.

2. **Differenced**: Differencing, as formulated in (14), followed by feature scaling and the application of a sliding window to create $\mathbf{S}^{\text{Windowed}}$. This preprocessing pipeline is consistent with the one utilized by Murray et al. [27] in the benchmark study and is at the base of the models that serve as benchmarks in this study.

3. **VMD**: Feature scaling followed by the application of a sliding window to create $\mathbf{S}^{\text{Windowed}}$, during which VMD is applied. This preprocessing pipeline is at the base of the proposed models VMD-PMB-TCN and VMD-PMB-CMHA-TCN, detailed in Sections 4.1.2 and 4.1.3.

4.3.1 Differencing

Differencing, as employed by Murray et al. [27], applies first-order differencing in an attempt to make $\mathbf{S}$ stationary. In other words, each time step t of $\mathbf{S}$, except $t = 0$, is transformed as follows:

$$\mathbf{S}'_t = \mathbf{S}_t - \mathbf{S}_{t-1}, \quad t = 1, \ldots, T-1 \tag{49}$$

After the application of first-order differencing, $\mathbf{S}$ is thus of length $T - 1$ instead of T.

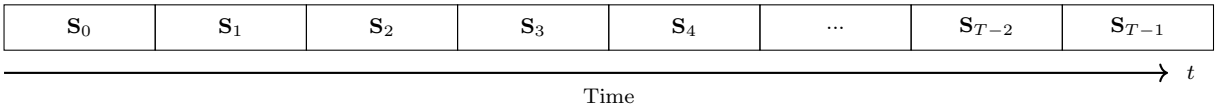
4.3.2 Scaling

An important step in the preprocessing procedure is to scale the features of $\mathbf{S}$. This ensures that all features are within a similar numerical range, thereby preventing features with larger magnitudes from dominating the learning process, which has been shown to enhance model performance [202]. In [27], Murray et al. adopted min-max normalization to scale their dataset. To ensure consistency in preprocessing, this study also adopts min-max normalization to scale the features of $\mathbf{S}$. The adopted scaling method, min-max normalization, can be defined as follows:

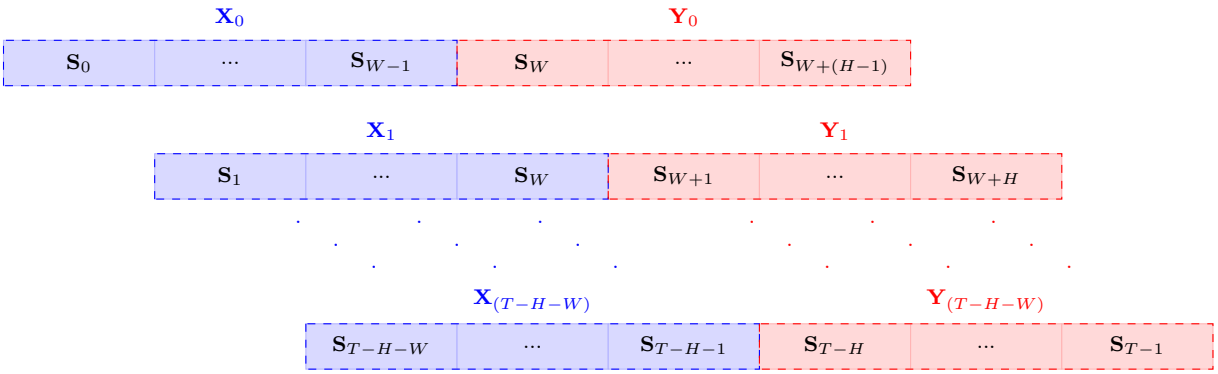
$$x'_t = \frac{x_t - \min(X)}{\max(X) - \min(X)} \tag{50}$$

where X denotes a univariate time series, x_t is the observation of X at time step t, $\min(X)$ and $\max(X)$ denote the minimum and maximum values of X across all time steps, and x'_t is x_t after scaling, such that $x'_t \in [0, 1]$.
Min-max normalization is applied to each feature in $\mathbf{S}$ independently. The parameters of the min-max normalization, $\min(X)$ and $\max(X)$, are defined based on the training subset $\mathbf{S}_{\text{Train}}$. Subsequently, the defined parameters are adopted to scale the training, validation, and test subsets, i.e., $\mathbf{S}_{\text{Train}}$, $\mathbf{S}_{\text{Val}}$, and $\mathbf{S}_{\text{Test}}$, respectively.

4.3.3 Sliding Window



(a) $\mathbf{S}$ before the transformation into $\mathbf{S}^{\text{Windowed}}$.



(b) $\mathbf{S}^{\text{Windowed}}$, after applying a sliding window of size W with a horizon H to $\mathbf{S}$, where $\mathbf{X}$ corresponds to the part of $\mathbf{S}^{\text{Windowed}}$ that will serve as input and $\mathbf{Y}$ to the part of $\mathbf{S}^{\text{Windowed}}$ that will serve as the expected output

Figure 8: The transformation of $\mathbf{S}$ into $\mathbf{S}^{\text{Windowed}}$ via the application of a sliding window.

Once the features of $\mathbf{S}$ have been scaled, a sliding window is applied to $\mathbf{S}$, resulting in the transformation of $\mathbf{S}$ into a windowed time series, denoted as $\mathbf{S}^{\text{Windowed}}$, consistent with the preprocessing applied by Murray et al. [27]. The transformation of $\mathbf{S}$ into $\mathbf{S}^{\text{Windowed}}$ is illustrated in Figure 8, where W denotes the size of the sliding window, and H the forecasting horizon, i.e, the number of future time steps to be forecasted. Specifically, Figure 8a depicts $\mathbf{S}$ before the transformation into $\mathbf{S}^{\text{Windowed}}$ and Figure 8b demonstrates the application of the sliding window to $\mathbf{S}$ leading to the conversion of $\mathbf{S}$ into $\mathbf{S}^{\text{Windowed}}$.
As shown in Figure 8b, starting from the first timestep, $\mathbf{S}_{t=0}$, each timestep up to $\mathbf{S}_{t=T-W-H}$ serves as the starting point for a sliding window of W timesteps to create the subset $\mathbf{X}$ of $\mathbf{S}^{\text{Windowed}}$ that will serve as input to the models. Each instance of $\mathbf{X}$ corresponds to the following subsequence:

$$\mathbf{S}_{t:t+W} := \{\mathbf{S}_i \mid i \in [t, t+W)\} \in \mathbb{R}^{W \times F} \tag{51}$$

Consequently, $\mathbf{X}$ can be defined as:

$$\mathbf{X} = \begin{bmatrix} \mathbf{S}_{0:W} \\ \mathbf{S}_{1:1+W} \\ \vdots \\ \mathbf{S}_{T-W-H:T-H} \end{bmatrix} \in \mathbb{R}^{(T-W-H+1) \times W \times F}. \tag{52}$$

The subset $\mathbf{Y}$ of $\mathbf{S}^{\text{Windowed}}$, which serves as the target output of the models, is constructed analogously to $\mathbf{X}$, with the number of time steps in each instance determined by the forecasting horizon H in line with the definition of forecasting given by (16), rather than the window size

W. For each sliding window applied to construct an instance of $\mathbf{X}$ corresponding to $\mathbf{S}_{t:t+W}$, a corresponding target sequence $\mathbf{Y}$ is given by:

$$\mathbf{S}_{t+W:t+W+H} = \{\mathbf{S}_i \mid i \in [t+W, t+W+H)\} \in \mathbb{R}^{H \times F} \tag{53}$$

Accordingly, $\mathbf{Y}$ can be formulated as:

$$\mathbf{Y} = \begin{bmatrix} \mathbf{S}_{W:W+H} \\ \mathbf{S}_{W+1:W+H+1} \\ \vdots \\ \mathbf{S}_{T-W-H:T} \end{bmatrix} \in \mathbb{R}^{(T-W-H+1) \times H \times F}. \tag{54}$$

Given that the focus of this study is on forecasting $\mathbf{S}_{\text{Close}}$, $\mathbf{Y}$ is constructed solely based on $\mathbf{S}_{\text{Close}}$, i.e., $\mathbf{Y} = \mathbf{Y}_{\text{Close}}$.
During the construction of $\mathbf{S}^{\text{Windowed}}$, the data split into $\mathbf{S}_{\text{Train}}$, $\mathbf{S}_{\text{Val}}$, and $\mathbf{S}_{\text{Test}}$ adopted during the scaling is preserved to prevent data leakage. Consequently, $\mathbf{S}^{\text{Windowed}}$ is partitioned as follows:

$$\mathbf{S}^{\text{Windowed}} = \mathbf{S}^{\text{Windowed}}_{\text{Train}} \cup \mathbf{S}^{\text{Windowed}}_{\text{Val}} \cup \mathbf{S}^{\text{Windowed}}_{\text{Test}} \tag{55}$$

Furthermore, the corresponding pairs of input and target output subsets satisfy:

$$\begin{aligned} &(\mathbf{X}_{\text{Train}}, \mathbf{Y}_{\text{Train}}) \subset \mathbf{S}^{\text{Windowed}}_{\text{Train}}, \\ &(\mathbf{X}_{\text{Val}}, \mathbf{Y}_{\text{Val}}) \subset \mathbf{S}^{\text{Windowed}}_{\text{Val}}, \\ &(\mathbf{X}_{\text{Test}}, \mathbf{Y}_{\text{Test}}) \subset \mathbf{S}^{\text{Windowed}}_{\text{Test}} \end{aligned} \tag{56}$$

4.3.4 VMD

The proposed models, described in Sections 4.1.2 and 4.1.3, are based on the application of VMD, as formalized in Section 3.2, to mitigate nonstationarity and produce subseries, i.e., modes from a univariate time series, $\mathbf{S}_{\text{Close}}$ in this case, that are simpler to process. To ensure that VMD is applied in a manner that prevents data leakage, we propose and apply two methods: Sliding Variational Mode Decomposition (SVMD) and Expanding Variational Mode Decomposition (EVMD). In addition to SVMD and EVMD, we adopt Variational Mode Decomposition with Data Leakage (DLVMD). DLVMD applies VMD in a manner that intentionally introduces data leakage consistent with the manner in which VMD is applied in the previous research highlighted in the Introduction and Section 2.5 [81–87, 89, 91–94, 98, 99, 101–109]. The adoption of DLVMD enables evaluation of the influence of data leakage on model performance when VMD is applied in a leakage-inducing manner, while also demonstrating the limitations of previous research that adopts this approach.

SVMD
In Figure 9, the SVMD application process is illustrated. As depicted, VMD applies VMD during the creation of $\mathbf{S}^{\text{Windowed}}$, described in Section 4.3.3, to the instances defined with respect to $\mathbf{X}_{\text{Close}}$. VMD decomposes each instance, i.e., each subsequence of length W, of $\mathbf{X}_{\text{Close}}$ into K modes. As a result, each subsequence is transformed from a univariate time series of shape $\mathbb{R}^{W \times 1}$ into a multivariate time series of shape $\mathbb{R}^{W \times K}$. In other words, $\mathbf{X}_{\text{Close}}$ is transformed from $\mathbf{X}_{\text{Close}} \in \mathbb{R}^{L \times W \times 1}$ to $\mathbf{X}_{\text{Close}} \in \mathbb{R}^{L \times W \times K}$, where L denotes the number of instances that

$\mathbf{X}_{\text{Close}}$ is composed of.

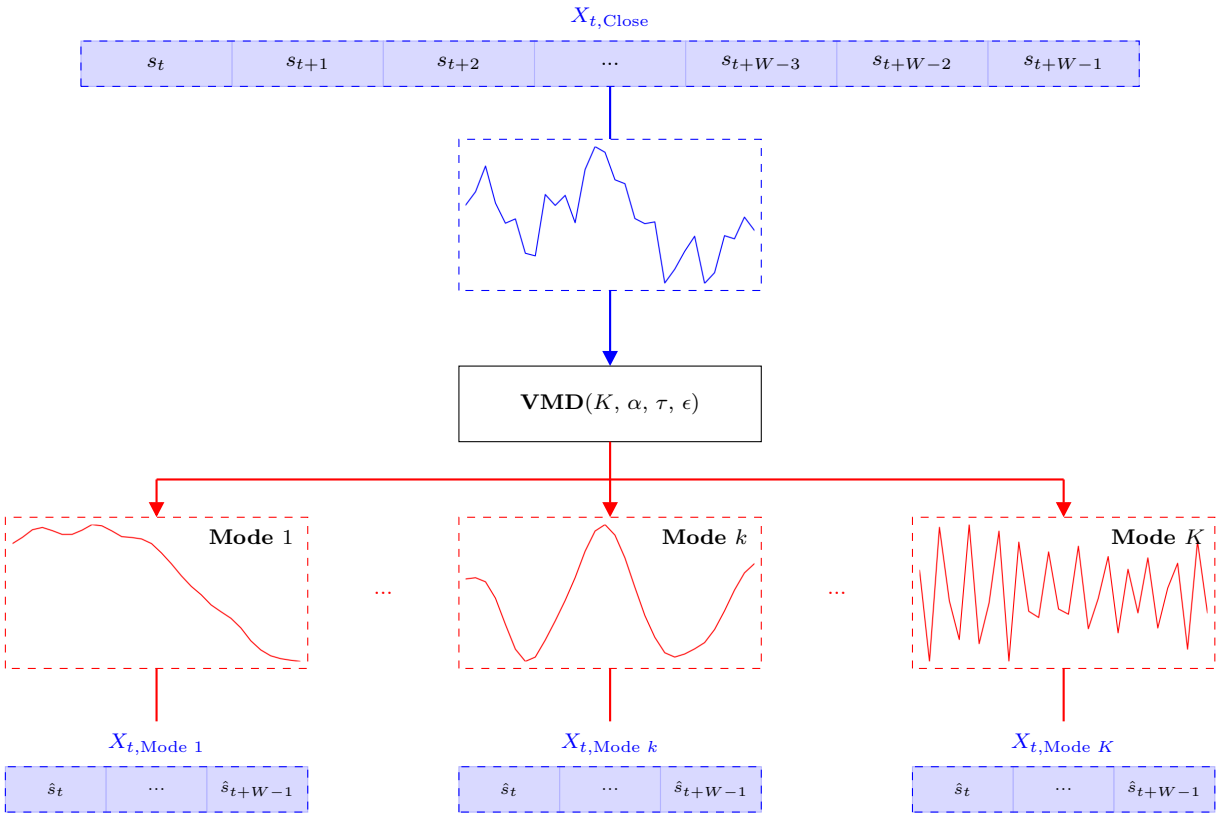


Figure 9: The process of applying VMD to an instance of $\mathbf{X}_{\text{Close}}$, $X_{t,\text{Close}}$, of length W as part of the Sliding Variational Mode Decomposition (SVMD) process resulting in K subsequences, i.e., modes given by $X_{t,\text{Mode 1}}, \ldots, X_{t,\text{Mode } k}, \ldots, X_{t,\text{Mode } K}$ part of $\mathbf{X}_{t,\text{Close}}$, the instance of $\mathbf{X}_{\text{Close}}$ after applying VMD.

EVMD

The other method, EVMD, also applies VMD during the construction of $\mathbf{S}^{\text{Windowed}}$. However, unlike SVMD, VMD is not applied to individual instances of $\mathbf{X}_{\text{Close}}$. Instead, it is applied prior to the formation of each instance, as illustrated in Figure 10. To create each instance of $\mathbf{X}_{\text{Close}}$, VMD is applied to a subset of $\mathbf{S}_{\text{Close}}$ consisting of all available time steps up to the final time step included in the corresponding sliding window. As shown in Figure 10, if the last time step of the sliding window currently utilized to create an instance of $\mathbf{X}_{\text{Close}}$ is $N-1$, the subsequence $S_{0:N,\text{Close}} \in \mathbb{R}^{N\times 1}$ is decomposed into K modes. This transforms $S_{0:N,\text{Close}}$ from a univariate time series into a multivariate time series of shape $S_{0:N,\text{Close}} \in \mathbb{R}^{N\times K}$. Subsequently, the final W time steps of the decomposed subsequence corresponding to the time steps included in the sliding window are used to create the corresponding instance of $\mathbf{X}_{\text{Close}}$ with shape $\mathbb{R}^{W\times K}$. The completion of the EVMD process results in $\mathbf{X}_{\text{Close}}$ being denoted as $\mathbf{X}_{\text{Close}} \in \mathbb{R}^{L\times W\times K}$, the same as after completing the SVMD process.

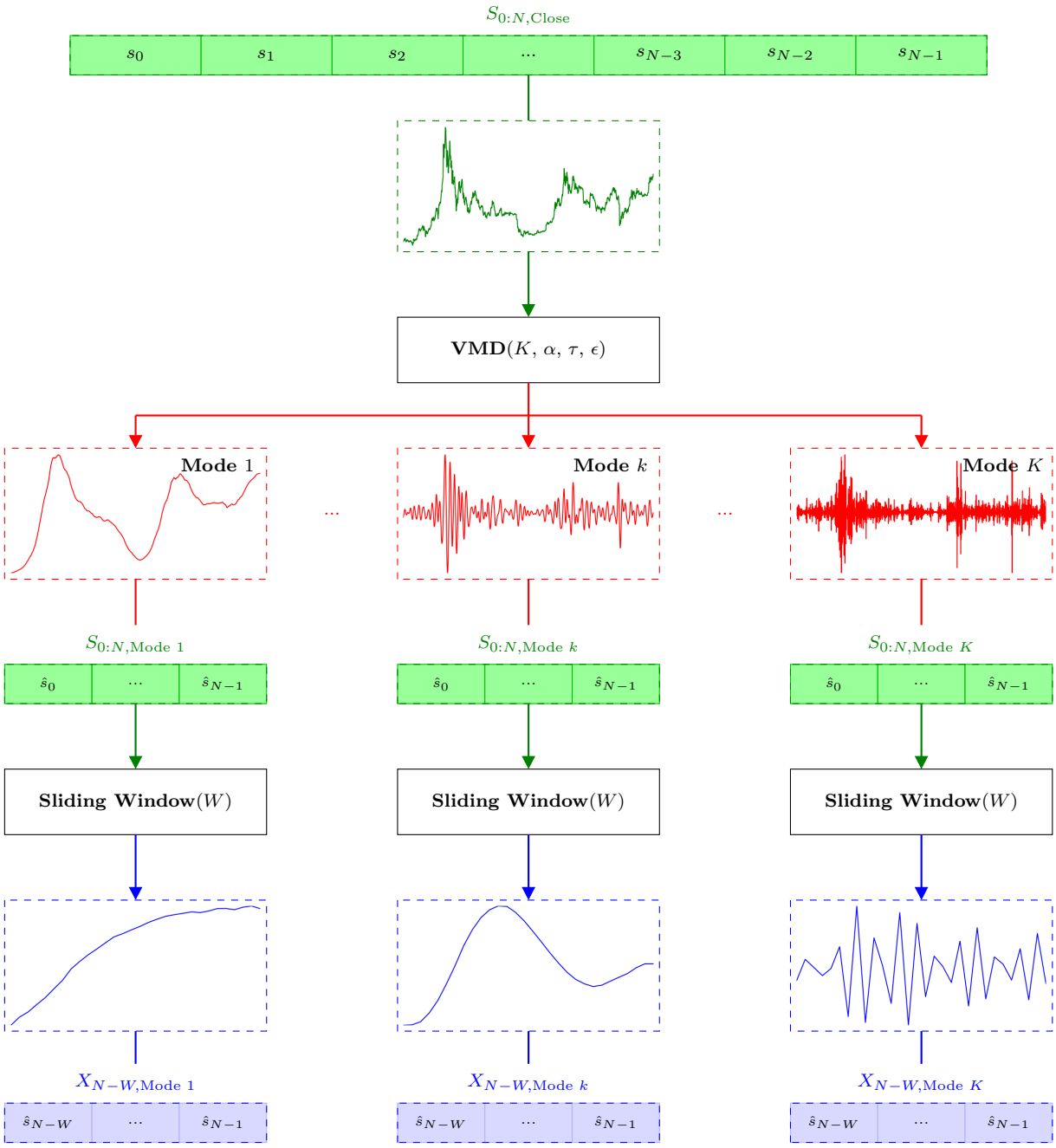


Figure 10: The process of applying VMD to a subsequence $S_{0:N,\text{Close}}$ of $\mathbf{S}_{\text{Close}}$ with length N as part of the Expanding Variational Mode Decomposition (EVMD) process resulting in K subsequences, i.e., modes given by $S_{0:N,\text{Mode 1}}, \ldots, S_{0:N,\text{Mode } k}, \ldots, S_{0:N,\text{Mode } K}$. Subsequently, the final W time steps of the subsequences correspond to the time steps included in a sliding window of size W and are used to create the subsequences $X_{N-W,\text{Mode 1}}, \ldots, X_{N-W,\text{Mode } k}, \ldots, X_{N-W,\text{Mode } K}$ part of $\mathbf{X}_{N-W,\text{Close}}$, an instance of $\mathbf{X}_{\text{Close}}$.

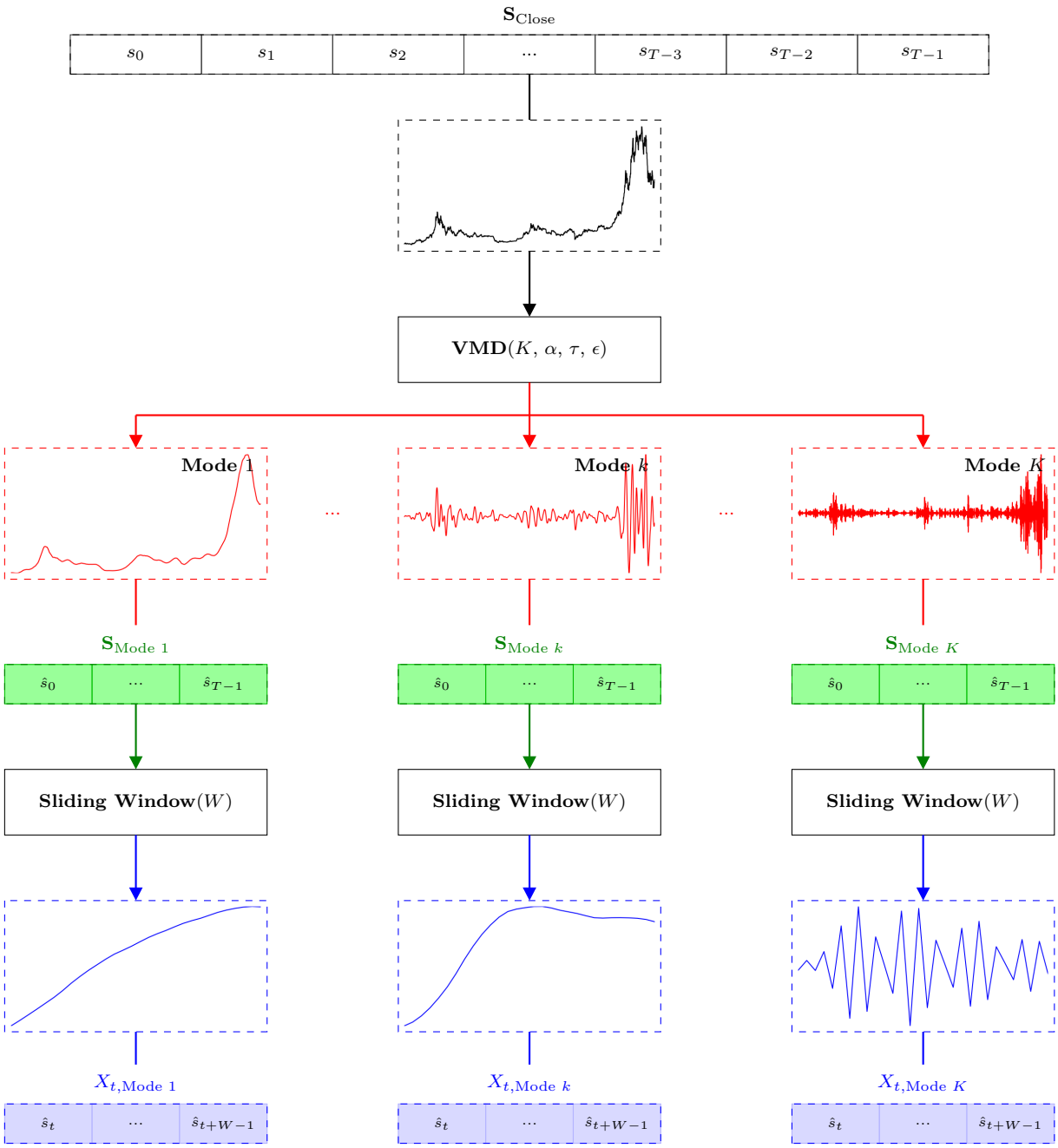


Figure 11: The process of applying VMD to the full time series $\mathbf{S}_{\text{Close}}$ of length T as part of the Variational Mode Decomposition with Data Leakage (DLVMD) process resulting in K full subsequences, i.e., modes given by $\mathbf{S}_{\text{Mode 1}}, \ldots, \mathbf{S}_{\text{Mode } k}, \ldots, \mathbf{S}_{\text{Mode } K}$. Subsequently, a sliding window of size W is applied to the full subsequences as part of the transformation of $\mathbf{S}$ into $\mathbf{S}^{\text{Windowed}}$ meaning that at each time step t of the full subsequences up to $t = L$, where L is the length of $\mathbf{S}_{\text{Windowed}}$, the next W time steps are used to create $X_{t,\text{Mode 1}}, \ldots, X_{t,\text{Mode } k}, \ldots, X_{t,\text{Mode } K}$ part of $\mathbf{X}_{t,\text{Close}}$, the instance of $\mathbf{X}_{\text{Close}}$ at time step t.

DLVMD

As shown in Figure 11 and in line with the previous research mentioned in the beginning of this section, DLVMD applies VMD prior to the construction of $\mathbf{S}_{\text{Windowed}}$ to the full time series $\mathbf{S}_{\text{Close}}$, thus not respecting its split into $\mathbf{S}_{\text{Train,Close}}$, $\mathbf{S}_{\text{Val,Close}}$, and $\mathbf{S}_{\text{Test,Close}}$ resulting in data

leakage [81–87, 89, 91–94, 98, 99, 101–109]. The application of VMD to $\mathbf{S}_{\text{Close}}$ results in $\mathbf{S}_{\text{Close}}$ being decomposed into K modes. In other words, $\mathbf{S}_{\text{Close}}$ is transformed from a univariate time series of shape $\mathbb{R}^{T\times 1}$ into a multivariate time series of shape $\mathbf{S}_{\text{Close}} \in \mathbb{R}^{T\times K}$. Once decomposed, a sliding window of size W is applied to $\mathbf{S}_{\text{Close}}$ as part of the transformation of $\mathbf{S}$ into $\mathbf{S}^{\text{Windowed}}$. The application of the sliding window to $\mathbf{S}_{\text{Close}}$, as described in Section 4.3.3, results in the transformation of $\mathbf{S}_{\text{Close}} \in \mathbb{R}^{T\times K}$ into $\mathbf{X}_{\text{Close}} \in \mathbb{R}^{L\times W\times K}$, where L is the length of $\mathbf{S}^{\text{Windowed}}$.

5 Experimental Setup

To facilitate a framework for the proposed methodology and an experimental setup consistent with the study conducted by Murray et al. [27], the framework utilized as part of their study, referred to as the *benchmark framework*[1] and described in Section 5.1.1, is adopted as the starting point for a new framework, referred to as the *novel framework* and described in Section 5.1.3. However, an inspection of the source code underlying the *benchmark framework* reveals several flaws in relation to the experimental setup, making the corresponding results unreliable. Consequently, these flaws are addressed and the resulting *revised benchmark framework*, described in Section 5.1.2, serves as the foundation of the *novel framework*[2].
For the most part, the experimental setup can be summarized as follows:

- Replication of the experiments conducted by Murray et al. [27], referred to as the *benchmark experiments* and described in Section 5.3, using the *benchmark framework*.
- Replication of the *benchmark experiments* using the *revised benchmark framework*. This revises both the results reported by Murray et al. [27] and those obtained after the rerun using the *benchmark framework*.
- Execution of both the *benchmark experiments* and the *extended experiments*, an extension on the *benchmark experiments* further described in Section 5.4. This produces the results corresponding to the models adopted in this study, described in Section 4, while also resulting in a further revision of the results in relation to the TCN proposed by Murray et al. [27], which serves as a benchmark in this study, due to the differences between the *novel framework* and the *revised benchmark framework*, listed in Section 5.1.3.

5.1 Frameworks

5.1.1 Benchmark Framework

The *benchmark framework* facilitates the execution of the experiments conducted by Murray et al. [27], referred to as the *benchmark experiments* and further described in Section 5.3, using ARIMA, CNN-LSTM, GRU, KNN, LSTM-GRU, RF, SVR, TCN, and TFT in combination with the *differenced* preprocessing pipeline defined in Section 4.3, and the hyperparameters and corresponding Python libraries listed in Table 46, where the hyperparameters were determined using *Talos* [203]. During training, each deep learning-based model is trained for a maximum of $E = 200$ epochs using the *Adam* optimizer with a batch size of $B = 256$, whilst being equipped with an early stopping mechanism and a model checkpointing mechanism. The models are trained to minimize the Mean Squared Error (MSE) loss with respect to the training set, with the MSE loss function being defined as follows:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2 \tag{57}$$

where y_t is the expected value at time step t, $\hat{y}_t$ is the predicted value at time step t, and T is the total number of time steps. While each model is being trained, the validation loss,

[1] https://github.com/katemurraay/tsa_crt
[2] https://github.com/cd3105/MSc_CS_Thesis_Novel_Method_Cryptocurrency_Price_Prediction

$\mathcal{L}_{\text{Val}}$, with respect to the validation set is tracked. The early stopping mechanism terminates the training of the model if it observes no improvement in the validation loss for $P = 50$ consecutive epochs, where P denotes the patience of the mechanism. The model checkpointing mechanism, on the other hand, stores the model weights corresponding to the lowest validation loss and reloads these weights for use during model evaluation.
Due to the results reported by Murray et al. [27] demonstrating the mean performance of the applied models across all cryptocurrencies using normalized error metrics, the *benchmark framework* is adjusted such that replication of the experiments results in a more detailed insight into the performance of each model with respect to each cryptocurrency and to obtain a better understanding of the prediction error in relation to a cryptocurrency's value. As such, the framework is adjusted to record the following metrics:

- Root Mean Squared Error (RMSE), defined in (31).
- Mean Absolute Error (MAE), defined in (33).
- Mean Absolute Percentage Error (MAPE), defined in (35).

In addition to the metrics that are already being recorded:

- Normalized Root Mean Squared Error (NRMSE), defined in (32).
- Normalized Mean Absolute Error (NMAE), defined in (34).
- Normalized Mean Absolute Percentage Error (NMAPE), defined in (36).
- Coefficient of Determination (R^2), defined in (37).

5.1.2 Revised Benchmark Framework

Inspection of the results in relation to a rerun of the *benchmark experiments* using the *benchmark framework* alongside a further review of the *benchmark framework* led to the discovery of several flaws in the *benchmark framework*, namely:

- Each model, apart from ARIMA, as part of the *benchmark experiments* is evaluated on misaligned data. The misalignment causes the models to perform predictions corresponding to 6 June 2021 to 31 May 2022 instead of from 1 June 2021 to 31 May 2022, resulting in the accuracy of the predictions being evaluated using expected values corresponding to 1 June 2021 to 26 May 2022.
- The manner in which min-max normalization is applied to scale the data leads to data leakage. As will be further detailed in Section 5.2, the validation set is derived from the training set after first splitting the data into a training set and test set. The framework, however, defines the min-max normalization parameters, described in Section 4.3.2, not exclusively based on the training set after it has been partitioned into a training and validation set, but prior to this partition. Consequently, the validation set influences the parameters that are used to scale the training, validation, and test sets.
- The training set used to train each model differs per model. ARIMA, CNN-LSTM, GRU, LSTM-GRU, TCN, and TFT make use of the same training, validation, and test set splits. However, for KNN, RF, and SVR, no validation set is split from the training set. This leads to these models essentially being trained on more data than the other models, leading to an unfair comparison of performance between these models and the others.

To address the aforementioned flaws, the following adjustments are made to the *benchmark framework*, resulting in the *revised benchmark framework*:

- The misaligned data is realigned so that each model performs predictions corresponding to 1 June 2021 to 31 May 2022. The corresponding predictions are then evaluated using expected values corresponding to 1 June 2021 to 31 May 2022.
- The min-max normalization process is altered so that the parameters are defined only based on the training set after the data has been divided into a training set, validation set, and test set.
- The training process for KNN, RF, and SVR is adjusted so that each model is trained using the training set after splitting the data into a training set, validation set, and test set for each model.

5.1.3 Novel Framework

Although the *novel framework* is largely identical to the *revised benchmark framework* in terms of its experimental setup, there are several differences:

- In addition to the *benchmark experiments*, the *novel framework* adds the *extended experiments*, further described in Section 5.4.
- The *novel framework* performs the relevant experiments using the models part of the proposed methodology, described in Section 4, and each of the preprocessing pipelines defined in Section 4.3. In other words, the models included in the framework are:
  - The TCN introduced by Murray et al. [27], shown in Figure 3a.
  - The TCN proposed by Bai et al. [131], displayed in Figure 3b.
  - The VMD-PMB-TCN proposed in Section 4.1.2, presented in Figure 4.
  - The VMD-PMB-CMHA-TCN proposed in Section 4.1.3, illustrated in Figure 5.
  - The CMHA-TCN proposed in Section 4.1.4, shown in Figure 6.
- Instead of implementing the models in the *novel framework* using *TensorFlow* [204], as was done in the *benchmark framework* for most deep learning-based models, including the TCN proposed by Murray et al. [27], the models in the *novel framework* are implemented using *PyTorch* [205].
- Instead of $\mathcal{L}_{\text{MSE}}$, the models in the *novel framework* are trained to minimize the Mean Absolute Error loss with respect to the training set, defined as follows:

$$\mathcal{L}_{\text{MAE}} = \frac{1}{T}\sum_{t=1}^{T}|y_t - \hat{y}_t| \tag{58}$$

  The decision to use a different loss function in the *novel framework* is motivated by the models demonstrating improved performance with respect to the recorded metrics on the validation set when trained to minimize $\mathcal{L}_{\text{MAE}}$ instead of $\mathcal{L}_{\text{MSE}}$.

- Instead of training the models for a maximum of $E = 200$ epochs, the maximum number of epochs in the *novel framework* is increased to $E = 5000$. This ensures that training is limited by the early stopping mechanism rather than by the maximum number of epochs.
- The patience of the early stopping mechanism utilized by the models in the *novel framework* is set to $P = 50$ during hyperparameter tuning in line with the *benchmark framework*; however, the patience during evaluation is set to a more relaxed value, $P = 500$, in an attempt to maximize performance.
- Instead of using *Talos* [203], each model, except for the TCN proposed by Murray et al. [27], is tuned using Bayesian hyperparameter tuning with *Optuna* [206], further detailed in Section 5.5.
- To improve the robustness of the results, each experiment in the *novel framework* is repeated six times instead of three times, as in the *revised benchmark framework*.
- In addition to the metrics recorded by the *revised benchmark framework*, the *novel framework* also records the Directional Accuracy (DA), defined in (38).

5.2 Evaluation Strategy

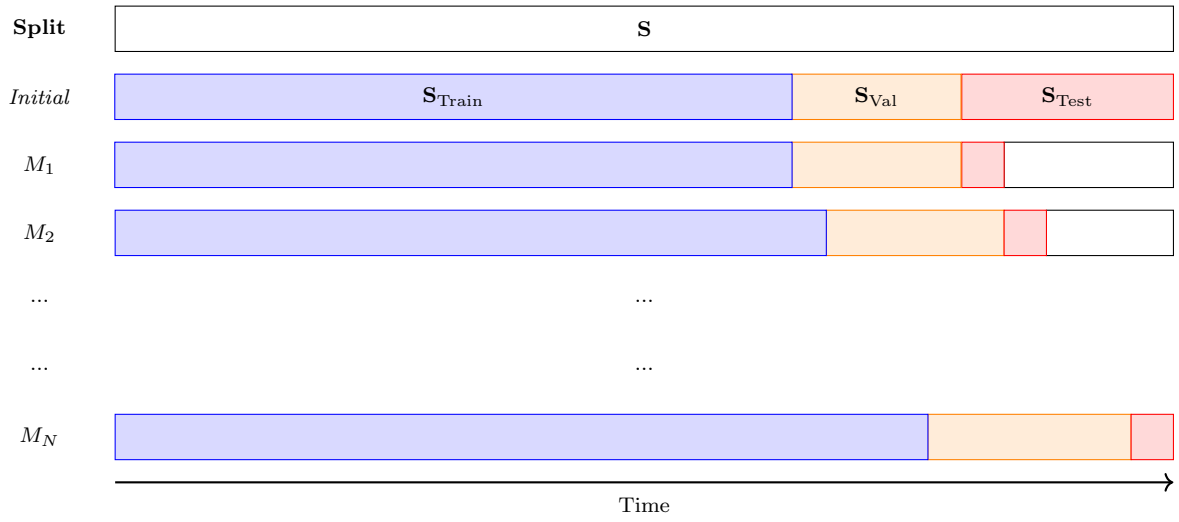


Figure 12: The incremental monthly-based evaluation strategy that evaluates the performance with respect to N monthly-based splits of $\mathbf{S}$ denoted as $M_1, M_2, \ldots, M_N$.

At the foundation of the experiments is the incremental monthly-based evaluation strategy depicted in Figure 12. This evaluation strategy is identical to the one adopted by Murray et al. [27].
The evaluation strategy comprises an *initial* split of time series $\mathbf{S}$, described in Section 4.2, into a training, validation, and test set resulting in $\mathbf{S}_{\text{Train}}$, $\mathbf{S}_{\text{Val}}$, and $\mathbf{S}_{\text{Test}}$. The *initial* split first divides $\mathbf{S}$ into $\mathbf{S}_{\text{Train}}$ and $\mathbf{S}_{\text{Test}}$, where $\mathbf{S}_{\text{Test}}$ consists of the last N months of $\mathbf{S}$. Subsequently, $\mathbf{S}_{\text{Train}}$ is further partitioned into $\mathbf{S}_{\text{Train}}$ and $\mathbf{S}_{\text{Val}}$ according to an 80:20 ratio, with $\mathbf{S}^{\text{Train}}$ corresponding to the first 80% and $\mathbf{S}_{\text{Val}}$ the final 20%.
Once the *initial* split has been determined, splits $M_1, \ldots, M_N$ are defined. For first of these

splits, M_1, its $\mathbf{S}_{\text{Train}}$ and $\mathbf{S}_{\text{Val}}$ are identical to those of the *initial* split, whereas its $\mathbf{S}_{\text{Test}}$ consists only of the first month of $\mathbf{S}_{\text{Test}}$ with respect to the *initial* split. The next split, M_2, includes $\mathbf{S}_{\text{Test}}$ of split M_1 into its $\mathbf{S}_{\text{Val}}$. Consequently, a portion of $\mathbf{S}_{\text{Val}}$ with respect to M_1 is assigned to $\mathbf{S}_{\text{Train}}$ of split M_2 to maintain the 80:20 split ratio in M_2, thereby increasing the sizes of both $\mathbf{S}_{\text{Train}}$ and $\mathbf{S}_{\text{Val}}$ relative to split M_1. In line with split M_1, $\mathbf{S}_{\text{Test}}$ with respect to split M_2 consists of the second month of $\mathbf{S}_{\text{Test}}$ in the *initial* split. This is repeated for each subsequent split until split M_N is defined, with $\mathbf{S}_{\text{Train}}$ and $\mathbf{S}^{\text{Val}}$ increasing incrementally in size with each subsequent split, with $\mathbf{S}_{\text{Test}}$ corresponding to the next month of $\mathbf{S}_{\text{Test}}$ in the *initial* split relative to the previous split.

It is important to note that each split, including the *initial* split, takes into account the window size W and horizon H that are used to create $\mathbf{S}^{\text{Windowed}}$, detailed in Section 4.3.3, when splitting $\mathbf{S}_{\text{Train}}$ into $\mathbf{S}_{\text{Train}}$ and $\mathbf{S}_{\text{Val}}$. This is due to W and H affecting the length of $\mathbf{S}^{\text{Windowed}}$. As detailed in Section 4.3.3, during the creation of $\mathbf{S}^{\text{Windowed}}$, the splits as defined are preserved to prevent data leakage resulting in $\mathbf{S}^{\text{Windowed}}$ being partitioned into $\mathbf{S}^{\text{Windowed}}_{\text{Train}}$, $\mathbf{S}^{\text{Windowed}}_{\text{Val}}$, and $\mathbf{S}^{\text{Windowed}}_{\text{Test}}$.

After splits $M_1, \ldots, M_N$ have been defined, each model is evaluated in a monthly-based manner. First, each model is trained using $\mathbf{S}^{\text{Windowed}}_{\text{Train}}$ and $\mathbf{S}^{\text{Windowed}}_{\text{Val}}$ with respect to split M_1, and subsequently evaluated using the corresponding test set, $\mathbf{S}^{\text{Windowed}}_{\text{Test}}$. This continues until each model has been evaluated on all N splits.

5.3 Benchmark Experiments

The *benchmark experiments* replicate the experiments conducted by Murray et al. [27] and therefore utilize the *benchmark dataset*, described in Section 4.2.1. In other words, for each *benchmark experiment*, $\mathbf{S}$ spans the period from 1 June 2017 to 31 May 2022.

The *initial* split adopted by Murray et al. [27] in relation to the evaluation strategy, depicted in Figure 12, first divides $\mathbf{S}$ into $\mathbf{S}_{\text{Train}}$ and $\mathbf{S}_{\text{Test}}$ according to an 80:20 ratio resulting in $\mathbf{S}_{\text{Train}}$ corresponding to all time steps from 1 June 2017 to 31 May 2021, while $\mathbf{S}_{\text{Test}}$ corresponds to the last 12 months, i.e., all time steps from 1 June 2021 to 31 May 2022. Subsequently, $\mathbf{S}_{\text{Train}}$, as described in Section 5.2, is partitioned into $\mathbf{S}_{\text{Train}}$ and $\mathbf{S}_{\text{Val}}$ according to an 80:20 ratio as well. This results in $\mathbf{S}_{\text{Train}}$ consisting of all time steps from 1 June 2017 to 17 August 2020 and $\mathbf{S}_{\text{Val}}$ consisting of all time steps from 18 August 2020 to 31 May 2021. Given that $\mathbf{S}_{\text{Test}}$ in the *initial* split consists of 12 months of time steps, $N = 12$ monthly-based splits, denoted as $M_1, \ldots, M_{12}$, are created as part of the evaluation strategy. Consequently, $\mathbf{S}_{\text{Test}}$ with respect to M_1 consists of the time steps pertaining to June 2021, $\mathbf{S}_{\text{Test}}$ with respect to M_2 consists of the time steps pertaining to July 2021, and so forth, with $\mathbf{S}_{\text{Test}}$ of the previous monthly-based split being added to $\mathbf{S}_{\text{Val}}$ of the next. Each model that is applied as part of the *benchmark experiments* is thus evaluated on their performance with respect to splits $M_1, \ldots, M_{12}$.

In accordance with the experiments performed by Murray et al. [27], the *benchmark experiments* utilize a window size $W = 30$ and a horizon $H = 1$ to create $\mathbf{S}^{\text{Windowed}}$, whilst only making use of $\mathbf{X}_{\text{Close}}$ as input to the models. Each *benchmark experiment* thus corresponds to the 1-step forecasting of $\mathbf{S}_{\text{Close}}$ on a monthly basis over the period from 1 June 2021 to 31 May 2022. The *benchmark experiments* as described are performed using each applied model with respect to *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD*.

5.3.1 Primary

The *benchmark experiments* conducted using the *novel framework* are initially performed with the following models:

- **TCN** [27]: the TCN proposed by Murray et al. [27], shown in Figure 3a, in combination with the *default* preprocessing pipeline, described in Section 4.3.
- **Differenced-TCN** [27]: the TCN proposed by Murray et al. [27] in combination with the *differenced* preprocessing pipeline, described in Section 4.3, identical to the manner in which Murray et al. [27] applied the TCN.
- **TCN**: the TCN proposed by Bai et al. [131], displayed in Figure 3b, in combination with the *default* preprocessing pipeline.
- **Differenced-TCN**: the TCN proposed by Bai et al. [131] in combination with the *differenced* preprocessing pipeline.
- **EVMD-PMB-TCN**: the VMD-PMB-TCN proposed in Section 4.1.2, presented in Figure 4, in combination with the *VMD* preprocessing pipeline, described in Section 4.3, using the EVMD procedure to apply VMD in a leakage-free manner, detailed in Section 4.3.4.
- **EVMD-PMB-CMHA-TCN**: the VMD-PMB-CMHA-TCN proposed in Section 4.1.3, illustrated in Figure 5, in combination with the *VMD* preprocessing pipeline using the EVMD procedure.
- **SVMD-PMB-TCN**: the VMD-PMB-TCN proposed in Section 4.1.2 in combination with the *VMD* preprocessing pipeline using the SVMD procedure, detailed in Section 4.3.4.
- **SVMD-PMB-CMHA-TCN**: the VMD-PMB-CMHA-TCN proposed in Section 4.1.3 in combination with the *VMD* preprocessing pipeline using the SVMD procedure.

The results corresponding to TCN [27], Differenced-TCN [27], TCN, and Differenced-TCN serve as the benchmark results of the experiments.

5.3.2 Ablation

To facilitate an ablation study with respect to EVMD-PMB-TCN, EVMD-PMB-CMHA-TCN, SVMD-PMB-TCN, and SVMD-PMB-CMHA-TCN, the *benchmark experiments* using the *novel framework* are performed with the following additional models:

- **CMHA-TCN**: the CMHA-TCN proposed in Section 4.1.4, shown in Figure 6, in combination with the *default* preprocessing pipeline.
- **Differenced-CMHA-TCN**: the CMHA-TCN proposed in Section 4.1.4 in combination with the *differenced* preprocessing pipeline.
- **EVMD-TCN**: the TCN proposed by Bai et al. [131] in combination with the *VMD* preprocessing pipeline using the EVMD procedure.

- **EVMD-CMHA-TCN**: the CMHA-TCN proposed in Section 4.1.4 in combination with the *VMD* preprocessing pipeline using the EVMD procedure.
- **SVMD-TCN**: the TCN proposed by Bai et al. [131] in combination with the *VMD* preprocessing pipeline using the SVMD procedure.
- **SVMD-CMHA-TCN**: the CMHA-TCN proposed in Section 4.1.4 in combination with the *VMD* preprocessing pipeline using the SVMD procedure.

5.3.3 Variational Mode Decomposition with Data Leakage

Besides the primarily performed *benchmark experiments* and the ones performed in relation to the ablation study, additional *benchmark experiments* are performed to review the impact of data leakage when applying the *VMD* preprocessing pipeline using the DLVMD procedure, detailed in Section 4.3.4. To achieve this, the *benchmark experiments* using the *novel framework* are also performed with these models:

- **DLVMD-TCN with EVMD-TCN Parameters**: the TCN proposed by Bai et al. [131] in combination with the *VMD* preprocessing pipeline using the DLVMD procedure, and the hyperparameters tuned with respect to EVMD-TCN.
- **DLVMD-TCN with SVMD-TCN Parameters**: the TCN proposed by Bai et al. [131] in combination with the *VMD* preprocessing pipeline using the DLVMD procedure and the hyperparameters tuned with respect to SVMD-TCN.

5.4 Extended Experiments

The *extended experiments* extend the *benchmark experiments* by evaluating the models in a more recent context using the *extended dataset*, described in Section 4.2.1. This means that for each *extended experiment*, $\mathbf{S}$ spans the period from 1 June 2017 to 31 May 2025.
The *initial* split adopted as part of the incremental monthly-based evaluation strategy, shown in Figure 12, with respect to the *extended experiments* first partitions $\mathbf{S}$ into $\mathbf{S}_{\text{Train}}$ and $\mathbf{S}_{\text{Test}}$ such that $\mathbf{S}_{\text{Train}}$ consists of all time steps adopted as part of the *benchmark experiments*. In other words, after doing so, $\mathbf{S}_{\text{Train}}$ consists of all time steps from 1 June 2017 to 31 May 2022, while $\mathbf{S}_{\text{Test}}$ contains all time steps from 1 June 2022 to 31 May 2025 corresponding to the last 36 months of $\mathbf{S}$. The subsequent split of $\mathbf{S}_{\text{Train}}$ into $\mathbf{S}_{\text{Train}}$ and $\mathbf{S}_{\text{Val}}$ according to an 80:20 ratio results in $\mathbf{S}_{\text{Train}}$ corresponding to all time steps from 1 June 2017 to 6 June 2021 and $\mathbf{S}_{\text{Val}}$ to all time steps from 7 June 2021 to 31 May 2022. Since $\mathbf{S}_{\text{Test}}$ in the *initial* split consists of 36 months of time steps, instead of 12, $N = 36$ monthly-based splits, denoted as $M_1, \ldots, M_{36}$, are created. In other words, $\mathbf{S}_{\text{Test}}$ in relation to M_1 consists of the time steps pertaining to June 2022, $\mathbf{S}_{\text{Test}}$ in relation to M_2 consists of the time steps pertaining to July 2022, and so forth, with $\mathbf{S}_{\text{Test}}$ of the previous monthly-based split being added to $\mathbf{S}_{\text{Val}}$ of the next. Each model that is applied as part of the *extended experiments* is thus evaluated on their performance with respect to splits $M_1, \ldots, M_{36}$.
Similar to the *benchmark experiments*, the *extended experiments* make use of a window size $W = 30$ and a horizon $H = 1$, with only $\mathbf{X}_{\text{Close}}$ serving as input to the models. Therefore, the *extended experiments* correspond to the 1-step forecasting of $\mathbf{S}_{\text{Close}}$ on a monthly basis over the period from 1 June 2022 to 31 May 2025. The *extended experiments* are conducted with regard to *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD* using each model applied in

the *benchmark experiments*, with the exception of TCN [27] and the DLVMD-based models. TCN [27] is excluded from the *extended experiments* due to the model demonstrating a relatively poor performance compared to the other models with regard to the *benchmark experiments*, as will be highlighted in Section 6.2.

5.5 Hyperparameter Tuning

The hyperparameter tuning involves three types of hyperparameters: VMD parameters, architectural parameters, and training parameters. Given that the TCN proposed by Murray et al. [27] and its corresponding hyperparameters serve as a benchmark model in the experiments, the hyperparameters of the newly applied models are tuned similarly to the approach taken by Murray et al. [27].

5.5.1 Tuning Process

In accordance with the approach taken by Murray et al. [27], the hyperparameters are tuned on the mean validation loss, $\bar{\mathcal{L}}_{\text{Val}}$, across three repetitions with respect to $\mathbf{S}_{\text{Val}}$ of the *initial* split used in the *benchmark experiments*, where a lower $\bar{\mathcal{L}}_{\text{Val}}$ corresponds to a better performing set of hyperparameters. In addition to $\bar{\mathcal{L}}_{\text{Val}}$, the standard deviation of $\bar{\mathcal{L}}_{\text{Val}}$ across three repetitions is used as a secondary indicator to assess the performance of a given set of hyperparameters. The standard deviation provides an indication of the consistency with which a given set of hyperparameters achieves a certain loss across the repetitions, where less standard deviation indicates a more consistent performance. The standard deviation of $\mathcal{L}$ is defined as follows:

$$\sigma_{\mathcal{L}} = \sqrt{\frac{\sum_{n=1}^{N_{\text{rep}}} \left|\mathcal{L}_n - \bar{\mathcal{L}}\right|^2}{N_{\text{rep}}}} \tag{59}$$

where N_{rep} denotes the number of repetitions and n the repetition index.
Consistent with Murray et al. [27], the goal of the hyperparameter tuning is to determine a single set of architectural and training hyperparameters per model that can be applied across each cryptocurrency. To achieve this, each model is tuned on $\bar{\mathcal{L}}_{\text{Val}}$ with respect to *BTC/USD*. The rationale behind this approach lies in the dominance of *BTC* within the cryptocurrency market and its lead-lag relationship with other cryptocurrencies, as well as the significant correlation of its price/returns with the prices/returns of the other cryptocurrencies, as explored in Section 4.2.3. Although the price of *BTC* and the other cryptocurrencies tend to be significantly correlated, the prices, when plotted, do demonstrate different characteristics, as highlighted by Figure 7. As such, the aim of the hyperparameter tuning with respect to the VMD hyperparameters is to determine a set of hyperparameters for each cryptocurrency and leakage-free VMD method, EVMD or SVMD.
Following the described approach and aim of the tuning, the architectural and training hyperparameters corresponding to each model that is adopted in this study, except for TCN [27], Differenced-TCN [27], and the DLVMD-based models, are tuned on $\bar{\mathcal{L}}_{\text{Val}}$ with respect to *BTC/USD* using $\mathbf{S}_{\text{Val}}$ of the *initial* split adopted by the *benchmark experiments*. To determine a set of VMD hyperparameters per cryptocurrency and leakage-free VMD method, the VMD, architectural, and training hyperparameters with respect to EVMD-PMB-TCN and SVMD-PMB-TCN are tuned jointly on $\bar{\mathcal{L}}_{\text{Val}}$ with respect to *BTC/USD*. Once the the VMD, architectural, and training hyperparameters of EVMD-PMB-TCN and SVMD-PMB-TCN with respect to *BTC/USD* have been tuned, the VMD hyperparameters of *ETH/USD*, *LTC/USD*,

XMR/USD, and *XRP/USD* are tuned using EVMD-PMB-TCN and SVMD-PMB-TCN in combination with the tuned architectural and training hyperparameters on *BTC/USD*. The determined VMD parameters of *BTC/USD* with respect to EVMD and SVMD are subsequently utilized to tune the architectural and training hyperparameters of the other EVMD- and SVMD-based models.

5.5.2 Hyperparameter Search Space

In Table 3, the hyperparameter search space of the hyperparameter tuning is shown. As displayed, the various hyperparameters are categorized by their corresponding type. The hyperparameters with respect to VMD, as detailed in Section 3.2, constitute the following:

- K: the number of modes into which an input is decomposed.
- α: a penalty factor that controls the bandwidth of the modes, where a larger α enforces a narrow bandwidth and a smaller α a wider bandwidth.
- τ: a step size parameter that influences the convergence of the ADMM algorithm underlying the decomposition of VMD and its sensitivity to noise.

The architectural hyperparameters, described in Sections 3.3 and 4.1, that are tuned for each relevant model include:

Type	**Hyperparameter**	**Space**
VMD	K	$\{2, 3, 4, 5, 6, 7, 8\}$
	α	$[200, 5000] \in \mathbb{R}$
	τ	$[0.0, 0.3] \in \mathbb{R}$
Architectural	D	$\{2, 3, 4\}$
	F_{out}	$\{16, 32, 48, 64, 80, 96\}$
	k	$\{2, 3, 4, 5, 6\}$
	p	$[0.0, 0.3] \in \mathbb{R}$
	Activation Function	{ELU, GELU, ReLU, SiLU}
	N_{head}	$\{1, 2, 4, 8\}$
	p_{mha}	$[0.0, 0.3] \in \mathbb{R}$
Training	η	$[10^{-5}, 10^{-2}] \in \mathbb{R}$
	λ	$[10^{-5}, 10^{-2}] \in \mathbb{R}$
	c	$[0.5, 5.0] \in \mathbb{R}$

Table 3: The hyperparameter search space adopted during the hyperparameter tuning.

- D: the number of residual blocks part of a TCN, according to the architecture illustrated in Figure 1.
- F_{out}: the number of kernels applied by the dilated causal convolutional layers adopted within a residual block.

- k: the size of the kernels applied by the dilated causal convolutional layers.
- p: the dropout rate of the dropout layers adopted within a residual block.
- Activation function: the nonlinear activation function adopted within a residual block, where the definitions of the possible activation functions are provided in Section 3.5.

The search space corresponding to these hyperparameters is selected such that the receptive field of the individual TCN or CMHA-TCN, defined in (18), can achieve full historical coverage, given that the input sequence length is equal to the window size adopted as part of the experiments, i.e., $W = 30$. If the model is a CMHA-based model, the following hyperparameters are tuned in addition to the previously listed ones:

- N_{head}: the number of attention heads utilized by the causal multi-head attention mechanism.
- p_{mha}: the dropout rate of the dropout layer applied to the attention weights produced by each attention head.

Although models such as SVMD-PMB-TCN and SVMD-PMB-CMHA-TCN consist of separate branches, each containing an individual TCN or CMHA-TCN, the same hyperparameters are used across all branches to limit the total number of hyperparameters to prevent suboptimal tuning. Lastly, besides the architectural hyperparameters, the following training hyperparameters are tuned:

- η: the learning rate.
- λ: the weight decay.
- c: the maximum gradient norm before gradient clipping.

The hyperparameters that are determined through the tuning as described and the hyperparameters of TCN [27] and Differenced-TCN [27] as adopted by Murray et al. [27] used during the execution of the experiments are detailed in Section D.2, where r represents the dilation rate and u the number of linear units used in relation the TCN proposed by Murray et al. [27].

5.6 Experimental Analysis

To improve interpretation of the experimental results, an analysis is conducted with respect to the splits adopted in the *benchmark experiments* and the *extended experiments*. The analysis consists of extracting statistics from five separate components across all splits of the benchmark and *extended experiments* for *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD*:

- $\mathbf{X}_{\text{Test}}$ without any further transformation, i.e., after applying the *default* preproccesing pipeline.
- The modes contained in $\mathbf{X}_{\text{Test}}$ after applying the *VMD* preproccesing pipeline using the EVMD procedure.
- The modes contained in $\mathbf{X}_{\text{Test}}$ after applying the *VMD* preproccesing pipeline using the SVMD procedure.
- $\mathbf{Y}_{\text{Test}}$.

5.6.1 Input Analysis

In relation to $\mathbf{X}_{\text{Test}}$ after applying the *default* preprocessing pipeline, the following statistics are extracted:

- **ADF** p: The mean p-value across the windows in $\mathbf{X}_{\text{Test}}$ by applying the ADF test.
- **KPSS** p: The mean p-value across the windows in $\mathbf{X}_{\text{Test}}$ by applying the KPSS test.
- **Volatility (%)**: The mean volatility across the windows in $\mathbf{X}_{\text{Test}}$, measured as the standard deviation of the log returns, expressed as a percentage.
- **Trend (%)**: The mean trend across the windows in $\mathbf{X}_{\text{Test}}$, measured as the percentage change between the value at the first time step and the value at the final time step.
- **Fluctuation (%)**: The mean fluctuation across the windows in $\mathbf{X}_{\text{Test}}$, measured as the percentage of time steps at which the movement direction changes.

The corresponding statistics can be found in Tables 68 and 69.

5.6.2 Input Modes Analysis

With regard to the modes part of $\mathbf{X}_{\text{Test}}$ after applying the *VMD* preproccesing pipeline, the following statistics are extracted with respect to each window and aggregated across all windows by taking the mean:

- **ADF (Min)**: The minimum p-value across the modes by applying the ADF test.
- **ADF (Mean)**: The mean p-value across the modes by applying the ADF test.
- **ADF (Max)**: the maximum p-value across the modes by applying the ADF test.
- **ADF (%)**: The percentage of nonstationary modes according to the ADF test, determined using the obtained p-values and a significance level of 0.05 (5%).
- **KPSS (Min)**: The minimum p-value across the modes by applying the KPSS test.
- **KPSS (Mean)**: The mean p-value across the modes by applying the KPSS test.
- **KPSS (Max)**: The maximum p-value across the modes by applying the KPSS test.
- **KPSS (%)**: The percentage of nonstationary modes according to the KPSS test, determined using the obtained p-values and a significance level of 0.05 (5%).
- **Residual Energy (%)**: The MAPE between the original time series and the time series reconstructed from the modes [207]. The residual energy measures the reconstruction error and the residual, i.e., the information of the original time series that is not captured by the modes.
- **Mode Overlap (%)**: The mean percentage of spectral overlap between the modes. Mode overlap measures the extent to which different modes contain information at similar frequencies.

- **Energy Ratio (%)**: The maximum percentage of the original time series energy contained within a single mode. The energy ratio measures the extent to which a single mode contains the information in the original time series.

The statistics retrieved in relation to the EVMD modes are shown in Tables 70 and 71, whereas those in relation to the SVMD modes are shown in Tables 72 and 73.

5.6.3 Expected Outputs Analysis

Lastly, with regard to $\mathbf{Y}_{\text{Test}}$, the following statistics are extracted:

- **ADF** p: The p-value of $\mathbf{Y}_{\text{Test}}$ by applying the ADF test.
- **KPSS** p: The p-value of $\mathbf{Y}_{\text{Test}}$ by applying the KPSS test.
- **Volatility (%)**: The volatility of $\mathbf{Y}_{\text{Test}}$.
- **Trend (%)**: The trend of $\mathbf{Y}_{\text{Test}}$.
- **Fluctuation (%)**: The fluctuation of $\mathbf{Y}_{\text{Test}}$.

The retrieved statistics in relation to $\mathbf{Y}_{\text{Test}}$ can be found in Tables 74 and 75.

6 Results

6.1 Benchmark Framework

In Table 4 and Tables 51 to 55 in Appendix E, the results of the *benchmark experiments* using the *benchmark framework* and *revised benchmark framework* are shown, where Table 4 contains the average results across all cryptocurrencies and Tables 4 to 51 contain the results per individual cryptocurrency. Each table contains three different types of results:

- *Reported*: The results as reported by Murray et al. [27].
- *Original*: The results of rerunning the *benchmark experiments* using the *benchmark framework*, described in Section 5.1.1, after making minor adjustments so it records the metrics RMSE, MAE, and MAPE besides NRMSE, NMAE, NMAPE, and R^2.
- *Revised*: The results of rerunning the *benchmark experiments* using the *revised benchmark framework*, detailed in Section 5.1.2.

Type	Model	NRMSE	NMAE	NMAPE (%)	RMSE	MAE	MAPE (%)	R^2
Reported	ARIMA	0.0234	0.0180	4.010	-	-	-	0.708
	CNN-LSTM	**0.0222**	**0.0173**	**3.862**	-	-	-	**0.735**
	GRU	0.0229	0.0176	3.939	-	-	-	0.720
	KNN	0.0233	0.0179	4.003	-	-	-	0.711
	LSTM-GRU	0.0230	0.0177	3.959	-	-	-	0.717
	RF	0.0240	0.0184	4.095	-	-	-	0.697
	SVR	0.0245	0.0189	4.240	-	-	-	0.681
	TCN	0.0233	0.0180	4.021	-	-	-	0.711
	TFT	0.0235	0.0181	4.062	-	-	-	0.707
Original	ARIMA	0.0234	0.0180	4.010	339.785	258.188	3.505	0.708
	CNN-LSTM	**0.0223**	**0.0173**	**3.868**	**322.616**	**250.937**	**3.380**	**0.734**
	GRU	0.0228	0.0176	3.919	328.989	253.061	3.424	0.722
	KNN	0.0233	0.0179	4.003	337.504	257.979	3.497	0.711
	LSTM-GRU	0.0228	0.0176	3.927	328.921	252.987	3.430	0.722
	RF	0.0240	0.0184	4.095	352.238	268.518	3.579	0.695
	SVR	0.0245	0.0189	4.240	338.108	260.531	3.701	0.681
	TCN	0.0234	0.0180	4.025	338.088	258.470	3.516	0.710
	TFT	0.0235	0.0180	4.044	339.866	259.118	3.529	0.707
Revised	ARIMA	0.0431	0.0334	4.022	341.815	259.632	3.515	0.706
	CNN-LSTM	0.0430	0.0340	4.137	342.834	266.908	3.619	0.697
	GRU	0.0426	0.0330	4.061	343.230	263.649	3.552	0.702
	KNN	0.0419	0.0326	4.019	**337.263**	258.587	3.513	0.708
	LSTM-GRU	0.0427	0.0332	4.069	347.188	265.874	3.559	0.702
	RF	0.0426	0.0331	4.130	346.936	266.510	3.608	0.695
	SVR	0.0438	0.0342	4.117	347.232	264.187	3.598	0.696
	TCN	**0.0418**	**0.0325**	**3.991**	338.275	**258.210**	**3.489**	**0.710**
	TFT	0.0420	0.0326	4.064	341.129	262.539	3.548	0.703

Table 4: Average results of the *benchmark experiments* across 3 repetitions, splits $M_1, \ldots, M_{12}$, and all cryptocurrencies with respect to forecasting $\mathbf{S}_{\text{Close}}$ using the *benchmark framework* and *revised benchmark framework*.

Consistent with the *reported* results, the *original* results demonstrate that CNN-LSTM achieves the best predictive performance, recording the lowest values for NRMSE, NMAE, NMAPE,

RMSE, MAE, and MAPE, as well as the highest R^2, both on average across all considered cryptocurrencies and for each cryptocurrency, as shown by Table 4 and Tables 51 to 55.
The *revised* results, however, paint a different picture. As shown in Table 4, TCN achieves the best predictive performance overall on average across all considered cryptocurrencies, recording the lowest NRMSE, NMAE, NMAPE, MAE, and MAPE, as well as the highest R^2. Although KNN records a marginally lower average RMSE, the lower NRMSE recorded by TCN suggests that this difference is attributable to differences in magnitude between the prices of the considered cryptocurrencies rather than superior performance in terms of RMSE on average. The cryptocurrency-specific results presented in Tables 51 to 55 demonstrate that, although the TCN is not the most accurate model for every cryptocurrency according to the reported metrics, it consistently achieves competitive performance when it does not attain the best results for a certain cryptocurrency.

6.2 Novel Framework

6.2.1 Overall Results

In Tables 5 and 6, the overall results of the *benchmark experiments* and *extended experiments* are displayed with respect to forecasting $\mathbf{S}_{\text{Close}}$ in *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, *XRP/USD*.

Comparison of Benchmark Models and Proposed Models
The overall results of both experiments demonstrate that the benchmark models Differenced-TCN [27], TCN, and Differenced-TCN are more accurate overall in terms of RMSE, MAE, MAPE, and R^2 than the proposed models EVMD-PMB-TCN, EVMD-PMB-CMHA-TCN, SVMD-PMB-TCN, and SVMD-PMB-CMHA-TCN. In contrast to the other benchmark models, TCN [27] is outperformed by a substantial margin in terms of RMSE, MAE, MAPE, and R^2 by every model. As evident from the substantial margins, the application of differencing has a significant impact on the performance of the TCN architecture proposed by Murray et al. [27]. This substantial margin is not shown when comparing the results of TCN and Differenced-TCN, indicating that the TCN architecture proposed by Bai et al. [131] is significantly more robust to nonlinearity and nonstationarity than the one proposed by Murray et al. [27].

Comparison of Ablation Models and Proposed Models
In terms of the ablation study, CMHA-TCN and Differenced-CMHA-TCN, similarly to the benchmark models, outperform the proposed models in all error metrics and R^2. The addition of the attention mechanism to the architectures of TCN and Differenced-TCN is particularly shown to occasionally result in an improvement in MAE and MAPE, where CMHA-TCN records the best overall MAE and MAPE with respect to *BTC/USD* and *ETH/USD* in the *benchmark experiments* and *LTC/USD* in the *extended experiments*, while Differenced-CMHA-TCN achieves the best overall MAE and MAPE for *LTC/USD* in the *benchmark experiments*.

Comparison of VMD-based Ablation Models and Proposed Models
When focusing on the VMD-based models applied as part of the ablation study, EVMD-TCN and EVMD-CMHA-TCN are indicated to be more accurate overall in comparison to EVMD-PMB-TCN and EVMD-PMB-CMHA-TCN given by lower RMSE, MAE, MAPE, and a higher

Crypto	Model	RMSE	MAE	MAPE (%)	R^2	DA (%)
BTC/USD	TCN [27]	3923.793 ± 708.134	3508.105 ± 726.226	7.658 ± 1.458	−0.986 ± 0.901	53.291 ± 1.187
	Differenced-TCN [27]	**1536.528** ± 0.427	1170.425 ± 0.712	2.718 ± 0.002	0.727 ± 0.000	49.776 ± 0.479
	TCN	1537.895 ± 3.118	1166.313 ± 3.024	2.709 ± 0.007	0.728 ± 0.001	51.636 ± 1.971
	Differenced-TCN	1539.113 ± 2.130	1174.197 ± 1.889	2.722 ± 0.004	0.727 ± 0.001	52.839 ± 1.334
	CMHA-TCN	1541.594 ± 5.044	**1163.752** ± 3.544	**2.703** ± 0.006	**0.728** ± 0.002	53.872 ± 1.254
	Differenced-CMHA-TCN	1538.946 ± 3.230	1173.069 ± 4.413	2.721 ± 0.010	0.727 ± 0.001	53.366 ± 1.059
	EVMD-TCN	1545.067 ± 4.061	1169.630 ± 1.618	2.714 ± 0.004	0.726 ± 0.002	52.988 ± 1.208
	EVMD-CMHA-TCN	1549.695 ± 4.151	1172.422 ± 3.539	2.721 ± 0.007	0.724 ± 0.001	50.929 ± 1.281
	EVMD-PMB-TCN	1549.994 ± 2.933	1179.282 ± 3.068	2.735 ± 0.006	0.725 ± 0.001	52.004 ± 1.348
	EVMD-PMB-CMHA-TCN	1573.109 ± 9.312	1197.340 ± 9.581	2.778 ± 0.018	0.716 ± 0.004	50.332 ± 2.070
	SVMD-TCN	1554.311 ± 3.203	1192.961 ± 4.597	2.769 ± 0.009	0.719 ± 0.001	**54.775** ± 0.899
	SVMD-CMHA-TCN	1557.996 ± 7.365	1193.417 ± 6.752	2.771 ± 0.012	0.719 ± 0.003	53.521 ± 1.022
	SVMD-PMB-TCN	1550.175 ± 7.420	1191.359 ± 2.180	2.767 ± 0.004	0.721 ± 0.003	53.423 ± 0.999
	SVMD-PMB-CMHA-TCN	1552.919 ± 4.157	1188.725 ± 6.436	2.764 ± 0.015	0.721 ± 0.002	54.503 ± 1.115
ETH/USD	TCN [27]	388.814 ± 36.112	354.681 ± 38.770	11.656 ± 1.088	−2.960 ± 0.831	51.630 ± 1.808
	Differenced-TCN [27]	130.944 ± 0.136	103.354 ± 0.092	3.431 ± 0.003	0.725 ± 0.001	52.545 ± 0.000
	TCN	132.277 ± 1.312	103.553 ± 0.938	3.443 ± 0.030	0.726 ± 0.005	53.734 ± 2.066
	Differenced-TCN	**130.232** ± 0.236	103.170 ± 0.212	3.425 ± 0.007	**0.730** ± 0.001	53.486 ± 0.952
	CMHA-TCN	131.549 ± 0.359	**102.804** ± 0.156	**3.418** ± 0.006	0.727 ± 0.001	53.722 ± 0.861
	Differenced-CMHA-TCN	131.228 ± 0.516	104.292 ± 0.526	3.457 ± 0.017	0.726 ± 0.003	51.250 ± 0.861
	EVMD-TCN	133.939 ± 0.403	104.889 ± 0.214	3.481 ± 0.008	0.713 ± 0.002	54.393 ± 1.021
	EVMD-CMHA-TCN	134.186 ± 0.587	105.181 ± 0.353	3.490 ± 0.012	0.711 ± 0.003	54.379 ± 0.760
	EVMD-PMB-TCN	134.733 ± 0.659	105.662 ± 0.460	3.502 ± 0.014	0.710 ± 0.003	54.059 ± 0.958
	EVMD-PMB-CMHA-TCN	135.425 ± 1.000	106.064 ± 0.835	3.522 ± 0.029	0.706 ± 0.004	**55.132** ± 1.151
	SVMD-TCN	132.156 ± 0.437	103.358 ± 0.149	3.441 ± 0.007	0.723 ± 0.002	53.390 ± 1.007
	SVMD-CMHA-TCN	133.602 ± 1.024	104.068 ± 0.580	3.456 ± 0.016	0.714 ± 0.005	53.559 ± 1.398
	SVMD-PMB-TCN	132.863 ± 0.516	103.670 ± 0.305	3.447 ± 0.009	0.720 ± 0.003	54.732 ± 2.184
	SVMD-PMB-CMHA-TCN	132.936 ± 1.472	103.354 ± 1.135	3.436 ± 0.032	0.718 ± 0.008	55.091 ± 0.765
LTC/USD	TCN [27]	8.226 ± 0.061	6.282 ± 0.047	4.295 ± 0.034	0.680 ± 0.007	51.132 ± 1.010
	Differenced-TCN [27]	**7.189** ± 0.002	5.388 ± 0.002	3.704 ± 0.001	**0.753** ± 0.000	49.819 ± 0.515
	TCN	7.250 ± 0.017	5.441 ± 0.019	3.765 ± 0.018	0.750 ± 0.001	52.687 ± 1.028
	Differenced-TCN	7.208 ± 0.011	5.386 ± 0.009	3.704 ± 0.006	0.753 ± 0.001	52.575 ± 0.638
	CMHA-TCN	7.260 ± 0.017	5.445 ± 0.014	3.767 ± 0.017	0.749 ± 0.001	52.452 ± 1.010
	Differenced-CMHA-TCN	7.193 ± 0.019	**5.375** ± 0.020	**3.699** ± 0.014	**0.754** ± 0.001	**53.249** ± 1.390
	EVMD-TCN	7.371 ± 0.011	5.532 ± 0.020	3.824 ± 0.016	0.741 ± 0.001	48.579 ± 0.741
	EVMD-CMHA-TCN	7.376 ± 0.010	5.523 ± 0.011	3.814 ± 0.010	0.740 ± 0.001	49.327 ± 0.652
	EVMD-PMB-TCN	7.447 ± 0.024	5.618 ± 0.009	3.871 ± 0.007	0.736 ± 0.003	49.184 ± 1.830
	EVMD-PMB-CMHA-TCN	7.415 ± 0.024	5.562 ± 0.026	3.838 ± 0.017	0.738 ± 0.001	49.147 ± 0.753
	SVMD-TCN	7.360 ± 0.043	5.522 ± 0.034	3.816 ± 0.030	0.743 ± 0.003	50.887 ± 1.737
	SVMD-CMHA-TCN	7.405 ± 0.076	5.568 ± 0.053	3.840 ± 0.033	0.741 ± 0.005	51.309 ± 1.091
	SVMD-PMB-TCN	7.374 ± 0.029	5.535 ± 0.028	3.827 ± 0.019	0.742 ± 0.002	51.111 ± 1.650
	SVMD-PMB-CMHA-TCN	7.332 ± 0.038	5.508 ± 0.025	3.800 ± 0.025	0.744 ± 0.003	52.296 ± 0.882
XMR/USD	TCN [27]	12.323 ± 0.086	9.642 ± 0.058	4.429 ± 0.019	0.571 ± 0.010	51.060 ± 1.089
	Differenced-TCN [27]	**11.172** ± 0.008	**8.590** ± 0.003	**3.926** ± 0.001	0.649 ± 0.000	52.339 ± 0.000
	TCN	11.255 ± 0.044	8.648 ± 0.028	3.969 ± 0.016	0.646 ± 0.002	52.825 ± 1.159
	Differenced-TCN	11.188 ± 0.017	8.638 ± 0.012	3.953 ± 0.005	**0.650** ± 0.001	53.112 ± 0.385
	CMHA-TCN	11.282 ± 0.017	8.661 ± 0.016	3.968 ± 0.007	0.646 ± 0.001	54.093 ± 1.805
	Differenced-CMHA-TCN	11.223 ± 0.032	8.672 ± 0.025	3.962 ± 0.014	0.647 ± 0.001	53.294 ± 1.346
	EVMD-TCN	11.654 ± 0.063	9.028 ± 0.036	4.150 ± 0.018	0.621 ± 0.004	53.557 ± 0.916
	EVMD-CMHA-TCN	11.643 ± 0.032	9.023 ± 0.032	4.155 ± 0.016	0.623 ± 0.001	**54.399** ± 0.923
	EVMD-PMB-TCN	11.807 ± 0.111	9.217 ± 0.084	4.237 ± 0.040	0.614 ± 0.006	50.824 ± 1.022
	EVMD-PMB-CMHA-TCN	12.041 ± 0.148	9.398 ± 0.148	4.345 ± 0.072	0.597 ± 0.008	52.487 ± 1.498
	SVMD-TCN	11.614 ± 0.015	8.947 ± 0.020	4.111 ± 0.008	0.627 ± 0.002	51.263 ± 1.372
	SVMD-CMHA-TCN	11.741 ± 0.034	9.013 ± 0.038	4.145 ± 0.018	0.619 ± 0.003	51.998 ± 1.179
	SVMD-PMB-TCN	11.587 ± 0.049	8.892 ± 0.034	4.083 ± 0.015	0.629 ± 0.003	52.733 ± 0.907
	SVMD-PMB-CMHA-TCN	11.647 ± 0.036	8.948 ± 0.023	4.119 ± 0.015	0.626 ± 0.004	53.012 ± 1.434
XRP/USD	TCN [27]	0.0457 ± 0.0007	0.0349 ± 0.0006	4.154 ± 0.056	0.596 ± 0.026	50.786 ± 1.363
	Differenced-TCN [27]	0.0412 ± 0.0000	0.0306 ± 0.0000	3.683 ± 0.001	0.695 ± 0.000	49.625 ± 0.716
	TCN	0.0413 ± 0.0001	0.0307 ± 0.0001	3.690 ± 0.017	0.694 ± 0.004	50.986 ± 1.391
	Differenced-TCN	**0.0412** ± 0.0000	**0.0306** ± 0.0000	**3.675** ± 0.004	**0.698** ± 0.000	51.883 ± 0.943
	CMHA-TCN	0.0413 ± 0.0001	0.0307 ± 0.0001	3.692 ± 0.008	0.694 ± 0.002	50.283 ± 0.956
	Differenced-CMHA-TCN	0.0413 ± 0.0001	0.0307 ± 0.0000	3.687 ± 0.007	0.695 ± 0.001	49.247 ± 2.120
	EVMD-TCN	0.0423 ± 0.0002	0.0314 ± 0.0002	3.792 ± 0.021	0.678 ± 0.002	**54.323** ± 1.301
	EVMD-CMHA-TCN	0.0426 ± 0.0002	0.0314 ± 0.0002	3.787 ± 0.026	0.671 ± 0.003	53.779 ± 1.494
	EVMD-PMB-TCN	0.0437 ± 0.0003	0.0328 ± 0.0002	3.965 ± 0.024	0.660 ± 0.007	53.403 ± 1.319
	EVMD-PMB-CMHA-TCN	0.0427 ± 0.0006	0.0317 ± 0.0005	3.818 ± 0.064	0.664 ± 0.007	53.907 ± 1.331
	SVMD-TCN	0.0420 ± 0.0001	0.0313 ± 0.0001	3.780 ± 0.015	0.683 ± 0.003	50.121 ± 1.572
	SVMD-CMHA-TCN	0.0418 ± 0.0001	0.0312 ± 0.0001	3.761 ± 0.012	0.684 ± 0.002	50.167 ± 1.174
	SVMD-PMB-TCN	0.0420 ± 0.0001	0.0313 ± 0.0000	3.768 ± 0.007	0.683 ± 0.002	50.088 ± 0.909
	SVMD-PMB-CMHA-TCN	0.0421 ± 0.0002	0.0314 ± 0.0002	3.778 ± 0.038	0.676 ± 0.006	50.509 ± 1.315

Table 5: Average results of the *benchmark experiments* across 6 repetitions and splits $M_1, \ldots, M_{12}$ with respect to forecasting $\mathbf{S}_{\text{Close}}$ in *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* using the novel framework.

Crypto	Model	RMSE	MAE	MAPE (%)	R^2	DA (%)
BTC/USD	Differenced-TCN [27]	1243.433 ± 0.077	902.252 ± 0.077	1.840 ± 0.000	0.688 ± 0.000	50.566 ± 0.198
	TCN	1251.000 ± 1.783	909.490 ± 1.474	1.861 ± 0.006	0.686 ± 0.001	50.182 ± 1.031
	Differenced-TCN	**1243.317** ± 0.451	**899.564** ± 0.466	**1.837** ± 0.002	**0.690** ± 0.001	52.075 ± 0.622
	CMHA-TCN	1250.904 ± 3.360	910.752 ± 3.366	1.868 ± 0.009	0.685 ± 0.001	50.410 ± 1.751
	Differenced-CMHA-TCN	1243.631 ± 0.467	900.857 ± 0.784	1.838 ± 0.002	0.689 ± 0.000	51.304 ± 0.857
	EVMD-TCN	1257.285 ± 1.811	912.592 ± 2.246	1.867 ± 0.004	0.685 ± 0.001	50.991 ± 0.518
	EVMD-CMHA-TCN	1274.174 ± 3.821	927.385 ± 3.382	1.886 ± 0.006	0.682 ± 0.003	52.111 ± 1.054
	EVMD-PMB-TCN	1262.898 ± 6.294	916.837 ± 5.315	1.876 ± 0.011	0.683 ± 0.001	51.409 ± 1.172
	EVMD-PMB-CMHA-TCN	1417.142 ± 33.464	1068.505 ± 33.476	2.108 ± 0.049	0.621 ± 0.021	51.004 ± 1.209
	SVMD-TCN	1263.976 ± 2.317	921.898 ± 2.075	1.889 ± 0.008	0.676 ± 0.003	**52.297** ± 0.768
	SVMD-CMHA-TCN	1262.187 ± 1.568	918.959 ± 1.069	1.874 ± 0.003	0.680 ± 0.001	52.038 ± 0.581
	SVMD-PMB-TCN	1265.849 ± 2.471	924.466 ± 3.117	1.885 ± 0.009	0.678 ± 0.002	51.861 ± 0.655
	SVMD-PMB-CMHA-TCN	1360.090 ± 29.153	1020.060 ± 27.521	2.034 ± 0.038	0.646 ± 0.020	51.149 ± 1.411
ETH/USD	Differenced-TCN [27]	74.271 ± 0.024	53.547 ± 0.022	2.429 ± 0.001	0.660 ± 0.000	49.583 ± 0.297
	TCN	75.080 ± 0.298	54.256 ± 0.291	2.479 ± 0.022	0.657 ± 0.002	48.796 ± 0.606
	Differenced-TCN	**74.111** ± 0.029	**53.429** ± 0.066	**2.422** ± 0.005	**0.661** ± 0.001	50.399 ± 0.603
	CMHA-TCN	75.089 ± 0.223	54.078 ± 0.203	2.463 ± 0.013	0.658 ± 0.001	49.455 ± 0.907
	Differenced-CMHA-TCN	74.361 ± 0.147	53.774 ± 0.098	2.439 ± 0.006	0.658 ± 0.000	49.653 ± 0.976
	EVMD-TCN	76.349 ± 0.144	55.310 ± 0.134	2.516 ± 0.010	0.647 ± 0.000	52.280 ± 0.579
	EVMD-CMHA-TCN	76.780 ± 0.210	55.482 ± 0.169	2.523 ± 0.007	0.645 ± 0.001	**52.752** ± 0.561
	EVMD-PMB-TCN	76.434 ± 0.134	55.348 ± 0.070	2.518 ± 0.006	0.647 ± 0.001	52.306 ± 0.535
	EVMD-PMB-CMHA-TCN	79.987 ± 0.427	58.537 ± 0.496	2.650 ± 0.024	0.621 ± 0.005	52.376 ± 0.819
	SVMD-TCN	75.951 ± 0.250	55.398 ± 0.262	2.533 ± 0.017	0.650 ± 0.002	50.115 ± 0.824
	SVMD-CMHA-TCN	75.713 ± 0.229	55.168 ± 0.215	2.514 ± 0.012	0.652 ± 0.001	51.021 ± 0.535
	SVMD-PMB-TCN	75.720 ± 0.177	55.284 ± 0.088	2.527 ± 0.007	0.652 ± 0.001	50.970 ± 0.629
	SVMD-PMB-CMHA-TCN	79.052 ± 0.615	57.749 ± 0.452	2.623 ± 0.021	0.631 ± 0.006	52.347 ± 1.189
LTC/USD	**Differenced-TCN** [27]	**3.068** ± 0.000	2.242 ± 0.000	2.767 ± 0.000	0.607 ± 0.000	50.968 ± 0.209
	TCN	3.070 ± 0.003	2.243 ± 0.006	2.770 ± 0.007	0.607 ± 0.001	52.831 ± 0.702
	Differenced-TCN	3.072 ± 0.003	2.240 ± 0.003	2.768 ± 0.004	0.608 ± 0.001	52.514 ± 0.556
	CMHA-TCN	3.069 ± 0.004	**2.238** ± 0.006	**2.764** ± 0.007	**0.608** ± 0.001	**53.113** ± 1.038
	Differenced-CMHA-TCN	3.074 ± 0.004	2.246 ± 0.005	2.774 ± 0.006	0.606 ± 0.001	51.483 ± 0.747
	EVMD-TCN	3.082 ± 0.002	2.244 ± 0.003	2.773 ± 0.004	0.605 ± 0.001	51.812 ± 0.544
	EVMD-CMHA-TCN	3.083 ± 0.003	2.245 ± 0.005	2.774 ± 0.007	0.606 ± 0.001	52.387 ± 0.453
	EVMD-PMB-TCN	3.081 ± 0.005	2.245 ± 0.003	2.773 ± 0.003	0.606 ± 0.001	52.531 ± 0.505
	EVMD-PMB-CMHA-TCN	3.097 ± 0.003	2.257 ± 0.003	2.790 ± 0.004	0.604 ± 0.001	52.523 ± 0.581
	SVMD-TCN	3.138 ± 0.015	2.296 ± 0.015	2.834 ± 0.018	0.585 ± 0.006	50.953 ± 0.582
	SVMD-CMHA-TCN	3.125 ± 0.004	2.291 ± 0.005	2.826 ± 0.006	0.591 ± 0.002	50.167 ± 0.482
	SVMD-PMB-TCN	3.126 ± 0.006	2.292 ± 0.006	2.831 ± 0.008	0.592 ± 0.001	49.653 ± 0.435
	SVMD-PMB-CMHA-TCN	3.123 ± 0.006	2.280 ± 0.007	2.814 ± 0.008	0.594 ± 0.001	50.451 ± 0.442
XMR/USD	Differenced-TCN [27]	4.984 ± 0.000	3.528 ± 0.000	2.135 ± 0.000	0.535 ± 0.000	55.149 ± 0.000
	TCN	4.995 ± 0.015	3.549 ± 0.020	2.152 ± 0.011	0.541 ± 0.002	55.047 ± 0.749
	Differenced-TCN	**4.968** ± 0.005	**3.493** ± 0.005	**2.110** ± 0.003	**0.545** ± 0.001	54.186 ± 0.569
	CMHA-TCN	4.993 ± 0.011	3.551 ± 0.010	2.152 ± 0.007	0.542 ± 0.003	54.837 ± 0.471
	Differenced-CMHA-TCN	4.980 ± 0.008	3.513 ± 0.008	2.127 ± 0.004	0.537 ± 0.002	54.652 ± 0.876
	EVMD-TCN	5.025 ± 0.021	3.546 ± 0.020	2.148 ± 0.014	0.542 ± 0.004	54.741 ± 0.870
	EVMD-CMHA-TCN	5.042 ± 0.008	3.558 ± 0.011	2.152 ± 0.006	0.544 ± 0.002	54.827 ± 0.589
	EVMD-PMB-TCN	5.051 ± 0.037	3.565 ± 0.028	2.157 ± 0.021	0.538 ± 0.003	55.080 ± 0.621
	EVMD-PMB-CMHA-TCN	5.122 ± 0.033	3.637 ± 0.021	2.194 ± 0.012	0.533 ± 0.010	54.303 ± 0.636
	SVMD-TCN	5.050 ± 0.009	3.604 ± 0.012	2.178 ± 0.009	0.536 ± 0.003	56.046 ± 0.652
	SVMD-CMHA-TCN	5.025 ± 0.004	3.578 ± 0.006	2.159 ± 0.005	0.541 ± 0.001	**56.287** ± 0.536
	SVMD-PMB-TCN	5.040 ± 0.011	3.593 ± 0.007	2.166 ± 0.004	0.536 ± 0.003	55.653 ± 0.888
	SVMD-PMB-CMHA-TCN	5.073 ± 0.031	3.618 ± 0.020	2.184 ± 0.014	0.534 ± 0.003	55.132 ± 0.511
XRP/USD	Differenced-TCN [27]	0.0380 ± 0.0000	0.0257 ± 0.0000	2.672 ± 0.003	0.588 ± 0.001	47.764 ± 0.514
	TCN	0.0386 ± 0.0001	0.0260 ± 0.0001	2.692 ± 0.009	0.584 ± 0.002	50.494 ± 1.006
	Differenced-TCN	**0.0380** ± 0.0000	**0.0257** ± 0.0000	**2.651** ± 0.002	**0.592** ± 0.001	**54.308** ± 0.795
	CMHA-TCN	0.0386 ± 0.0001	0.0261 ± 0.0001	2.690 ± 0.008	0.587 ± 0.002	51.855 ± 0.863
	Differenced-CMHA-TCN	0.0380 ± 0.0001	0.0257 ± 0.0000	2.661 ± 0.005	0.589 ± 0.001	50.104 ± 0.826
	EVMD-TCN	0.0399 ± 0.0001	0.0272 ± 0.0001	2.789 ± 0.016	0.559 ± 0.003	52.486 ± 0.506
	EVMD-CMHA-TCN	0.0399 ± 0.0001	0.0271 ± 0.0001	2.757 ± 0.008	0.565 ± 0.001	53.677 ± 0.634
	EVMD-PMB-TCN	0.0401 ± 0.0002	0.0275 ± 0.0002	2.811 ± 0.008	0.552 ± 0.002	51.104 ± 0.533
	EVMD-PMB-CMHA-TCN	0.0401 ± 0.0002	0.0272 ± 0.0003	2.760 ± 0.015	0.562 ± 0.003	53.687 ± 0.963
	SVMD-TCN	0.0387 ± 0.0001	0.0265 ± 0.0002	2.700 ± 0.006	0.584 ± 0.001	52.717 ± 0.468
	SVMD-CMHA-TCN	0.0388 ± 0.0001	0.0263 ± 0.0001	2.692 ± 0.006	0.584 ± 0.001	53.063 ± 0.562
	SVMD-PMB-TCN	0.0385 ± 0.0002	0.0263 ± 0.0001	2.685 ± 0.010	0.584 ± 0.001	53.249 ± 0.771
	SVMD-PMB-CMHA-TCN	0.0391 ± 0.0003	0.0266 ± 0.0002	2.703 ± 0.012	0.584 ± 0.001	53.696 ± 0.400

Table 6: Average results of the *extended experiments* across 6 repetitions and splits $M_1, \ldots, M_{36}$ with respect to forecasting $\mathbf{S}_{\text{Close}}$ in *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* using the novel framework.

R^2 recorded across both experiments with respect to *BTC*/*USD*, *ETH*/*USD*, *LTC*/*USD*, *XMR*/*USD*, *XRP*/*USD*.
The findings when comparing SVMD-TCN and SVMD-CMHA-TCN to SVMD-PMB-TCN and SVMD-PMB-CMHA-TCN are less straightforward. The separate processing and forecasting of SVMD modes to forecast $\mathbf{S}_{\text{Close}}$ by SVMD-PMB-TCN and SVMD-PMB-CMHA-TCN is shown to be more effective overall than the individual processing of SVMD modes to forecast $\mathbf{S}_{\text{Close}}$ on several occasions. In terms of the *benchmark experiments*, SVMD-PMB-TCN achieves lower error metrics and a higher R^2 than both SVMD-TCN and SVMD-CMHA-TCN for *BTC*/*USD* and *XMR*/*USD*. Furthermore, SVMD-PMB-CMHA-TCN achieves the lowest MAE and MAPE for *BTC*/*USD* and *ETH*/*USD* in comparison to the other SVMD-based models, while also producing lower error metrics and a higher R^2 for *LTC*/*USD*. In terms of the *extended experiments*, SVMD-PMB-TCN produces lower error metrics and a higher R^2 than any other SVMD-based model with respect to *XRP*/*USD*, while SVMD-PMB-CMHA-TCN does so for *LTC*/*USD*. Even when SVMD-PMB-TCN does not produce the lowest error metrics nor the highest R^2 among the SVMD-based models, it remains competitive.

Impact of Mode Quality on Proposed Models
When considering Tables 70 to 73 alongside Tables 5 and 6, a correlation can be observed between the efficacy of separately processing and forecasting modes to forecast $\mathbf{S}_{\text{Close}}$ in the proposed models and the quality and stability of the decomposition. From Tables 70 to 73, it can be derived that the EVMD modes show more evidence of nonstationarity, exhibit greater mode overlap, and tend to have a higher residual energy than the SVMD modes. The fact that EVMD modes tend to be nonstationary more often would make it more difficult for the individual TCN branches to capture the characteristics of a respective mode and forecast it accurately. Furthermore, greater mode overlap indicates that the EVMD modes suffer from more mode mixing than the SVMD modes, resulting in noisier EVMD modes. The higher residual energy can further limit the efficacy of models that separately process and forecast VMD modes, as a larger part of the information with respect to the original time series is not represented by the extracted modes. This results in the combined forecasts of the individual modes not being able to fully capture the dynamics of the original time series and result in decreased performance. The factors as described would explain why SVMD-PMB-TCN and SVMD-PMB-CMHA-TCN are, overall, shown to be capable of improving upon SVMD-TCN and SVMD-CMHA-TCN, whilst EVMD-PMB-TCN and EVMD-PMB-CMHA-TCN do not with respect to EVMD-TCN and EVMD-CMHA-TCN.

Comparison of the Proposed Models
Among the proposed models, SVMD-PMB-TCN produces the best results overall, achieving lower error metrics and a higher R^2 with respect to *ETH*/*USD*, *XMR*/*USD*, and *XRP*/*USD* in both the *benchmark experiments* and *extended experiments*. In addition, SVMD-PMB-CMHA-TCN achieves the best overall performance for *LTC*/*USD* in the *benchmark experiments*, while SVMD-PMB-TCN outperforms EVMD-PMB-TCN and EVMD-PMB-CMHA-TCN. Furthermore, SVMD-PMB-CMHA-TCN outperforms EVMD-PMB-TCN and EVMD-PMB-CMHA-TCN for *ETH*/*USD*, *XMR*/*USD*, and *XRP*/*USD* in the *benchmark experiments*, as well as for *XRP*/*USD* in the *extended experiments*.
On the other hand, EVMD-PMB-TCN outperforms both SVMD-PMB-TCN and SVMD-PMB-CMHA-TCN across the considered regression metrics with respect to *BTC*/*USD* in both experiments and *LTC*/*USD* in the *extended experiments*. The efficacy of EVMD-PMB-TCN

with respect to *BTC/USD* in both experiments and in the *extended experiments* coincides with the quality of the corresponding EVMD modes. Although the SVMD modes seemingly tend to be of a higher quality and more stable as previously stated, the statistics of the EVMD modes in Tables 70 to 73 demonstrate that the EVMD modes with respect to *BTC/USD* rival the respective SVMD modes in quality, with the residual energy of the EVMD modes being significantly lower than that of the SVMD modes.
EVMD-PMB-CMHA-TCN is overall the worst-performing model among the proposed models. The results overall suggest that adding an attention mechanism to the separate branches does not consistently improve performance, as EVMD-PMB-CMHA-TCN and SVMD-PMB-CMHA-TCN are, for the most part, outperformed overall by EVMD-PMB-TCN and SVMD-PMB-TCN.

Comparison in terms of Directional Accuracy
Although the models are trained to optimize regression accuracy, the overall results demonstrate that the VMD-based models tend to achieve higher directional accuracy than the other models. This suggests that, despite being outperformed by the benchmark models from a regression perspective, the VMD modes provide a more informative input for capturing the direction of $\mathbf{S}_{\text{Close}}$ than the inputs obtained through the *default* and *differenced* pipelines.

Impact of VMD on Performance
Ignoring the overall results of TCN [27], the margins between the overall recorded metrics of the various models across both experiments and all cryptocurrencies are, for the most part, modest, with the VMD-based models overall being outperformed. This is contradictory to the findings in previous studies that report the application of VMD in combination with a machine learning model leading to substantial improvements in performance with respect to forecasting time series, including cryptocurrency prices [81–87, 89, 91–94, 98, 99, 101–109]. This highlights the impact of data leakage on the results reported in those studies, as VMD was not applied in a leakage-free manner, unlike the EVMD-based and SVMD-based models. This is further highlighted by Table 56, which contains the overall results of DLVMD-TCN with respect to the *benchmark experiments* in comparison to EVMD-TCN and SVMD-TCN, where DLVMD-TCN makes use of the *VMD* preprocessing pipeline and the DLVMD procedure, which applies VMD in the same way as the mentioned previous research. Table 56 shows that DLVMD-TCN outperforms both EVMD-TCN and SVMD-TCN, as well as the models not included in the table, by an extremely large margin due to data leakage from using the DLVMD procedure.
The lack of impact when applying VMD in a leakage-free manner, shown by the overall results with respect to the EVMD-based and SVMD-based models in comparison to the other models, can be attributed to the limited quality of the decompositions with the determined parameters according to Tables 70 to 73. The resulting modes overall appear to suffer from mode mixing, retain a significant residual energy, and frequently remain nonstationary, where the vast majority of the information in the original time series is concentrated in a singular mode. This can result in noisier modes, which could decrease the model's capacity to extract important information related to the original time series.

Overfitting
An inspection of the performance in terms of the training and validation loss of each model during and after training suggests that the models, especially the models based on the *differenced* preprocessing pipelines, suffer from significant overfitting. This is highlighted by Table 57,

which shows that the gap between the training and validation loss with respect to the *benchmark experiments* is often considerable, especially foro the models based on the *differenced* preprocessing pipeline. The tendency to overfit is less pronounced for the models based on the *default* and *VMD* preprocessing pipelines, although it is still observed, but to a lower degree. A certain degree of overfitting can be expected given that the only feature utilized for forecasting $\mathbf{S}_{\text{Close}}$ is the historical values of $\mathbf{S}_{\text{Close}}$ itself, while the prices of cryptocurrencies can be affected by a wide range of external factors. If one were to include these factors as data for the model to utilize, the model would have an added understanding of $\mathbf{S}_{\text{Close}}$ and would be less reliant on patterns present solely within the historical values of $\mathbf{S}_{\text{Close}}$, potentially reducing its tendency to overfit on the training data.

6.2.2 Monthly Results

In Tables 58 to 67, the results of forecasting $\mathbf{S}_{\text{Close}}$ in *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, *XRP/USD* for each month corresponding to $\mathbf{Y}_{\text{Test}}$ in the respective splits of the *benchmark experiments* and *extended experiments* is shown.
Although the overall results show the proposed models are outperformed by the benchmark models, with the exception of TCN [27] and models introduced as part of the ablation study, the monthly results reveal that the proposed models can outperform all other models for specific months with respect to certain cryptocurrencies. In Table 7, the months for which the proposed models achieve the best forecasting performance in terms of all (error) metrics, only in terms of RMSE and R^2, and only in terms of MAE and MAPE are shown.
The improved accuracy shown by the proposed models in forecasting $\mathbf{S}_{\text{Close}}$ in comparison to the benchmark models and the models part of the ablation study with respect to the months highlighted in Table 7 appears to coincide with the quality of the relevant decomposition, previously discussed in Section 6.2.1. When comparing the monthly results with Tables 70 to 73, it can be seen that months in which EVMD-PMB-TCN, EVMD-PMB-CMHA-TCN, SVMD-PMB-TCN, and SVMD-PMB-CMHA-TCN achieve an improved performance it is generally the case that the modes of the associated decomposition using either EVMD or SVMD exhibit less evidence of nonstationarity, lower residual energy, display less mode overlap, and a lower energy ratio.

Model	Crypto	All (Error) Metrics	Only RMSE/R^2	Only MAE/MAPE
EVMD-PMB-TCN	*BTC/USD*	February 2022 September 2024	–	April 2023 May 2024
	ETH/USD	–	August 2022 October 2023	June 2021 April 2022 December 2022
	LTC/USD	July 2022	December 2023 November 2024	May 2023 September 2023 February 2024
	XMR/USD	February 2023	September 2023 May 2024	–
	XRP/USD	–	July 2024	April 2022
EVMD-PMB-CMHA-TCN	*BTC/USD*	–	–	–
	ETH/USD	–	–	September 2022
	LTC/USD	October 2022	May 2024	February 2024 November 2024
	XMR/USD	–	February 2024	March 2022 November 2023 May 2024
	XRP/USD	February 2023 June 2023 March 2024	May 2024 March 2025	April 2023 July 2023
SVMD-PMB-TCN	*BTC/USD*	January 2024 June 2024	July 2021 December 2021	–
	ETH/USD	February 2022 January 2023	–	–
	LTC/USD	January 2025	–	November 2023 December 2023 October 2024 April 2025
	XMR/USD	–	October 2021 May 2023 June 2023 June 2024	July 2024
	XRP/USD	February 2025 May 2025	November 2021 November 2022 November 2023	–
SVMD-PMB-CMHA-TCN	*BTC/USD*	–	November 2021 September 2022 March 2025	–
	ETH/USD	November 2021 May 2023 June 2023	–	May 2022 August 2023 September 2024
	LTC/USD	March 2022 May 2022 April 2024 July 2024	November 2023	June 2023 March 2024 May 2025
	XMR/USD	–	September 2022 March 2024	October 2021, July 2024
	XRP/USD	–	March 2023 April 2023 June 2024	May 2024

Table 7: Months corresponding to $\mathbf{Y}_{\text{Test}}$ of the respective splits across both the *benchmark experiments* and the *extended experiments* for which the proposed models achieve the best forecasting performance with respect to $\mathbf{S}_{\text{Close}}$ in terms of all (error) metrics, only in terms of RMSE and R^2, and only in terms of MAE and MAPE.

7 Conclusion and Future Work

Over the past few years, the cryptocurrency market has experienced substantial growth, with a significant proportion of the population participating in the market. Although cryptocurrencies were designed as a decentralized payment method, cryptocurrencies have become stock-like financial assets that are traded and serve as investments. The significant interest in investing in and trading cryptocurrencies means that there is a high demand for methods that can predict cryptocurrency prices, either from a regression perspective, *cryptocurrency price prediction*, or from a classification perspective, *cryptocurrency price movement prediction*. Due to how volatile cryptocurrency prices are, investing in cryptocurrencies and trading them comes with high risk and thus requires methods capable of predicting cryptocurrency prices with high accuracy.

After an extensive review of the literature on *cryptocurrency price prediction*, it can be concluded that the field of *cryptocurrency price prediction* is scattered with no clear state-of-the-art. To address this, we build upon the study conducted by Murray et al. [27] given its widespread application of different models to *cryptocurrency price prediction*, its publicly available dataset, and publicly available source code. In their study, Murray et al. [27] apply ARIMA, Gated Recurrent Unit (GRU), k-Nearest Neighbours (KNN), Long Short-Term Memory (LSTM) with a convolutional layer (CNN-LSTM), Random Forest (RF), Support Vector Regression (SVR), Temporal Convolutional Network (TCN), Temporal Fusion Transformer (TFT), LSTM-GRU, and various ensembles with respect to the daily close price prediction of *Bitcoin* (*BTC*), *Ethereum* (*ETH*), *Litecoin* (*LTC*), *Monero* (*XMR*), and *Ripple* (*XRP*) in *United States Dollars* (*USD*) on a monthly basis from 1 June 2021 to 31 May 2022 using a univariate approach. According to the results reported by Murray et al. [27], the CNN-LSTM model is the most accurate model with respect to predicting the daily close prices of all cryptocurrencies. The reported results are consistent with a repetition of the experiments conducted by Murray et al. [27] using their framework, the *benchmark framework*. However, an inspection of the framework revealed several flaws in its experimental setup. After addressing these flaws, repeating the same experiments using the *revised benchmark framework* reveals that, instead of CNN-LSTM, TCN is the most accurate model overall.

Based on the efficacy of TCN demonstrated by the revised experimental results of Murray et al. [27] and the promising research avenues identified through the extensive review of the existing literature on *cryptocurrency price prediction*, we propose Temporal Convolutional Network with Variational Mode Decomposition and Parallel Mode Branches (VMD-PMB-TCN) and Variational Mode Decomposition and Parallel Mode Branches (VMD-PMB-CMHA-TCN). Both models are based on the application of Variational Mode Decomposition (VMD), which decomposes the time series serving as input into several simpler, smoother, and more stationary modes to mitigate the nonlinearity and nonstationarity of the original time series. The proposed models specifically apply VMD in a manner that prevents data leakage. This addresses a limitation of previous studies that reported substantial improvements when applying VMD for time series forecasting, despite applying VMD in a manner that leads to data leakage [81–87, 89, 91–94, 98, 99, 101–109]. Given the efficacy of decomposition-based ensemble approaches reported in previous research [82–85, 92, 96–102], the proposed models are equipped with separate branches to forecast the modes independently and subsequently sum the resulting forecasts to produce the final prediction of the original time series in line with the constraint of VMD. In VMD-PMB-TCN, each branch consists of a TCN based on the architecture proposed by Bai et al. [131]. On the other hand, each branch of VMD-PMB-

CMHA-TCN employs the same TCN architecture followed by a causal multi-head attention mechanism, as proposed by Vaswani et al. [208]. The addition of the attention mechanism is utilized to highlight the most important time steps with respect to the corresponding forecast. For evaluating the proposed models, we set up a new framework, the *novel framework*, built upon the *revised benchmark framework*. The experimental setup of the *novel framework* consists of the same experiments conducted by Murray et al. [27], referred to as the *benchmark experiments*, together with the *extended experiments*, which extend the *benchmark experiments* by forecasting the daily close prices from 1 June 2022 to 31 May 2025. Furthermore, the *novel framework* includes five models: the TCN proposed by Murray et al. [27], the TCN proposed by Bai et al. [131], VMD-PMB-TCN, VMD-PMB-CMHA-TCN, and CMHA-TCN, where the latter is included as part of an ablation study. In terms of the experimentation, several variants of these models are evaluated by combining them with different preprocessing pipelines: the *default* pipeline, the *differenced* pipeline adopted by Murray et al. [27], and the *VMD* pipeline using either the EVMD, SVMD, or DLVMD procedures. Due to slight differences in the experimental setup between the *novel framework* and the *revised benchmark framework*, the results corresponding to the TCN proposed by Murray et al. [27] in combination with the *differenced* preprocessing pipeline are revised once again with the corresponding results, the results with respect to the *default* preprocessing pipeline as well as the results corresponding to both pipelines with respect to the TCN proposed by Bai et al. [131] serve as the benchmark results of the experiments.
After performing the *benchmark experiments* and the *extended experiments* with the respective models, we can conclude the following:

- Across both experiments, the proposed models, VMD-PMB-TCN and VMD-PMB-CMHA-TCN, tend to be competitive, but ultimately less accurate overall than the benchmark and ablation models in terms of the considered error metrics, especially compared to the benchmark and ablation models making use of the *default* and *differenced* preprocessing pipelines.

- Although VMD-PMB-TCN and VMD-PMB-CMHA-TCN are less accurate than the benchmark and ablation models overall. The proposed models are capable of outperforming the benchmark and ablation models with respect to forecasting the close prices of the relevant cryptocurrencies in certain months. Based on the relevant months, it can be stated that the quality of the decomposition plays a significant role in the corresponding performance. For the months in which VMD-PMB-TCN and VMD-PMB-CMHA-TCN outperform the benchmark and ablation models, the modes resulting from the decomposition tend to show less evidence of nonstationarity, leave a smaller residual, or show fewer signs of overlapping (i.e., mode-mixing).

- Between VMD-PMB-TCN and VMD-PMB-CMHA-TCN, VMD-PMB-TCN is overall shown to produce more accurate and stable forecasts; however, the monthly results show that adding the attention mechanism can result in VMD-PMB-CMHA-TCN outperforming VMD-PMB-TCN in specific months.

- Leakage-free VMD is nowhere near as effective as the application of VMD was reported to be in previous research [81–87, 89, 91–94, 98, 99, 101–109]. This, together with the results obtained by applying VMD in the same manner as in the aforementioned studies, suggests that the performance reported in those studies is substantially inflated due to data leakage.

- The analysis of the modes resulting from decompositions with leakage-free VMD shows that the overall quality of the modes is lacking. The modes appear to suffer from mode mixing and frequently remain nonstationary, where the vast majority of the information in the original time series is concentrated in a singular mode, and the decomposition results in a significant residual. Based on this, it appears that the VMD parameters after tuning are not optimal and are only effective depending on the corresponding time regime, limiting the overall accuracy of the VMD-based models. This means that, in principle, the VMD-based models, including the proposed models, could be more accurate than the other models given an optimal decomposition.

7.1 Future Work

Future work will focus on addressing the limitations of the current study while further exploring the efficacy of the proposed models.

Modifications to Proposed Models
Considering that the decompositions using VMD produce an at times significant residual, due to which information of the original time series is missing in the modes and decreases the accuracy of the proposed models, we will explore making the following modifications to the proposed models to mitigate this:

- Adding an additional branch that processes and models the residual.
- Adding several additional branches after re-decomposing the residual using VMD or an alternative decomposition method. In [82] and [83], the re-decomposition of the residual with VMD, Empirical Mode Decomposition (EMD), and Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) is shown to result in substantial improvements with respect to *cryptocurrency price prediction*.

Modifactions to Tuning
When evaluating the hyperparameter tuning, it can be stated that it is limited and can be improved. To address these limitations, we will look into making the following adjustments to the tuning:

- Instead of keeping the window size fixed in line with the study conducted by Murray et al. [27], the window size will be added as an additional parameter. This is an important adjustment considering the proposed models could be limited if there are window sizes that would result in improved performance.
- Instead of tuning a single set of hyperparameters for TCN and CMHA-TCN that are used across all separate branches of VMD-PMB-TCN and VMD-PMB-CMHA-TCN, the tuning of VMD-PMB-TCN and VMD-PMB-CMHA-TCN will be adjusted such that the TCN and CMHA-TCN in each branch have their own hyperparameters. This follows from the fact that different modes tend to have distinct properties and, as such, would likely require different hyperparameters to be modeled optimally.
- Instead of tuning the hyperparameters of VMD based on the model's performance with respect to the validation set, we will explore determining the optimal hyperparameters visually to ensure that the modes are properly separated and do not exhibit mode-mixing or by tuning the hyperparameters using heuristic measures in combination with

an optimization algorithm, in line with previous research [84, 87, 99, 209–220]. This follows from the analysis of the modes produced by VMD, which indicates that the decompositions are overall not optimal with the hyperparameters determined using the current tuning.

Further Evaluation of Robustness and Accuracy
To further assess the robustness and the accuracy of the models, we will further evaluate the models on *cryptocurrency price prediction* using:

- Multi-step forecasting, where instead of solely predicting the next day based on a window, the next 5 days, for example, are predicted.
- Higher-frequency datasets for higher-frequency forecasting, where cryptocurrency prices are captured at a minute-level or hourly rate.
- Different sources for the cryptocurrency prices than solely *Binance* and *Investing.com*. Although cryptocurrency prices on different exchanges generally follow a similar trajectory, there are differences in recorded prices between the various exchanges [72, 221].

Incorporation of Additional Features
In this study, *cryptocurrency price prediction* is approached from a univariate perspective with only the close price itself serving as input to the models. This likely constrains the predictive performance of the models, resulting in prediction errors that are too substantial for the models to be applicable in real-world trading and investment scenarios. As such, future work will explore using the other types of prices included in the dataset, namely the open price, the high price, and the low price, for forecasting the close price.
Besides these other types of prices, previous research on cryptocurrency price prediction has highlighted that numerous other features have been shown to influence cryptocurrency prices and hold significant predictive power [12–15]. As such, future work will include evaluating the models applied in this study using these features to assess whether predictive accuracy can be improved and whether the efficacy of the proposed models can be elevated compared to other models when utilizing these features. The additional feature could improve the separate forecasts of the modes in VMD-PMB-TCN and VMD-PMB-CMHA-TCN. Based on their efficacy in previous research, the additional features, besides the prices, that we will utilize in the future include:

- Blockchain-related features of the respective cryptocurrencies [44, 52, 55, 59, 95, 135, 141, 145, 222].
- Technical indicators derived from the market data of the respective cryptocurrencies [57, 146, 162, 164, 169, 223].
- Market sentiment captured through social media platforms, such as *Reddit* and *Twitter* [19, 45, 49, 69, 76, 139, 172, 224, 225].

Other Tasks
Lastly, we will evaluate the models on other tasks besides *cryptocurrency price prediction*, namely:

- *Cryptocurrency price movement prediction*: Besides accurately predicting actual prices, accurately predicting price movements can be valuable for trading and investing in cryptocurrencies [54, 169, 225, 226]. Given that, in this study, the proposed models seemed to be more adept at capturing the direction of prices after regression-based training, it would be interesting to explore how well the proposed models perform in comparison to others with classification-based training.

- Benchmark datasets on time series forecasting: The proposed models will be evaluated further using benchmark datasets on time series forecasting with a specific focus on nonstationary benchmark datasets. This follows from the fact that at its core, the proposed models are designed to forecast nonstationary time series rather than solely designed to forecast cryptocurrency prices.

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A Reviewed Studies Overview

A.1 Abbreviations in Overview

A.1.1 Columns

Abbreviation	Meaning
Ref.	Reference
Obs. (#)	Number of observations used for evaluating the models
Freq.	The time granularity of the forecast interval
RMSE	Root Mean Squared Error
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
rAcc. (%)	Regression Accuracy
cAcc. (%)	Classification Accuracy
Prec. (%)	Precision
Rec. (%)	Recall
F1 (%)	F1-score
Norm.	Normalization of Metrics

Table 8: Meaning of the column name abbreviations used in the overview of the reviewed studies.

A.1.2 Cryptocurrencies

Abbreviation	Meaning
ADA	*Cardano*
AMP	*Amp*
ATOM	*Cosmos*
AVAX	*Avalanche*
BCH	*Bitcoin Cash*
BNB	*Binance Coin*
BTC	*Bitcoin*
DASH	*Dash*
DOGE	*Dogecoin*
DOT	*Polkadot*
EOS	*EOS.IO*
ETH	*Ethereum*
LINK	*Chainlink*
LTC	*Litecoin*
LUNA	*Terra*
MATIC	*Polygon*
NEM	*New Economy Market*
SOL	*Solana*
TRX	*TRON*
USDT	*Tether*
XLM	*Stellar*
XMR	*Monero*
XRP	*Ripple*
ZEC	*Zcash*

Table 9: Meaning of cryptocurrency abbreviations used in the overview of the reviewed studies.

A.1.3 Time Granularities

Abbreviation	Meaning
s	Second(s)
m	Minute
ms	Minutes
hr	Hour
hrs	Hours
d	Day
ds	Days
mo	Month

Table 10: Meaning of time granularity abbreviations with respect to the time intervals used in the overview of the reviewed studies.

A.1.4 Models

Abbreviation	Meaning
AE-GRU	Auto-Encoder Gated Recurrent Unit
AE-LSTM	Auto-Encoder Long Short-Term Memory
AODE	Averaged One-Dependence Estimators
AR	AutoRegression
ARFIMA	AutoRegressive Fractionally Integrated Moving Average
ARIMA	AutoRegressive Integrated Moving Average
ARIMA-CNN	AutoRegressive Integrated Moving Average Convolutional Neural Network
ARIMA-FFNN	AutoRegressive Integrated Moving Average Feedforward Neural Network
ARIMA-LSTM	AutoRegressive Integrated Moving Average Long Short-Term Memory
ARIMA-MLP	AutoRegressive Integrated Moving Average Multilayer Perceptron
ARIMA-SVR	AutoRegressive Integrated Moving Average Support Vector Regression
ARIMAX	AutoRegressive Integrated Moving Average with eXogenous inputs
BART	Binary AutoRegressive Tree
BiGRU	Bidirectional Gated Recurrent Unit
BiLSTM	Bidirectional Long Short-Term Memory
BNN	Bayesian Neural Network
BPNN	BackPropagation Neural Network
BR	Bayesian Regression
BRNN	Bayesian Regularization Neural Network
BRR	Bayesian Ridge Regression
BVAR	Bayesian Vector AutoRegression
CNN	Convolutional Neural Network
CNN-BiLSTM	Convolutional Neural Network Bidirectional Long Short-Term Memory
CNN-GRU	Convolutional Neural Network Gated Recurrent Unit
CNN-LSTM	Convolutional Neural Network Long Short-Term Memory
CNN-LSTM-AM	Convolutional Neural Network Long Short-Term Memory with Attention Mechanism
CNN-RNN	Convolutional Neural Network Recurrent Neural Network
ConvLSTM	Convolutional Long Short-Term Memory
DAM-LSTM	Long Short-Term Memory with Dual Attention Mechanism
DNDT	Deep Neural Decision Trees
DNN	Deep Neural Network
DNN-LSTM	Deep Neural Network Long Short-Term Memory
DRCNN	Deep Recurrent Convolutional Neural Network
DSVR	Deep Learning Linear Support Vector Regression
DT	Decision Trees
ED-LSTM	Encoder Decoder Long Short-Term Memory
EMD-LSTM	Long Short-Term Memory with Empirical Mode Decomposition
ET	Extra Trees
EWT-LSTM	Long Short-Term Memory with Empirical Wavelet Transform
EWT-LSTM-CS	Long Short-Term Memory with Empirical Wavelet Transform and Cuckoo Search
FBProphet	FaceBook Prophet
FFNN	Feedforward Neural Network
GB	Gradient Boosting
GBM	Gradient Boosting Machine
GBT	Gradient Boosted Trees
GLM	Generalized Linear Model
GPR	Gaussian Poisson Regression
GRNN	Generalized Regression Neural Networks
GRU	Gated Recurrent Unit

Abbreviation	Meaning
GRU-AM	Gated Recurrent Unit with Attention Mechanism
GRU-TCN	Gated Recurrent Unit Temporal Convolutional Network
HR	Huber Regression
KNN	K-Nearest Neighbours
LDA	Linear Discriminant Analysis
LGBM	Light Gradient Boosting Machine
LR	Linear/Logistic Regression
LSSVR	Least-Squares Support Vector Regression
LSTM	Long Short-Term Memory
LSTM-AR	Long Short-Term Memory AutoRegression
LSTM-AM	Long Short-Term Memory with Attention Mechanism
LSTM-CPD	Long Short-Term Memory with Change Point Detection
LSTM-AM-CPD	Long Short-Term Memory with Attention Mechanism and Change Point Detection
LSTM-GRU	Long Short-Term Memory Gated Recurrent Unit
LSTM-RNN	Long Short-Term Memory Recurrent Neural Network
LSTM-TCN	Long Short-Term Memory Temporal Convolutional Network
MA	Moving Average
MI-CNN-LSTM	Multi-Input Convolutional Neural Network Long Short-Term Memory
MLP	Multilayer Perceptron
MRC-LSTM	Multi-Scale Residual Convolutional Neural Network Long Short-Term Memory
NB	Naive Bayes
OLS	Ordinary Least Squares
P-BiGRU	Probablistic Bidirectional Gated Recurrent Unit
P-BiLSTM	Probablistic Bidirectional Long Short-Term Memory
P-GRU	Probablistic Gated Recurrent Unit
P-LSTM	Probablistic Long Short-Term Memory
PCA	Principal Component Analysis
PCA-SVR	Support Vector Regression with Principal Component Analysis
QDA	Quadratic Discriminant Analysis
RBFNN	Radial Basis Function Neural Network
ResNet	Residual Neural Network
RF	Random Forest
RL	Reinforcement Learning
RNN	Recurrent Neural Network
RT	Regression Trees
SAM-LSTM-CPD	Self-Attention based Multiple Long Short-Term Memory with Change Point Detection
SARIMA	Seasonal AutoRegressive Integrated Moving Average
SDAE	Stacked Denoising Autoencoder
Seq2Seq RNN	Sequence-to-Sequence Recurrent Neural Network
SFM	State-Frequency Memory Recurrent Neural Network
SVM	Support Vector Machine
SVR	Support Vector Regression
TCN	Temporal Convolutional Network
TD-BiGRU	Time Distributed Bidirectional Gated Recurrent Unit
TD-BiLSTM	Time Distributed Bidirectional Long Short-Term Memory
TD-GRU	Time Distributed Gated Recurrent Unit
TD-LSTM	Time Distributed Long Short-Term Memory
TFT	Temporal Fusion Transformer
TSR	Theil-Sen Regression
TWSVR	Twin Support Vector Regression
VAR	Vector AutoRegression
VMD-BiLSTM	Bidirectional Long Short-Term Memory with Variational Mode Decomposition

Abbreviation	Meaning
WAMC	Weighted and Attentive Memory channels
WT-CATCN	Causal Multi-Head Attention Temporal Convolutional Network with Wavelet Transform
XGBoost	eXtreme Gradient Boosting

Table 11: Meaning of model abbreviations used in the overview of the reviewed studies.

A.2 Studies on Cryptocurrency Price Prediction

A.2.1 Overview

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
BTC	[16]	40ms 03/2023	235	Multivariate	*BTC* Price Data	1s	DNN LSTM GRU	LSTM	1.137	0.02	0.039	-	N/A	No
...	[159]	25/02/2021 - 28/02/2021 11/02/2021 - 14/02/2021	-	Univariate OR Multivariate	*BTC* Price Data	10s	LSTM GRU	GRU	7.164	-	20.346	-	N/A	No
ETH	[16]	40ms 03/2023	235	Multivariate	*ETH* Price Data	1s	DNN LSTM GRU	LSTM GRU	0.116	0.01	0.001	-	N/A	No
...	[159]	25/02/2021 - 28/02/2021 11/02/2021 - 14/02/2021	-	Univariate OR Multivariate	*ETH* Price Data	10s	LSTM GRU	GRU	0.58	-	0.651	-	N/A	No
LTC	[159]	25/02/2021 - 28/02/2021 11/02/2021 - 14/02/2021	-	Univariate OR Multivariate	*LTC* Price Data	10s	LSTM GRU	LSTM GRU	0.007	-	0.108	-	N/A	No

Table 12: Studies on cryptocurrency price prediction at second-level intervals sorted by the reported MAPE & RMSE, where the definitions of the utilized abbreviations with respect to the columns, cryptocurrencies, time granularities, and models can be found in Tables 8, 9, 10, and 11.

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
BTC	[151]	16/05/2022 - 17/05/2023	21024	Univariate	*BTC* Close Price	5ms	LSTM BiLSTM P-LSTM P-BiLSTM TD-LSTM TD-BiLSTM GRU P-GRU BiGRU P-BiGRU TD-GRU TD-BiGRU	P-GRU P-LSTM	-	0.145	-	-	LINK	No
...	[132]	0:00 21/12/2020 - 16:00 21/12/2021	261	Univariate	*BTC* Close Price	10ms	ARIMA LSTM	LSTM	151.95	0.27	126.97	99.73	N/A	No
...	[57]	24/09/2017 - 30/11/2020	11184	Multivariate	*BTC* OHLCV *Twitter* Sentiment Technical Indicators	30ms	LSTM GRU Stacking Ensemble Averaging Ensemble Blending Ensemble	Stacking Ensemble	167.01	0.6976	88.741	-	N/A	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[43]	25/09/2017 - 24/05/2024	18001	Univariate	*BTC* Close Price	30ms	MLP DLinear TimeMixer LSTM LSTMNet SegRNN TCN TimesNet ModernTCN Transformer PatchTST ITransformer	DLinear TimeMixer SegRNN ModernTCN PatchTST	0.04359	-	-	-	LINK	Yes
...	[17]	01/2016 - 16/03/2018	13107	Univariate	*BTC* Price	5ms	SVR GPR RT KNN FFNN BRNN RBFNN	BRNN	0.8443	-	-	-	N/A	No
...	[18]	01/2016 - 16/03/2018	13107	Univariate	*BTC* Price	5ms	FFNN	FFNN	1.4406	-	-	-	N/A	No
...	[78]	01/01/2012 - 31/03/2021	-	Univariate	*BTC* Close Price	1m	ARIMA RNN FBProphet GRU LSTM CNN-LSTM BiLSTM XGBoost CNN-GRU	CNN-GRU	43.933	-	-	-	N/A	No
ETH	[151]	16/05/2022 - 17/05/2023	21024	Univariate	*ETH* Close Price	5ms	P-GRU	P-GRU	-	0.188	-	-	LINK	No
...	[43]	25/09/2017 - 24/05/2024	18001	Univariate	*ETH* Close Price	30ms	MLP DLinear TimeMixer LSTM LSTMNet SegRNN TCN TimesNet ModernTCN Transformer PatchTST ITransformer	DLinear TimeMixer SegRNN TimesNet ModernTCN PatchTST	0.03742	-	-	-	LINK	Yes
...	[155]	08/08/2015 - 28/05/2018 29/05/2018 - 31/12/2018 12/01/2019 - 14/04/2019 31/05/2019 - 23/09/2019 28/09/2019 - 23/12/2019 03/01/2020 - 01/03/2020 09/03/2020 - 16/04/2020	- 62496 - 26784 - 33408 - 25056 - 16992 - 11232	Multivariate	*ETH* Close Price *ETH* Weighted Average Price	5ms	LSTM BiLSTM GRU Stacked LSTM 2-Layer CNN 3-Layer CNN	LSTM	0.92	-	0.5	-	N/A	No
...	[78]	2021	-	Univariate	*ETH* Close Price	1m	ARIMA RNN FBProphet GRU LSTM CNN-LSTM BiLSTM XGBoost CNN-GRU	CNN-GRU	3.511	-	-	-	N/A	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
LTC	[151]	16/05/2022 - 17/05/2023	21024	Univariate	*LTC* Close Price	5ms	P-GRU	P-GRU	-	0.282	-	-	LINK	No
XRP	[78]	2021	-	Univariate	*XRP* Close Price	1m	ARIMA RNN FBProphet GRU LSTM CNN-LSTM BiLSTM XGBoost CNN-GRU	CNN-GRU	0.00128	-	-	-	N/A	No
...	[43]	25/09/2017 - 24/05/2024	18001	Univariate	*XRP* Close Price	30ms	MLP DLinear TimeMixer LSTM LSTMNet SegRNN TCN TimesNet ModernTCN Transformer PatchTST ITransformer	DLinear TimeMixer SegRNN TimesNet ModernTCN PatchTST	0.04	-	-	-	LINK	Yes
ADA	[151]	16/05/2022 - 17/05/2023	21024	Univariate	*ADA* Close Price	5ms	P-GRU	P-GRU	-	0.203	-	-	LINK	No
XLM	[151]	16/05/2022 - 17/05/2023	21024	Univariate	*XLM* Close Price	5ms	P-GRU	P-GRU	-	0.252	-	-	LINK	No
DOT	[151]	16/05/2022 - 17/05/2023	21024	Univariate	*DOT* Close Price	5ms	P-GRU	P-GRU	-	0.224	-	-	LINK	No
TRX	[151]	16/05/2022 - 17/05/2023	21024	Univariate	*TRX* Close Price	5ms	P-GRU	P-GRU	-	0.220	-	-	LINK	No

Table 13: Studies on cryptocurrency price prediction at minute-level intervals sorted by the reported MAPE & RMSE, where the definitions of the utilized abbreviations with respect to the columns, cryptocurrencies, time granularities, and models can be found in Tables 8, 9, 10, and 11.

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
BTC	[19]	01/2021 - 03/2023	10920	Multivariate	*BTC* Market Data Technical Indicators Other Crypto Prices *Twitter* Data	1h	RF XGBoost CatBoost CNN GRU LSTM	LSTM	0.003	1.2	0.002	-	N/A	Unclear
...	[156]	10/03/2021 - 18/05/2021	338	Multivariate	*BTC* OHLCV Technical Indicators *BTC* Blockchain Data	1h	CNN LSTM CNN-LSTM ConvLSTM	ConvLSTM	0.0469	2.4076	0.0123	-	N/A	Yes
...	[171]	15/05/2018 - 19/01/2024	-	Univariate	*BTC* Price	1h	DNN-LSTM LSTM-AM	LSTM-AM	1210.72	4.8	816256	99.84	N/A	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[139]	01/01/2020 - 20/11/2022	-	Multivariate	*BTC* OHLCV *Reddit* Sentiment	1h	LSTM SVR BRR TSR LR	LSTM	0.0054	-	0.102	-	N/A	Yes
...	[20]	01/01/2018 - 31/08/2019	4415	Univariate	*BTC* Price	1h	Stacking Ensemble or Averaging Ensemble or Bagging Ensemble using CNN-LSTM or CNN-BiLSTM	Stacking Ensemble (LR) using CNN-BiLSTM or CNN-LSTM	0,0085	-	-	-	N/A	Yes
...	[21]	01/01/2018 - 31/08/2019	4415	Univariate OR Multivariate	*BTC* Price Data	1h	Ensemble using CNN-LSTM or CNN-BiLSTM	Ensemble using CNN-BiLSTM	0.0107	-	-	-	N/A	Yes
...	[43]	25/09/2017 - 24/05/2024	9001	Univariate	*BTC* Close Price	1hr	MLP DLinear TimeMixer LSTM LSTMNet SegRNN TCN TimesNet ModernTCN Transformer PatchTST ITransformer	DLinear ModernTCN	0.06245	-	-	-	LINK	Yes
...	[160]	-	-	Multivariate	*BTC* OHLCV *USD* Volume	1h	LSTM GRU LSTM-RNN	LSTM-RNN	0.105	-	-	-	N/A	Yes
...	[43]	25/09/2017 - 24/05/2024	2250	Univariate	*BTC* Close Price	4hrs	MLP DLinear TimeMixer LSTM LSTMNet SegRNN TCN TimesNet ModernTCN Transformer PatchTST ITransformer	SegRNN	0.1334	-	-	-	LINK	Yes
ETH	[19]	01/2021 - 03/2023	10920	Multivariate	*ETH* Market Data Technical Indicators Other Crypto Prices *Twitter* Data	1h	RF XGBoost CatBoost CNN GRU LSTM	LSTM	0.003	1.2	0.002	-	N/A	Unclear
...	[20]	01/01/2018 - 31/08/2019	4415	Univariate	*ETH* Price	1h	Stacking Ensemble or Averaging Ensemble or Bagging Ensemble using CNN-LSTM or CNN-BiLSTM	Stacking Ensemble (LR) using CNN-LSTM	0.0093	-	-	-	N/A	Yes

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[21]	01/01/2018 - 31/08/2019	4415	Univariate OR Multivariate	*ETH* Price Data	1h	Ensemble using CNN-LSTM or CNN-BiLSTM	Ensemble using CNN-LSTM or CNN-BiLSTM	0.0152	-	-	-	N/A	Yes
...	[139]	01/01/2020 - 20/11/2022	-	Multivariate	*ETH* OHLCV *Reddit* Sentiment	1h	LSTM SVR BRR TSR LR	LSTM	0.0174	-	0.140	-	N/A	Yes
...	[43]	25/09/2017 - 24/05/2024	9001	Univariate	*ETH* Close Price	1h	MLP DLinear TimeMixer LSTM LSTMNet SegRNN TCN TimesNet ModernTCN Transformer PatchTST ITransformer	DLinear TimeMixer SegRNN ModernTCN	0.0374	-	-	-	LINK	Yes
...	[43]	25/09/2017 - 24/05/2024	2250	Univariate	*ETH* Close Price	4hrs	MLP DLinear TimeMixer LSTM LSTMNet SegRNN TCN TimesNet ModernTCN Transformer PatchTST ITransformer	SegRNN	0.1105	-	-	-	LINK	Yes
...	[145]	-	-	Multivariate	*ETH* Price *ETH* Blockchain Data	1hr	LR SVM	SVM	-	-	-	99	N/A	No
LTC	[19]	01/2021 - 03/2023	10920	Multivariate	*LTC* Market Data Technical Indicators Other Crypto Prices *Twitter* Data	1h	RF XGBoost CatBoost CNN GRU LSTM	LSTM	0.003	1.2	0.002	-	N/A	Unclear
...	[139]	01/01/2020 - 20/11/2022	-	Multivariate	*LTC* OHLCV *Reddit* Sentiment	1h	LSTM SVR BRR TSR LR	LSTM	0.0050	-	0.1740	-	N/A	Yes
XRP	[20]	01/01/2018 - 31/08/2019	4415	Univariate	*XRP* Price	1h	Stacking Ensemble or Averaging Ensemble or Bagging Ensemble using CNN-LSTM or CNN-BiLSTM	Stacking Ensemble (LR) using CNN-BiLSTM	0.0092	-	-	-	N/A	Yes
...	[21]	01/01/2018 - 31/08/2019	4415	Univariate OR Multivariate	*XRP* Price Data	1h	Ensemble using CNN-LSTM or CNN-BiLSTM	Ensemble using CNN-BiLSTM	0.0098	-	-	-	N/A	Yes

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[43]	25/09/2017 - 24/05/2024	9001	Univariate	*XRP* Close Price	1h	MLP DLinear TimeMixer LSTM LSTMNet SegRNN TCN TimesNet ModernTCN Transformer PatchTST ITransformer	DLinear ModernTCN	0.0557	-	-	-	LINK	Yes
...	[43]	25/09/2017 - 24/05/2024	2250	Univariate	*XRP* Close Price	4hrs	MLP DLinear TimeMixer LSTM LSTMNet SegRNN TCN TimesNet ModernTCN Transformer PatchTST ITransformer	SegRNN	0.1082	-	-	-	LINK	Yes
DOGE	[19]	01/2021 - 03/2023	10920	Multivariate	*DOGE* Market Data Technical Indicators Other Crypto Prices *Twitter* Data	1h	RF XGBoost CatBoost CNN GRU LSTM	LSTM	0.003	1.2	0.002	-	N/A	Unclear
...	[74]	05/07/2019 - 28/04/2021	849	Multivariate	*DOGE* OHLCV	1h	Transformer	Transformer	25.873	-	3.217	98.47	N/A	No
DOT	[19]	01/2021 - 03/2023	10920	Multivariate	*DOT* Market Data Technical Indicators Other Crypto Prices *Twitter* Data	1h	RF XGBoost CatBoost CNN GRU LSTM	LSTM	0.003	1.2	0.002	-	N/A	Unclear
SOL	[19]	01/2021 - 03/2023	10920	Multivariate	*SOL* Market Data Technical Indicators Other Crypto Prices *Twitter* Data	1h	RF XGBoost CatBoost CNN-1D GRU LSTM	LSTM	0.003	1.2	0.002	-	N/A	Unclear
TRX	[19]	01/2021 - 03/2023	10920	Multivariate	*TRX* Market Data Technical Indicators Other Crypto Prices *Twitter* Data	1h	RF XGBoost CatBoost CNN GRU LSTM	LSTM	0.003	1.2	0.002	-	N/A	Unclear
XLM	[19]	01/2021 - 03/2023	10920	Multivariate	*XLM* Market Data Technical Indicators Other Crypto Prices *Twitter* Data	1h	RF XGBoost CatBoost CNN GRU LSTM	LSTM	0.003	1.2	0.002	-	N/A	Unclear

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
MATIC	[19]	01/2021 - 03/2023	10920	Multivariate	*MATIC* Market Data Technical Indicators Other Crypto Prices *Twitter* Data	1h	RF XGBoost CatBoost CNN GRU LSTM	LSTM	0.003	1.2	0.002	-	N/A	Unclear
ATOM	[19]	01/2021 - 03/2023	10920	Multivariate	*ATOM* Market Data Technical Indicators Other Crypto Prices *Twitter* Data	1h	RF XGBoost CatBoost CNN GRU LSTM	LSTM	0.003	1.2	0.002	-	N/A	Unclear
AVAX	[19]	01/2021 - 03/2023	10920	Multivariate	*AVAX* Market Data Technical Indicators Other Crypto Prices *Twitter* Data	1h	RF XGBoost CatBoost CNN GRU LSTM	LSTM	0.003	1.2	0.002	-	N/A	Unclear

Table 14: Studies on cryptocurrency price prediction at hourly intervals sorted by the reported MAPE & RMSE, where the definitions of the utilized abbreviations with respect to the columns, cryptocurrencies, time granularities, and models can be found in Tables 8, 9, 10, and 11.

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
BTC	[58]	1/01/2018 - 30/06/2021	252	Multivariate	*BTC* OHLC	1d	LSTM GRU BiLSTM	GRU	174.129	0.2454	-	-	N/A	No
...	[79]	07/01/2014 - 03/06/2021	21	Multivariate	*BTC* OHLCV *USD* Trade Volume	1d	LSTM GRU Multi-Layer GRU	Multi-Layer GRU	251.609	0.31	164.49	-	N/A	No
...	[170]	2014 - 2023	-	Univariate OR Multivariate	*BTC* Price Data	5ds 10ds 14ds 21ds 30ds	AE-LSTM AE-GRU	AE-GRU	-	0.5	-	-	N/A	No
...	[72]	01/01/2018 - 31/12/2021	219 305	Multivariate	*BTC* OHLCV Technical Indicators	1d	XGBoost GBM ADAB GRU FFNN CNN	CNN DFFN	-	1	-	-	LINK	No
...	[42]	01/04/2016 - 01/01/2020 01/01/2020 - 31/09/2023	-	Univariate	*BTC* **Log** Close Price	1d	ARIMA LSTM MLP ARIMA-LSTM ARIMA-MLP ADAB LGBM RNN GRU	LSTM LGBM	0.0221	1.0865	0,0168	-	LINK	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[144]	13/09/2011 - 21/07/2017	214	Multivariate	*BTC* **Log** Price *BTC* Volume Data *BTC* Blockchain Data Macroeconomic Data	1d	LR BNN SVR	BNN	0.0031	1.19	-	-	N/A	No
...	[81]	29/04/2013 - 01/01/2021	280	Multivariate	*BTC* CV *USD* Exchange Volume Blockchain Data Macroeconomic Data *Google Trends* Index	1d 2ds 3ds	EMD-LSTM BiLSTM ARIMA LR SVR VMD-BiLSTM	VMD-BiLSTM	0.0075	1.2	0.0069	-	N/A	Yes
...	[95]	27/03/2018 - 16/11/2021	266	Univariate AND Multi-variate	*BTC* Price Data *BTC* Blockchain Data *ETH* Price *XRP* Price *LTC* Price *USDT* Market Cap *USDT* Blockchain Data	1d	LSTM LSTM-CPD LSTM-AM-CPD SAM-LSTM-CPD	SAM-LSTM-CPD	0.5944	1.5381	0.427	-	N/A	Yes
...	[157]	25/10/2015 - 17/10/2020	364	Multivariate	*BTC* OHLCV Macroeconomic Data *Google Trends* Index	1d	MLP LSTM CNN CNN-LSTM MRC-LSTM	MRC-LSTM	261.44	1.56	166.52	-	N/A	No
...	[154]	01/01/2019 - 31/12/2023	365	Multivariate	*BTC* OHLCV	1d	BiLSTM	BiLSTM	674.3738	1.6042	-	-	N/A	No
...	[161]	01/10/2021 - 04/10/2022	3	Univariate	*BTC* Close Price	1d	GRU	GRU	366.060	1.7268	-	-	N/A	No
...	[54]	19/08/2013 - 19/07/2016 01/04/2013 - 01/04/2017	107 146	Multivariate	*BTC* OHLCV *BTC* Blockchain Data Macroeconomic Data	1d	DNN RNN SVM	SVM	15.92	1.81	9.63	-	No	No
...	[164]	16/06/2019 - 16/06/2023	146	Multivariate	*BTC* OHLCV Technical Indicators	1d	LSTM Transformer	Transformer	704.57	1.96	506.17	-	N/A	No
...	[23]	30/12/2016 - 31/08/2018	20	Multivariate	*BTC* OHLCV Technical Indicators *BTC* Blockchain Data Macroeconomic Data *Baidu* Index	1d	BPNN CNN LSTM CNN-LSTM	CNN-LSTM CNN	258.31	2.35	209.89	-	N/A	No
...	[133]	28/04/2013 - 11/05/2018	-	Multivariate	*BTC* OHLCV	1d	BR SVM ARIMA LSTM	LSTM	33.7091	2.3564	33.6811	-	N/A	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[52]	04-01-2009 - 22-11-2016 10-12-2013 - 22-11-2016 01-01-2016 - 22-11-2016 01-01-2011 - 01-08-2020 01-01-2017 - 01-08-2020 01-01-2020 - 01-08-2020	- 199 - 30 - 30 - 182 - ... - ...	Multivariate	*BTC* OHLC *BTC* Blockchain Data	1d	VAR BVAR ARIMA BR	VAR	0.2708	2.48	0.2212	-	N/A	Yes
...	[24]	01/01/2018 - 28/07/2018	71	Multivariate	*BTC* Price Data	1d	LSTM LSTM-AR	LSTM-AR	247.33	2.553	176.37	-	N/A	No
...	[22]	15/11/2015 - 12/03/2020	316	Univariate AND Multi-variate	*BTC* OHLCV	1d	Univariate LR Multivariate LR Univariate LSTM Multivariate LSTM	Multivariate LR	182.4581	2.6	-	-	LINK	No
...	[27]	01/06/2017 - 31/05/2022	365	Univariate	*BTC* Close Price	1d	CNN-LSTM GRU LSTM-GRU KNN TCN ARIMA TFT RF SVR Ensemble	CNN-LSTM	0.0239	2.76	0.0173	-	LINK	Yes
...	[45]	01/01/2020 - 28/06/2023	70	Multivariate	*BTC* OHLCV News Sentiment *Twitter* Sentiment	1d	LSTM CNN-LSTM DAM-LSTM TFT NeuralProphet	DAM-LSTM	-	2.97	431.86	-	LINK	No
...	[134]	05/02/2021 - 21/08/2021	40	Multivariate	*BTC* OHLC *Twitter* Sentiment	1d	MLP ARIMA LSTM	ARIMA	0.03855	3.03698	0.03036	-	N/A	Yes
...	[50]	01/03/2021 - 25/07/2022	95	Univariate	*BTC* Average Price	1d	ARIMA SARIMA LSTM	LSTM	1447.648	3.059	-	-	N/A	No
...	[165]	Mid 2017 - End 2019	213	Multivariate	*BTC* HLV *BTC* Market Cap *BTC* Blockchain Data *Twitter* Data *Google Trends* Index	1d	MLP LSTM Stochastic MLP Stochastic LSTM	Stochastic MLP	0.04438	3.06223	0.03062	-	N/A	Yes
...	[57]	24/09/2017 - 30/11/2020	233	Multivariate	*BTC* OHLCV *Twitter* Sentiment Technical Indicators	1d	LSTM GRU Stacking Ensemble Averaging Ensemble Blending Ensemble	Stacking Ensemble	516.90	3.18	359.08	-	N/A	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[148]	31/03/2015 – 30/09/2018 01/10/2018 – 01/04/2022	- 183 - 182	Multivariate	*BTC* OHLCV *BTC* Blockchain Data Macroeconomic Data *LTC* Price *ETH* Price *XRP* Price *DASH* Price *DOGE* Price *Twitter* Data *Google Trends* Index	1d	RF LSTM	RF	321.61	3.29	-	-	N/A	No
...	[80]	07/08/2015 - 12/10/2021	452	Multivariate	*BTC* OHLCV	1d	LSTM GRU BiLSTM	GRU	1777.31	3.4927	1167.35	-	N/A	No
...	[25]	18/07/2010 - 28/03/2019	476	Univariate	*BTC* Price	1d	LSTM EWT-LSTM EWT-LSTM-CS	EWT-LSTM-CS	623.41	3.55	500.16	-	N/A	No
...	[26]	01/01/2018 - 01/01/2023	365	Multivariate	*BTC* OHLCV	1d	LSTM GRU BiLSTM	BiLSTM	1029.36	3.6	-	-	N/A	No
...	[55]	29/11/2011 - 31/12/2018	518	Multivariate	*BTC* Market Cap *BTC* Blockchain Data	1d	DNN LSTM CNN CNN-LSTM SVM ResNet Ensemble	LSTM	-	3.61	-	-	N/A	No
...	[135]	01/01/2018 - 01/04/2022	205	Multivariate	*BTC* Price Data *ETH* Price Data *LTC* Price Data *BCH* Price Data *USDT* Price Data *BTC* Blockchain Data Market Sentiment Macroeconomic Data	1d	ARIMA SVR LSSVR TWSVR	TWSVR	0.042	4.33	0.031	-	N/A	Yes
...	[153]	17/09/2014 - 09/08/2022	278	Multivariate	*BTC* OCV *BTC* Adjusted Close Price	1d	GRU BiLSTM	GRU	0.01711	7.036	0.02214	-	N/A	Yes
...	[150]	01/01/2017 - 30/04/2020	-	Multivariate	Technical Indicators	1d	BNN FFNN LSTM SVR-BNN SVR-LSTM SVR-FFNN	BNN	-	7.7	-	-	N/A	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[28]	07/2013 - 12/2019	272	Multivariate	*BTC* Price *LTC* Price *XRP* Price *BTC* Volume *LTC* Volume *XRP* Volume *BTC* Market Cap *LTC* Market Cap *XRP* Market Cap *BTC* Blockchain Data Macroeconomic Data *Baidu* Index *Google Trends* Index	1d	BPNN PCA-SVR SVR SDAE	SDAE	160.63	10.19	-	-	N/A	No
...	[59]	2011 - 2019	20 %	Multivariate	*BTC* Blockchain Data Macroeconomic Data Forum Data	1d	DRCNN DNDT DSVR	DRCNN	0.77	40	-	-	N/A	Unclear
...	[142]	01/01/2012 - 08/01/2018	439	Multivariate	*BTC* OHLCV *USD* Volume	1d	LSTM GRU TSR HR	GRU	0.0044	-	-	-	N/A	Yes
...	[29]	16/09/2010 - 21/05/2019	-	Univariate OR Multivariate	*BTC* Price Data	1d	LSTM	LSTM	0.006	-	0.003	-	N/A	Yes
...	[141]	04/2016 - 05/2018	-	Multivariate	*BTC* Volume *BTC* Blockchain Data	-	LSTM RF GB LR	RF	0.0141	-	0.0072	-	N/A	Yes
...	[60]	29/04/2013 - 01/06/2021 01/03/2020 - 01/04/2024	887 448	Univariate AND Multivariate	*BTC* OHL Gold Price Close Price Other Crypto	1d 2ds 3ds 4ds 5ds	ARIMA MLP CNN LSTM ED-LSTM BiLSTM ConvLSTM Transformer	ConvLSTM	0.0147	-	-	-	LINK	Yes
...	[158]	01/01/2010 - 30/06/2019	181	Multivariate	*BTC* Price *BTC* Returns *BTC* Volume *XRP* Price *BTC* Blockchain Data Technical Indicators Macroeconomic Data *Google Trends* Index	1d	DNN LSTM GRU	GRU	0.017	-	-	-	N/A	Yes
...	[149]	4:00AM 17/08/2017 - 0:00AM 27/02/2021	258	Univariate OR Multivariate	*BTC* Price Data	1d	SVM MLP LSTM TCN Transformer	LSTM	0.0387	-	-	-	N/A	Yes

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[138]	9/11/2017 - 27/06/2022	423	Multivariate	*BTC* CV CV Other Cryptos	1d	LR DT RF GB XGBoost SVR AdaBoost LGBM KNN Ridge Lasso DNN CNN	RF	0.05614	-	0.0246	-	N/A	Yes
...	[147]	12/09/2013 - 18/06/2019	80	Multivariate	*BTC* Price Financial News Sentiment	1d	LSTM RF CNN	LSTM	0.0965	-	-	-	No	Yes
...	[160]	-	-	Multivariate	*BTC* OHLCV *USD* Volume	1d	LSTM GRU LSTM-RNN	LSTM-RNN	0.1378	-	-	-	N/A	Yes
...	[43]	25/09/2017 - 24/05/2024	375	Univariate	*BTC* Close Price	1d	MLP DLinear TimeMixer LSTM LSTMNet SegRNN TCN TimesNet ModernTCN Transformer PatchTST ITransformer	SegRNN	0.2381	-	-	-	LINK	Yes
...	[140]	08/2016 - End 06/2022	20 %	Multivariate	*BTC* Price Price Other Cryptos Macroeconomic Data *Google Trends* Index *Twitter* Sentiment News Sentiment	1d	LSTM DNN SVM LR RF XGBoost ET	LSTM	2.031	-	-	-	N/A	No
...	[146]	11/10/2016 - 12/06/2017 01/01/2018 - 05/06/2018	-	Multivariate	*BTC* Volume *BTC* Market Cap Technical Indicators *BTC* Blockchain Data Macroeconomic Data Microeconomic Data	1d 1mo	OLS SVR MLP ENS	SVR	8.59	-	-	-	N/A	No
...	[166]	2013 - 2018	500	Univariate	*BTC* High Price	1d	LSTM	LSTM	32.84	-	-	-	N/A	No
...	[34]	27/12/2013 – 31/01/2019	31	Multivariate	*BTC* OHLCV *BTC* Market Cap	1d	GBT DNN KNN Ensemble	GBT	32.863	-	-	-	N/A	No
...	[69]	-	-	Multivariate	*BTC* Price Data Gold Price Twitter Sentiment	1d	CNN LSTM GRU	LSTM	32.98	-	-	-	N/A	No
...	[32]	04/01/2018 - 03/31/2019	90	Univariate OR Multivariate	*BTC* Price *LTC* Price *ETH* Price *ZEC* Price	1d	ARIMA SVR LR RF GB	GBR	135.496	-	-	-	N/A	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[136]	01/10/2013 - 08/06/2019	207	Univariate	*BTC* Close Price	1d	ARIMA FFNN CNN SVR LSTM ARIMA-FFNN ARIMA-CNN ARIMA-LSTM ARIMA-SVR	ARIMA-CNN ARIMA-LSTM	213.0082	-	2.5347	-	N/A	No
...	[33]	-	-	Multivariate	*BTC* OHLCV *USD* Volume	1d	ARIMAX XGBoost FBProphet	FBProphet ARIMAX	229.5	-	227.3	-	N/A	No
...	[41]	01/01/2017 - 31/10/2020	152	Univariate AND Multi-variate	*BTC* Price *ETH* Price *XRP* Price	1d	CNN-LSTM MI-CNN-LSTM	CNN-LSTM	256.318	-	169.604	-	N/A	No
...	[167]	27/06/2014 - 27/06/2019	367	Multivariate	*BTC* OHLCV	1d	LSTM	LSTM	288.5987	-	-	-	N/A	No
...	[152]	01/03/2016 - 26/02/2021	366	Multivariate	*BTC* Price Data	1d	GRU BiGRU LSTM BiLSTM	BiGRU	427.85	-	295.43	-	N/A	No
...	[46]	01/01/2017 - 31/12/2020	153	Multivariate	*BTC* OHLCV	1d	CNN-LSTM CNN-LSTM-AM	CNN-LSTM-AM	492.86	-	-	-	N/A	No
...	[168]	01/01/2020 - 03/05/2023	244	Univariate OR Multivariate	*BTC* Price Data	1d	LSTM LSTM-CPD	LSTM-CPD	829.36	-	920.07	-	N/A	No
...	[44]	01/01/2016 - 31/12/2018	434	Multivariate	*BTC* OHLCV *Google Trends* Index Blockchain Data	1d	ARIMA ARIMAX CNN MLP LSTM Seq2Seq RNN BNN SFM WT-CATCN	WT-CATCN	1204.091	-	1044.38	-	N/A	No
...	[48]	17/09/2014 - 30/06/2022	200	Univariate	*BTC* Close Price	1d	LSTM ARIMA	LSTM	1334.76	-	-	-	LINK	No
...	[35]	17/09/2014 - 01/02/2022	540	Univariate	*BTC* Close Price	1d	RNN LSTM GRU BiLSTM CNN	LSTM	1978.68	-	1537.14	-	N/A	No
...	[36]	16/07/2010 - 01/10/2018	301	Univariate	*BTC* Price	1d	LSTM GRNN	LSTM	2750	-	-	-	N/A	No
...	[37]	21/09/2013 - 21/09/2021	292	Multivariate	*BTC* OCV *BTC* Adjusted Close Price	1d	DT LR Ridge Lasso BRR RF KNN DNN GB SVM	DT GB	3599.17	-	1274.24	-	N/A	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[30]	01/01/2017 - 01/03/2019 11/09/2018 - 09/11/2018 27/12/2018 - 25/02/2019 06/01/2018 - 09/02/2018 12/03/2018 - 10/04/2018 04/12/2017 - 02/01/2018 22/04/2018 - 21/05/2018 02/03/2018 - 04/05/2018 09/10/2017 - 19/12/2017 10/02/2018 - 11/03/2018	20 %	Univariate	*BTC* Close Price	5ds 10ds 14ds 21ds 30ds	ARIMA ARFIMA BART	BART	2.25 %	-	-	-	N/A	No
...	[70]	19/08/2013 - 19/07/2016	214	Multivariate	*BTC* OHLC *BTC* Blockchain Data Technical Indicators	1d	RNN LSTM ARIMA	RNN	5.45 %	-	-	-	N/A	No
...	[31]	28/4/2013 - ...	-	Multivariate	*BTC* OHLCV *BTC* Market Cap	1d	RF LSTM LR	LSTM	-	-	0.0043	-	N/A	Unclear
...	[47]	07/2013 - 10/08/2017	10	Univariate	*BTC* Price	1d	ARIMA AR MA	ARIMA	-	-	-	90.31	N/A	No
ETH	[79]	09/02/2016 - 15/04/2020	21	Multivariate	*ETH* OHLCV *USD* Trade Volume	1d	ML-GRU GRU LSTM	ML-GRU	251.609	0.31	164.49	-	N/A	No
...	[58]	1/01/2018 - 30/06/2021	252	Multivariate	*ETH* OHLC	1d	LSTM GRU BiLSTM	GRU	26.59	0.8267	-	-	N/A	No
...	[42]	01/04/2016 - 01/01/2020 01/01/2020 - 31/09/2023	-	Univariate	*ETH* **Log** Close Price	1d	ARIMA LSTM MLP ARIMA-LSTM ARIMA-MLP ADAB LGBM RNN GRU	ARIMA-LSTM LSTM ADAB LGBM	0.0294	1.1498	0.0219	-	LINK	No
...	[72]	01/01/2018 - 31/12/2021	219 305	Multivariate	*ETH* OHLCV Technical Indicators	1d	XGBoost GBM ADAB GRU FFNN CNN	CNN DFFN GRU	-	2	-	-	LINK	No
...	[134]	05/02/2021 - 21/08/2021	40	Multivariate	*ETH* OHLC *Twitter* Sentiment	1d	MLP ARIMA LSTM	LSTM	0.029212	2.32336	0.02323	-	N/A	Yes
...	[161]	01/10/2021 - 04/10/2022	3	Univariate	*ETH* Close Price	1d	GRU	GRU	37.6678	2.3342	-	-	N/A	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[164]	16/06/2019 - 16/06/2023	146	Multivariate	*ETH* OHLCV Technical Indicators	1d	LSTM Transformer	Transformer	54.78	2.38	41.6	-	N/A	No
...	[165]	Mid 2017 - End 2019	213	Multivariate	*ETH* HLV *ETH* Market Cap *ETH* Blockchain Data *Twitter* Data *Google Trends* Index	1d	MLP LSTM Stochastic MLP Stochastic LSTM	Stochastic MLP	0.039	2.70989	0.0271	-	N/A	Yes
...	[22]	15/11/2015 - 12/03/2020	316	Univariate AND Multi-variate	*ETH* OHLCV	1d	Univariate LR Multivariate LR Univariate LSTM Multivariate LSTM	Univariate LR	10.6232	3.1	-	-	LINK	No
...	[39]	15/09/2016 - 05/11/2018	-	Univariate	*ETH* Close Price	1d	ARIMA SVR RF XGBoost MLP LSTM GRU CNN CNN-LSTM CNN-GRU LSTM-RNN	LSTM-RNN	7.48	3.21	59.3	-	N/A	No
...	[40]	23/07/2017 - 15/07/2020	217	Multivariate	*ETH* Close Price Other Crypto Prices	1d	ARIMA SVR RF XGBoost MLP LSTM GRU CNN CNN-LSTM CNN-GRU WAMC	WAMC	9.7	3.28	5.97	-	No	No
...	[27]	01/06/2017 - 31/05/2022	365	Univariate	*ETH* Close Price	1d	CNN-LSTM GRU LSTM-GRU KNN TCN ARIMA TFT RF SVR Ensemble	CNN-LSTM	0.03	3.38	0.0173	-	LINK	Yes
...	[51]	30/06/2016 - 30/08/2021	378	Univariate	*ETH* Close Price	1d	ARIMA	ARIMA	91.2	3.5	-	-	N/A	No
...	[162]	16/09/2018 - 16/04/2020	58	Multivariate	*ETH* Volume *ETH* Blockchain Data *BTC* Price *USD* Volume Technical Indicators *Google Trends* Index	1d 1w	LSTM GRU TCN LSTM-GRU LSTM-TCN GRU-TCN Ensemble	LSTM-GRU TCN	8.6	3.6	-	-	N/A	No
...	[49]	01/01/2021 - 31/12/2021	73	Multivariate	*ETH* OHLC *Twitter* Sentiment	1d	LSTM GRU LSTM-GRU	LSTM-GRU	197.5	4.11	172.04	-	N/A	No
...	[150]	01/01/2017 - 30/04/2020	-	Multivariate	Technical Indicators	1d	BNN FFNN LSTM SVR-BNN SVR-LSTM SVR-FFNN	BNN	-	4.91	-	-	N/A	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[38]	01/11/2020 - 28/09/2022	210	Univariate	*ETH* Adjusted Close Price	1d	SVR ARIMA FBProphet LSTM BiLSTM Stacked LSTM	ARIMA	88.54	5.4	72.28	-	N/A	No
...	[157]	15/04/2016 - 17/10/2020	364	Multivariate	*ETH* OHLCV	1d	MLP LSTM CNN CNN-LSTM MRC-LSTM	MRC-LSTM	1.13	5.43	0.7	-	N/A	No
...	[80]	07/08/2015 - 12/10/2021	452	Multivariate	*ETH* OHLCV	1d	LSTM GRU BiLSTM	BiLSTM GRU	147.8453	5.9719	100.138	-	N/A	No
...	[26]	01/01/2018 - 01/01/2023	365	Multivariate	*ETH* OHLCV	1d	LSTM GRU BiLSTM	BiLSTM	83.9531	12.43	-	-	N/A	No
...	[153]	09/11/2017 - 09/08/2022	163	Multivariate	*ETH* OCV *ETH* Adjusted Close Price	1d	GRU BiLSTM	GRU	0.02662	19.671	0.0535	-	N/A	Yes
...	[141]	04/2016 - 05/2018	-	Multivariate	*ETH* Blockchain Data	1d	LSTM RF GB LR	GB	0.0022	-	0.0012	-	N/A	Yes
...	[60]	29/04/2013 - 01/06/2021 01/03/2020 - 01/04/2024	887 448	Univariate AND Multi-variate	*ETH* OHL Gold Price Close Price Other Crypto	1d 2ds 3ds 4ds 5ds	ARIMA MLP CNN LSTM ED-LSTM BiLSTM ConvLSTM Transformer	ConvLSTM	0.0158	-	-	-	LINK	Yes
...	[73]	03/10/2016 - 04/04/2022	180	Multivariate	*ETH* OHLCV	1d	LSTM	LSTM	0.042	-	-	-	N/A	Yes
...	[43]	25/09/2017 - 24/05/2024	375	Univariate	*ETH* Close Price	1d	MLP DLinear TimeMixer LSTM LSTMNet SegRNN TCN TimesNet ModernTCN Transformer PatchTST ITransformer	SegRNN	0.1914	-	-	-	LINK	Yes
...	[41]	01/01/2017 - 31/10/2020	152	Univariate AND Multi-variate	*ETH* Price *BTC* Price *XRP* Price	1d	CNN-LSTM MI-CNN-LSTM	MI-CNN-LSTM	13.492	-	9.146	-	N/A	No
...	[48]	17/09/2014 - 30/06/2022	200	Univariate	*ETH* Close Price	1d	LSTM ARIMA	LSTM	117.655	-	-	-	LINK	No
...	[37]	21/09/2013 - 21/09/2021	292	Multivariate	*ETH* OCV *ETH* Adjusted Close Price	1d	DT LR Ridge Lasso BRR RF KNN DNN GB SVM	DT GB	215.2646	-	71.9531	-	N/A	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[30]	01/01/2017 - 01/03/2019 11/09/2018 - 09/11/2018 27/12/2018 - 25/02/2019 06/01/2018 - 09/02/2018 12/03/2018 - 10/04/2018 04/12/2017 - 02/01/2018 22/04/2018 - 21/05/2018 02/03/2018 - 04/05/2018 09/10/2017 - 19/12/2017 10/02/2018 - 11/03/2018	20 %	Univariate	*ETH* Close Price	5ds 10ds 14ds 21ds 30ds	ARIMA ARFIMA BART	BART	2.25 %	-	-	-	N/A	No
...	[143]	28/04/2013 - 21/11/2018	407	Multivariate	*ETH* OHLCV *ETH* Market Cap *ETH* Market Cap Rank *ETH* Spread *ETH* Close Ratio *BTC* OHLCV *BTC* Market Cap *BTC* Market Cap Rank *BTC* Spread *BTC* Close Ratio	1d	CNN LR KNN	KNN	-	-	-	97.2	N/A	Yes
LTC	[58]	01/01/2018 - 30/06/2021	252	Multivariate	*LTC* OHLC	1d	LSTM GRU BiLSTM	GRU	0.825	0.2116	-	-	N/A	No
...	[42]	01/04/2016 - 01/01/2020 01/01/2020 - 31/09/2023	-	Univariate	*LTC* **Log** Close Price	1d	ARIMA LSTM MLP ARIMA-LSTM ARIMA-MLP AdaBoost LGBM RNN GRU	ARIMA LGBM RNN MLP	0.0287	0.9989	0.0196	-	LINK	No
...	[72]	01/01/2018 - 31/12/2021	219 305	Multivariate	*LTC* OHLCV Technical Indicators	1d	XGBoost GBM ADAB GRU FFNN CNN	CNN GRU	-	1	-	-	LINK	No
...	[161]	01/10/2021 - 04/10/2022	3	Univariate	*LTC* Close Price	1d	GRU	GRU	1.0902	1.7278	-	-	N/A	No
...	[71]	24/08/2016 - 23/02/2020	1d 3ds 7ds	Multivariate	*LTC* Average Price *LTC* OHLCV	1d 3ds 7ds	LSTM LSTM-GRU	LSTM-GRU	2.0327	2.0581	1.54245	-	N/A	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[164]	16/06/2019 - 16/06/2023	146	Multivariate	*LTC* OHLCV Technical Indicators	1d	LSTM Transformer	Transformer	3.28	2.65	2.26	-	N/A	No
...	[165]	Mid 2017 - End 2019	213	Multivariate	*LTC* HLV *LTC* Market Cap *LTC* Blockchain Data *Twitter* Data *Google* Trends Index	1d	MLP LSTM Stochastic MLP Stochastic LSTM	Stochastic MLP	0.04097	2.67675	0.02677	-	N/A	Yes
...	[25]	24/08/2016 - 28/03/2019	142	Univariate	*LTC* Price	1d	LSTM EWT-LSTM EWT-LSTM-CS	EWT-LSTM-CS	1.7989	2.77	1.1066	-	N/A	No
...	[227]	2016 - 2020	3ds 7ds 30ds	Multivariate	*LTC* OHLCV *LTC* Blockchain Data *Twitter* Data *Google Trends* Index	3d 7ds 30ds	RL Non-RL	RL	3.1438	3.1692	2.6535	-	N/A	No
...	[157]	15/04/2016 - 17/10/2020	364	Multivariate	*LTC* OHLCV	1d	MLP LSTM CNN CNN-LSTM MRC-LSTM	MRC-LSTM	0.26	3.17	0.14	-	N/A	No
...	[22]	15/11/2015 - 12/03/2020	316	Univariate AND Multi-variate	*LTC* OHLCV	1d	Univariate LR Multivariate LR Univariate LSTM Multivariate LSTM	Univariate LR	2.795	3.4	-	-	LINK	No
...	[26]	01/01/2018 - 01/01/2023	365	Multivariate	*LTC* OHLCV	1d	LSTM GRU BiLSTM	BiLSTM	8.0249	4.11	-	-	N/A	No
...	[27]	01/06/2017 - 31/05/2022	365	Univariate	*LTC* Close Price	1d	CNN-LSTM GRU LSTM-GRU KNN TCN ARIMA TFT RF SVR Ensemble	CNN-LSTM	0.0189	4.36	0.0173	-	LINK	Yes
...	[60]	29/04/2013 - 01/06/2021 01/03/2020 - 01/04/2024	887 448	Univariate AND Multi-variate	*LTC* OHL Gold Price Close Price Other Crypto	1d 2ds 3ds 4ds 5ds	ARIMA MLP CNN LSTM ED-LSTM BiLSTM ConvLSTM Transformer	ConvLSTM	0.0223	-	-	-	LINK	Yes
...	[163]	24/08/2016 - 26/05/2021	536	Multivariate	*LTC* Average Price *LTC* OHLV *BTC* Price Direction	1d 3 ds 7ds 30ds	LSTM GRU LSTM-GRU	LSTM-GRU	0.1428	-	-	-	N/A	Yes
...	[37]	21/09/2013 - 21/09/2021	292	Multivariate	*LTC* OCV Data *LTC* Adjusted Close Price	1d	DT LR Ridge Lasso BRR RF KNN DNN GB SVM	DT DNN	29.005	-	13.782	-	N/A	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[143]	28/04/2013 - 21/11/2018	407	Multivariate	*LTC* OHLCV *LTC* Market Cap *LTC* Market Cap Rank *LTC* Spread *LTC* Close Ratio *BTC* OHLCV *BTC* Market Cap *BTC* Market Cap Rank *BTC* Spread *BTC* Close Ratio	1d	CNN LR KNN	CNN	-	-	-	95.1	N/A	Yes
XRP	[42]	01/04/2016 - 01/01/2020 01/01/2020 - 31/09/2023	-	Univariate	*XRP* **Log** Close Price	1d	ARIMA LSTM MLP ARIMA-LSTM ARIMA-MLP ADAB LGBM RNN GRU	ARIMA LGBM GRU	0.0197	0.9997	0.0285	-	LINK	No
...	[25]	22/01/2015 - 28/03/2019	229	Univariate	*XRP* Price	1d	LSTM EWT-LSTM EWT-LSTM-CS	EWT-LSTM-CS	0.0088	1.72	0.0064	-	N/A	No
...	[134]	05/02/2021 - 21/08/2021	40	Multivariate	*XRP* OHLC *Twitter* Sentiment	1d	MLP ARIMA LSTM	LSTM	0.02441	1.92201	0.01922	-	N/A	Yes
...	[27]	01/06/2017 - 31/05/2022	365	Univariate	*XRP* Close Price	1d	CNN-LSTM GRU LSTM-GRU KNN TCN ARIMA TFT RF SVR Ensemble	CNN-LSTM	0.03907	4.32	0.0173	-	LINK	Yes
...	[41]	01/01/2017 - 31/10/2020	152	Univariate AND Multi-variate	*XRP* Price *BTC* Price *ETH* Price	1d	CNN-LSTM MI-CNN-LSTM	CNN-LSTM MI-CNN-LSTM	0.007	-	0.005	-	N/A	No
...	[36]	21/01/2015 - 01/10/2018	136	Univariate	*XRP* Price	1d	LSTM GRNN	LSTM	0.0499	-	-	-	N/A	No
...	[73]	25/05/2015 - 04/04/2022	180	Multivariate	*XRP* OHLCV	1d	LSTM	LSTM	0.06913	-	-	-	N/A	Yes
...	[43]	25/09/2017 - 24/05/2024	375	Univariate	*XRP* Close Price	1d	MLP DLinear TimeMixer LSTM LSTMNet SegRNN TCN TimesNet ModernTCN Transformer PatchTST ITransformer	SegRNN	0.1712	-	-	-	LINK	Yes

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[37]	21/09/2013 - 21/09/2021	292	Multivariate	*XRP* OCV *XRP* Adjusted Close Price	1d	DT LR Ridge Lasso BRR RF KNN DNN GB SVM	DT	0.18061	-	0.07289	-	N/A	No
...	[30]	01/01/2017 - 01/03/2019 11/09/2018 - 09/11/2018 27/12/2018 - 25/02/2019 06/01/2018 - 09/02/2018 12/03/2018 - 10/04/2018 04/12/2017 - 02/01/2018 22/04/2018 - 21/05/2018 02/03/2018 - 04/05/2018 09/10/2017 - 19/12/2017 10/02/2018 - 11/03/2018	20 %	Univariate	*XRP* Close Price	5ds 10ds 14ds 21ds 30ds	ARIMA ARFIMA BART	BART	2.25 %	-	-	-	N/A	No
...	[143]	28/04/2013 - 21/11/2018	407	Multivariate	*XRP* OHLCV *XRP* Market Cap *XRP* Market Cap Rank *XRP* Spread *XRP* Close Ratio *BTC* OHLCV *BTC* Market Cap *BTC* Market Cap Rank *BTC* Spread *BTC* Close Ratio	1d	CNN LR KNN	CNN	-	-	-	96.3	N/A	Yes
ADA	[134]	05/02/2021 - 21/08/2021	40	Multivariate	*ADA* OHLC *Twitter* Sentiment	1d	MLP ARIMA LSTM	ARIMA	0.04172	2.64566	0.02645	-	N/A	Yes
...	[38]	01/01/2021 - 28/09/2022	168	Univariate	*ADA* Adjusted Close Price	1d	SVR ARIMA FBProphet LSTM BiLSTM Stacked LSTM	ARIMA	0,019	3	0.016	-	N/A	No
...	[80]	01/10/2017 - 12/10/2021	295	Multivariate	*ADA* OHLCV	1d	LSTM GRU BiLSTM	GRU	0.1134	5.7024	0.07823	-	N/A	No
...	[153]	09/11/2017 - 09/08/2022	163	Multivariate	*ADA* OCV *ADA* Adjusted Close Price	1d	GRU BiLSTM	GRU	0.00852	6.256	0.00971	-	N/A	Yes

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[37]	21/09/2013 - 21/09/2021	292	Multivariate	*ADA* OCV *ADA* Adjusted Close Price	1d	DT LR Ridge Lasso BRR RF KNN DNN GB SVM	DT	0.1924	-	0.05407	-	N/A	No
DOGE	[79]	17/09/2014 - 06/07/2021	21	Multivariate	*DOGE* OHLCV *USD* Trade Volume	1d	Multi-Layer GRU GRU LSTM	Multi-Layer GRU	0.00098	0.28281	0.00076	-	N/A	No
...	[72]	01/01/2018 - 31/12/2021	219 305	Multivariate	*DOGE* OHLCV Technical Indicators	1d	XGBoost GBM AdaBoost GRU FFNN CNN	GRU	-	6	-	-	LINK	No
...	[34]	27/12/2013 – 31/01/2019	31	Multivariate	*DOGE* OHLCV *DOGE* Market Cap	1d	GBT DNN KNN Ensemble	GBT	0.000	-	-	-	N/A	No
...	[48]	17/09/2014 - 30/06/2022	200	Univariate	*DOGE* Close Price	1d	LSTM ARIMA	LSTM	0.007	-	-	-	LINK	No
...	[60]	29/04/2013 - 01/06/2021 01/03/2020 - 01/04/2024	887 448	Univariate AND Multi-variate	*DOGE* OHL Gold Price Close Price Other Crypto	1d 2ds 3ds 4ds 5ds	ARIMA MLP CNN LSTM ED-LSTM BiLSTM ConvLSTM Transformer	ConvLSTM	0.0168	-	-	-	LINK	Yes
...	[37]	21/09/2013 - 21/09/2021	292	Multivariate	*DOGE* OCV *DOGE* Adjusted Close Price	1d	DT LR Ridge Lasso BRR RF KNN DNN GB SVM	GB	0,023221	-	0.00930	-	N/A	No
BNB	[72]	01/01/2018 - 31/12/2021	219 305	Multivariate	*BNB* OHLCV Technical Indicators	1d	XGBoost GBM AdaBoost GRU FFNN CNN	AdaBoost CNN GRU	-	1	-	-	LINK	No
...	[38]	01/11/2020 - 28/09/2022	210	Univariate	*BNB* Adjusted Close Price	1d	SVR ARIMA FBProphet LSTM BiLSTM Stacked LSTM	ARIMA	13.96	3.4	10.47	-	N/A	No
...	[80]	25/07/2017 - 12/10/2021	308	Multivariate	*BNB* OHLCV	1d	LSTM GRU BiLSTM	LSTM	27.62451	5.7045	18.0877	-	N/A	No
...	[37]	21/09/2013 - 21/09/2021	292	Multivariate	*BNB* OCV *BNB* Adjusted Close Price	1d	DT LR Ridge Lasso BRR RF KNN DNN GB SVM	GB	17.70865	-	5.3521	-	N/A	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
BCH	[40]	23/07/2017 - 15/07/2020	217	Multivariate	*BCH* Close Price Other Crypto Prices	1d	ARIMA SVR RF MLP LSTM GRU CNN CNN-LSTM CNN-GRU WAMC XGBoost	WAMC	17.3	4.38	11.5	-	N/A	No
...	[172]	... - 01/04/2021	-	Multivariate	*BCH* OHLCV *BCH* Tweets *LTC* OHLCV *LTC* Tweets *BTC* OHLCV *BTC* Tweets	1d	LSTM-GRU	LSTM-GRU	0.0332	4.4089	0.0196	-	N/A	Yes
...	[37]	21/09/2013 - 21/09/2021	292	Multivariate	*BCH* OCV *BCH* Adjusted Close Price	1d	DT LR Ridge Lasso BRR RF KNN DNN GB SVM	BRR	91.45620	-	64.8679	-	N/A	No
...	[143]	28/04/2013 - 21/11/2018	407	Multivariate	*BCH* OHLCV *BCH* Market Cap *BCH* Market Cap Rank *BCH* Spread *BCH* Close Ratio *BTC* OHLCV *BTC* Market Cap *BTC* Market Cap Rank *BTC* Spread *BTC* Close Ratio	1d	CNN LR KNN	CNN	-	-	-	97	N/A	Yes
DASH	[25]	14/02/2014 - 28/03/2019	280	Univariate	*DASH* Price	1d	LSTM EWT-LSTM EWT-LSTM-CS	EWT-LSTM-CS	2.7776	1.47	2.0746	-	N/A	No
...	[172]	... - 01/04/2021	-	Multivariate	*DASH* OHLCV *DASH* Tweets *LTC* OHLCV *LTC* Tweets *BTC* OHLCV *BTC* Tweets	1d	LSTM-GRU	LSTM-GRU	0.136	4.7928	0.0805	-	N/A	Yes
...	[14]	24/01/2018 - 01/04/2021	163	Multivariate	*DASH* Average Price *LTC* Average Price *BTC* Average Price	1d	LSTM GRU LSTM-GRU	GRU LSTM-GRU	0.133	-	-	-	N/A	Yes
...	[36]	27/03/2014 - 01/10/2018	170	Univariate	*DASH* Price	1d	LSTM GRNN	LSTM	19.2923	-	-	-	N/A	No
XMR	[71]	30/01/2015 - 23/02/2020	1d 3ds 7ds	Multivariate	*XMR* Average Price *XMR* OHLCV	1d 3ds 7ds	LSTM LSTM-GRU	LSTM-GRU	3.2715	4.0727	3.2715	-	N/A	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[27]	01/06/2017 - 31/05/2022	365	Univariate	*XMR* Close Price	1d	CNN-LSTM GRU LSTM-GRU KNN TCN ARIMA TFT RF SVR Ensemble	CNN-LSTM	0.0236	4.43	0.0173	-	LINK	Yes
...	[227]	2015 - 2020	3ds 7ds 30ds	Multivariate	*XMR* OHLCV *XMR* Blockchain Data *Twitter* Data *Google Trends* Index	3d 7ds 30ds	RL NON-RL	RL	4.3826	5.1838	4.3826	-	N/A	No
ZEC	[163]	29/10/2016 - 26/05/2021	470	Multivariate	*ZEC* Average Price *ZEC* OHLV *BTC* Price Direction	1d 3ds 7ds 30ds	LSTM GRU LSTM-GRU	LSTM-GRU	0.1428	-	-	-	N/A	Yes
EOS	[134]	05/02/2021 - 21/08/2021	40	Multivariate	*EOS* OHLC *Twitter* Sentiment	1d	MLP ARIMA LSTM	ARIMA	0.018705	1.42875	0.01429	-	N/A	Yes
...	[73]	09/11/2017 - 04/04/2022	180	Multivariate	*EOS* OHLCV	1d	LSTM	LSTM	0.03855	-	-	-	No	Yes
...	[48]	17/09/2014 - 30/06/2022	200	Univariate	*EOS* Close Price	1d	LSTM ARIMA	LSTM	0.119	-	-	-	LINK	No
...	[143]	28/04/2013 - 21/11/2018	407	Multivariate	*EOS* OHLCV *EOS* Market Cap *EOS* Market Cap Rank *EOS* Spread *EOS* Close Ratio *BTC* OHLCV *BTC* Market Cap *BTC* Market Cap Rank *BTC* Spread *BTC* Close Ratio	1d	CNN LR KNN	CNN	-	-	-	97.2	N/A	Yes
SOL	[49]	01/01/2021 - 31/12/2021	73	Multivariate	*SOL* OHLC *Twitter* Sentiment	1d	LSTM GRU LSTM-GRU	LSTM-GRU	10.02	4.13	8.41	-	N/A	No
AMP	[73]	09/11/2020 - 03/04/2022	180	Multivariate	*AMP* OHLCV	1d	LSTM	LSTM	0.04289	-	-	-	N/A	Yes
XLM	[72]	01/01/2018 - 31/12/2021	219 305	Multivariate	*XLM* OHLCV Technical Indicators	1d	XGBoost GBM ADAB GRU FFNN CNN	AdaBoost	-	1	-	-	LINK	No

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	RMSE	MAPE (%)	MAE	rAcc. (%)	Code	Norm.
...	[143]	28/04/2013 - 21/11/2018	407	Multivariate	*XLM* OHLCV *XLM* Market Cap *XLM* Market Cap Rank *XLM* Spread *XLM* Close Ratio *BTC* OHLCV *BTC* Market Cap *BTC* Market Cap Rank *BTC* Spread *BTC* Close Ratio	1d	CNN LR KNN	CNN	-	-	-	98.0	N/A	Yes
USDT	[80]	25/02/2015 - 12/10/2021	484	Multivariate	*USDT* OHLCV	1d	LSTM GRU BiLSTM	LSTM	0.003415	0.2496	0.00250	-	N/A	No
LUNA	[37]	21/09/2013 - 21/09/2021	292	Multivariate	*LUNA* OCV *LUNA* Adjusted Close Price	1d	DT LR Ridge Lasso BRR RF KNN DNN GB SVM	DT RF	7.131063	-	2.402397	-	N/A	No
LINK	[37]	21/09/2013 - 21/09/2021	292	Multivariate	*LINK* OCV *LINK* Adjusted Close Price	1d	DT LR Ridge Lasso BRR RF KNN DNN GB SVM	DT GB	2.35428	-	1.00167	-	N/A	No
NEM	[34]	01/04/2015 – 31/01/2019	31	Multivariate	*NEM* OHLCV *NEM* Market Cap	1d	GBT DNN KNN Ensemble	GBT	0.001	-	-	-	N/A	No

Table 15: Studies on cryptocurrency price prediction at daily intervals sorted by the reported MAPE & RMSE, where the definitions of the utilized abbreviations with respect to the columns, cryptocurrencies, time granularities, and models can be found in Tables 8, 9, 10, and 11.

A.2.2 Overview Statistics

Model	Count	Papers
LSTM	61	[14, 16, 19, 22–26, 29, 31, 35, 36, 38–40, 42–45, 48–50, 55, 57, 58, 60, 69–71, 73, 78–80, 95, 132–134, 136, 139–142, 147–152, 155–160, 162–168]
GRU	28	[14, 16, 19, 26, 27, 35, 39, 40, 42, 49, 57, 58, 69, 72, 78–80, 142, 151–153, 155, 158–163]
ARIMA	22	[27, 30, 32, 38–40, 42, 44, 47, 48, 50–52, 60, 70, 78, 81, 132–136]
SVM / SVR	21	[17, 27, 28, 32, 37–40, 54, 55, 81, 133, 135, 136, 138–140, 144–146, 149]
CNN	17	[19, 23, 35, 39, 40, 44, 55, 60, 69, 72, 136, 138, 143, 147, 155–157]
CNN-LSTM	13	[20, 21, 23, 27, 39–41, 45, 46, 55, 78, 156, 157]
BiLSTM	13	[26, 35, 38, 58, 60, 78, 80, 81, 151–155]
LR	12	[22, 31, 32, 37, 81, 138–141, 143–145]
RF	12	[19, 27, 31, 32, 37, 39, 40, 138, 140, 141, 147, 148]
MLP	11	[39, 40, 42–44, 60, 134, 146, 149, 157, 165]
DNN	8	[16, 34, 37, 54, 55, 138, 140, 158]
Ensemble	8	[20, 21, 27, 34, 55, 57, 146, 162]
XGBoost	8	[19, 33, 39, 40, 72, 78, 138, 140]
LSTM-GRU	7	[14, 27, 49, 71, 162, 163, 172]
KNN	6	[17, 27, 34, 37, 138, 143]
Transformer	5	[43, 60, 74, 149, 164]
FFNN	5	[17, 18, 72, 136, 150]
RNN	5	[35, 42, 54, 70, 78]
GB	4	[32, 37, 138, 141]
TCN	4	[27, 43, 149, 162]
AdaBoost	3	[42, 72, 138]
BNN	3	[44, 144, 150]
BRR	2	[37, 139]
CNN-GRU	3	[39, 40, 78]
ARIMA-LSTM	2	[42, 136]
ARIMAX	2	[33, 44]
Averaging Ensemble	2	[20, 57]
BiGRU	2	[151, 152]
BPNN	2	[23, 28]
BR	2	[52, 133]
CNN-BiLSTM	2	[20, 21]

Model	Count	Papers
ConvLSTM	2	[60, 156]
DT	2	[37, 138]
FBProphet	2	[33, 38]
Lasso	2	[37, 138]
LGBM	2	[42, 138]
LSTM-CPD	2	[95, 168]
LSTM-RNN	2	[39, 160]
Ridge	2	[37, 138]
Stacking Ensemble	2	[20, 57]
TFT	2	[27, 45]
TSR	2	[139, 142]
AE-GRU	1	[170]
AE-LSTM	1	[170]
AR	1	[47]
ARFIMA	1	[30]
ARIMA-CNN	1	[136]
ARIMA-FFNN	1	[136]
ARIMA-MLP	1	[42]
ARIMA-SVR	1	[136]
Bagging Ensemble	1	[20]
BART	1	[30]
Blending Ensemble	1	[57]
BRNN	1	[17]
BVAR	1	[52]
CatBoost	1	[19]
CNN-LSTM-AM	1	[46]
DAM-LSTM	1	[45]
DLinear	1	[43]
DNDT	1	[59]
DNN-LSTM	1	[171]
DRCNN	1	[59]
DSVR	1	[59]
ED-LSTM	1	[60]
EMD-LSTM	1	[81]
ET	1	[140]
EWT-LSTM	1	[25]
EWT-LSTM-CS	1	[25]

Model	Count	Papers
GBM	1	[72]
GBT	1	[34]
GPR	1	[17]
GRNN	1	[36]
GRU-TCN	1	[162]
HR	1	[142]
ITransformer	1	[43]
LSSVR	1	[135]
LSTM-AR	1	[24]
LSTM-AM	1	[171]
LSTM-AM-CPD	1	[95]
LSTM-TCN	1	[162]
LSTMNet	1	[43]
MA	1	[47]
MI-CNN-LSTM	1	[41]
ModernTCN	1	[43]
MRC-LSTM	1	[157]
NeuralProphet	1	[45]
OLS	1	[146]
P-BiGRU	1	[151]
P-BiLSTM	1	[151]
P-GRU	1	[151]
P-LSTM	1	[151]
PatchTST	1	[43]
PCA-SVR	1	[28]
RBFNN	1	[17]
ResNet	1	[55]
RL	1	[227]
RT	1	[17]
SAM-LSTM-CPD	1	[95]
SARIMA	1	[50]
SDAE	1	[28]
SegRNN	1	[43]
Seq2Seq RNN	1	[44]
SFM	1	[44]
Stochastic LSTM	1	[165]
Stochastic MLP	1	[165]

Model	Count	Papers
SVR-BNN	1	[150]
SVR-FFNN	1	[150]
SVR-LSTM	1	[150]
TD-BiGRU	1	[151]
TD-BiLSTM	1	[151]
TD-GRU	1	[151]
TD-LSTM	1	[151]
TimeMixer	1	[43]
TimesNet	1	[43]
TWSVR	1	[135]
VAR	1	[52]
VMD-BiLSTM	1	[81]
WAMC	1	[40]
WT-CATCN	1	[44]

Table 16: Application count of models in cryptocurrency price prediction studies.

Cryptocurrency	Count	Papers
BTC	79	[16–37, 41–48, 50, 52, 54, 55, 57–60, 69, 70, 72, 78–81, 95, 132–136, 138–142, 144, 146–154, 156–161, 164–168, 170, 171]
ETH	40	[16, 19–22, 26, 27, 30, 37–43, 48, 49, 51, 58, 60, 72, 73, 78–80, 134, 139, 141, 143, 145, 150, 151, 153, 155, 157, 159, 161, 162, 164, 165]
LTC	21	[19, 22, 25–27, 37, 42, 58, 60, 71, 72, 139, 143, 151, 157, 159, 161, 163–165, 227]
XRP	14	[20, 21, 25, 27, 30, 36, 37, 41–43, 73, 78, 134, 143]
DOGE	8	[19, 34, 37, 48, 60, 72, 74, 79]
ADA	6	[37, 38, 80, 134, 151, 153]
BCH	4	[37, 40, 143, 172]
BNB	4	[37, 38, 72, 80]
DASH	4	[14, 25, 36, 172]
EOS	4	[48, 73, 134, 143]
XLM	4	[19, 72, 143, 151]
XMR	3	[27, 71, 227]
DOT	2	[19, 151]
SOL	2	[19, 49]
TRX	2	[19, 151]
AMP	1	[73]
ATOM	1	[19]
AVAX	1	[19]
LINK	1	[37]
LUNA	1	[37]
MATIC	1	[19]
NEM	1	[34]
USDT	1	[80]
ZEC	1	[163]

Table 17: Application count of cryptocurrencies in cryptocurrency price prediction studies.

Data Type	Count	Papers
Multivariate	61	[14, 16, 19, 23, 24, 26, 28, 31, 33, 34, 37, 40, 44–46, 49, 52, 54, 55, 57–59, 69–74, 79–81, 133–135, 138–148, 150, 152–158, 160, 162–165, 167, 172, 227]
Univariate	23	[17, 18, 20, 25, 27, 30, 35, 36, 38, 39, 42, 43, 47, 48, 50, 51, 78, 132, 136, 151, 161, 166, 171]
Univariate or Multivariate	7	[21, 29, 32, 149, 159, 168, 170]
Univariate & Multivariate	4	[22, 41, 60, 95]

Table 18: Application count of data types in cryptocurrency price prediction studies.

Feature Category	Count	Papers
Market Data	93	[14, 16–52, 54, 55, 57, 58, 60, 69–74, 78–81, 95, 132–136, 138–149, 151–168, 170–172, 227]
Blockchain Data	21	[23, 28, 44, 52, 54, 55, 59, 70, 81, 95, 135, 141, 144–146, 148, 156, 158, 162, 165, 227]
Market Data of Other Crypto	17	[14, 19, 28, 32, 40, 41, 60, 95, 135, 138, 140, 143, 148, 158, 162, 163, 172]
Macroeconomic Data	14	[23, 28, 54, 59, 60, 69, 81, 135, 140, 144, 146, 148, 157, 158]
Twitter Data & Sentiment	11	[19, 45, 49, 57, 69, 134, 140, 148, 165, 172, 227]
Technical Indicators	11	[19, 23, 57, 70, 72, 146, 150, 156, 158, 162, 164]
Google Trends Index	10	[28, 44, 81, 140, 148, 157, 158, 162, 165, 227]
News Data & Sentiment	3	[45, 140, 147]
Baidu Index	2	[23, 28]
Forum Data	1	[59]
Market Sentiment	1	[135]
Microeconomic Data	1	[146]
Reddit Data & Sentiment	1	[139]

Table 19: Application count of feature categories in cryptocurrency price prediction studies.

Publically Available Code?	Count	Papers
Yes	9	[22, 27, 42, 43, 45, 48, 60, 72, 151]
No	86	[14, 16–21, 23–26, 28–41, 44, 46, 47, 49–52, 54, 55, 57–59, 69–71, 73, 74, 78–81, 95, 132–136, 138–150, 152–168, 170–172, 227]

Table 20: Source code availability count in cryptocurrency price prediction studies.

A.3 Studies on Cryptocurrency Price Movement Prediction

A.3.1 Overview

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	cAcc. (%)	Prec. (%)	Rec. (%)	F1 (%)	Code
BTC	[228]	2010 - 2015	30 %	Multivariate	*BTC* Blockchain Data	10s	GLM RF SVM	GLM	8.5	57.4	-	-	N/A

Table 21: Studies on *cryptocurrency price movement prediction* at second-level intervals sorted by the reported classification accuracy, where the definitions of the utilized abbreviations with respect to the columns, cryptocurrencies, time granularities, and models can be found in Tables 8, 9, 10, and 11.

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	cAcc. (%)	Prec. (%)	Rec. (%)	F1 (%)	Code
BTC	[75]	17/07/2017 - 17/01/2018	13248	Multivariate	*BTC* Blockchain Data *Google* Trends Index *Baidu* Index Gold Price	5ms	LR LDA QDA SVM RF XGBoost LSTM	LSTM	67.2	72.2	84	77.6	N/A
...	[56]	01/07/2018 - 30/06/2019	78840	Multivariate	Technical Indicators	1m	MLP RBFNN CNN CNN-LSTM	CNN-LSTM	61.36	-	-	-	N/A
...	[222]	02/11/2016 - 11/06/2018	-	Multivariate	*BTC* Market Cap. *BTC* Blockchain Data Gold Price *Google* Trends Index	5ms	LR LDA RF XGBoost QDA KNN DT SVM	XGBoost	59.4	71	47	44	LINK
...	[228]	2010 - 2015	30 %	Multivariate	*BTC* Blockchain Data	10ms	GLM RF SVM	RF	57.4	58.1	-	-	N/A
...	[229]	02/01/2020 - 10/09/2020	30 %: - 15520 - 7766 - 5181 - 2596 - 1304 20 %: - 10347 - 5177 - 3454 - 1731 - 869 10 %: - 5174 - 2589 - 1727 - 866 - 435	Univariate	*BTC* Mid-Price	5ms 10ms 15ms 30ms 60ms	KNN NB LR RF SVM XGBoost	KNN SVM RF	56	-	-	-	N/A

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	cAcc. (%)	Prec. (%)	Rec. (%)	F1 (%)	Code
...	[57]	24/09/2017 - 30/11/2020	11184	Multivariate	*Twitter* Sentiment Technical Indicators	30ms	LSTM GRU Stacking Ensemble Averaging Ensemble Blending Ensemble	Stacking Ensemble	52.14	-	-	-	N/A
ETH	[155]	08/08/2015 - 28/05/2018 29/05/2018 - 31/12/2018 12/01/2019 - 14/04/2019 31/05/2019 - 23/09/2019 28/09/2019 - 23/12/2019 03/01/2020 - 01/03/2020 09/03/2020 - 16/04/2020	- 62496 - 26784 - 33408 - 25056 - 16992 - 11232	Multivariate	*ETH* Close Price *ETH* Weighted Avg. Price	5ms	2-Layer CNN 3-Layer CNN LSTM Stacked LSTM BiLSTM GRU	LSTM GRU	71	-	-	-	N/A
...	[56]	01/07/2018 - 30/06/2019	78840	Multivariate	Technical Indicators	1m	MLP RBFNN CNN CNN-LSTM	CNN-LSTM	59.39	-	-	-	N/A
LTC	[56]	01/07/2018 - 30/06/2019	78840	Multivariate	Technical Indicators	1m	MLP RBFNN CNN CNN-LSTM	CNN-LSTM	68.05	-	-	-	N/A
XRP	[56]	01/07/2018 - 30/06/2019	78840	Multivariate	Technical Indicators	1m	MLP RBFNN CNN CNN-LSTM	CNN-LSTM	67.83	-	-	-	N/A
DASH	[56]	01/07/2018 - 30/06/2019	78840	Multivariate	Technical Indicators	1m	MLP RBFNN CNN CNN-LSTM	CNN-LSTM	74.52	-	-	-	N/A
XMR	[56]	01/07/2018 - 30/06/2019	78840	Multivariate	Technical Indicators	1m	MLP RBFNN CNN CNN-LSTM	CNN-LSTM	80.29	-	-	-	N/A

Table 22: Studies on *cryptocurrency price movement prediction* at minute-level intervals sorted by the reported classification accuracy, where the definitions of the utilized abbreviations with respect to the columns, cryptocurrencies, time granularities, and models can be found in Tables 8, 9, 10, and 11.

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	cAcc. (%)	Prec. (%)	Rec. (%)	F1 (%)	Code
BTC	[230]	15/11/2015 - 03/12/2015	139	Univariate OR Multivariate	*Twitter* Sentiment	1hr	LR SVM NB	LR	98.58	-	-	-	N/A

...	[68]	01/02/2012 - 01/04/2013	-	Multivariate	*BTC* Price *BTC* Blockchain Data	4hrs	LR SVM DNN	DNN	55.1	-	-	-	N/A

Table 23: Studies on *cryptocurrency price movement prediction* at hourly intervals sorted by the reported classification accuracy, where the definitions of the utilized abbreviations with respect to the columns, cryptocurrencies, time granularities, and models can be found in Tables 8, 9, 10, and 11.

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	cAcc. (%)	Prec. (%)	Rec. (%)	F1 (%)	Code
BTC	[228]	2010 - 2015	30 %	Multivariate	*BTC* Volume *BTC* Market Cap. *BTC* Blockchain Data	1d	GLM RF SVM	GLM	98.79	97.9	-	-	N/A
...	[59]	2011 - 2019	20 %	Multivariate	*BTC* Blockchain Data Macroeconomic Data Forum Data	1d	DRCNN DNDT DSVR	DRCNN	95.27	-	-	-	N/A
...	[230]	15/11/2015 - 03/12/2015	139	Univariate OR Multivariate	*Twitter* Sentiment	1d	LR SVM NB	NB	95	-	-	-	N/A
...	[231]	01/01/2018 - 01/06/2018	30	Univariate AND Multivariate	*Twitter* Sentiment	1d	NB DT RT SVM KNN LDA PCA	NB	89.65	-	-	-	N/A
...	[225]	01/01/2015 - 31/05/2021	365	Multivariate	*BTC* OHLCV *ETH* Price Gold Price Technical Indicators Tweets	1d	CNN SVM SVM+CNN-SVM	SVM+CNN-SVM	81.37	-	-	80	LINK
...	[232]	03/08/2010 - 20/10/2017	1300	Multivariate	*BTC* Price Data *BTC* Blockchain Data	2ds ... 60ds	MLP RNN	MLP	81.3	-	-	-	N/A
...	[233]	01/12/2013 - 01/02/2016	95	Multivariate	*BTC* Price Data *BTC* Transaction Count *BTC* Forum Data	1d	AODE	AODE	79.57	-	-	79.6	N/A
...	[224]	01/12/2017 - 30/06/2018	64	Multivariate	*BTC* Price Data *Google Trends* Index *Telegram* Sentiment	1d 4ds 5ds 7ds	LSTM	LSTM	76	74	-	74	N/A
...	[77]	28/04/2013 - 15/02/2020	487	Multivariate	*BTC* Close Price *BTC* Blockchain Data *Twitter* Sentiment Technical Indicators	1d	CNN LSTM	CNN	74.24	-	-	-	N/A

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	cAcc. (%)	Prec. (%)	Rec. (%)	F1 (%)	Code
...	[169]	30/09/2018 - 30/09/2024	438	Multivariate	*BTC* OHLCV Technical Indicators	1d	GB SVM RF CNN-1D RNN LSTM GRU LSTM-AM GRU-AM	LSTM-AM	73.84	73.27	54.26	62.35	N/A
...	[234]	16/02/2018 - 21/04/2018	18	Multivariate	*BTC* OHLCV *Twitter* Sentiment	1d	MLP SVM RF	MLP	72	76	72	72	LINK
...	[235]	01/01/2021 - 31/12/2021	-	Multivariate	*BTC* OHLCV News Sentiment	1d	LSTM BiLSTM GRU BiGRU	BiGRU	70	-	-	70	N/A
...	[75]	17/07/2017 - 01/02/2019	183	Multivariate	*BTC* Blockchain Data *Google Trends* Index *Baidu* Media Gold Price	1d	LR LDA QDA SVM RF XGBoost LSTM	SVM	65.3	70.8	35.4	47.2	N/A
...	[222]	02/11/2016 - 11/06/2018	-	Multivariate	*BTC* Market Cap. *BTC* Blockchain Data Gold Price *Google* Trends Index	1d	LR LDA RF XGBoost QDA KNN DT SVM	XGBoost	64.8	61	65	63	LINK
...	[21]	01/01/2018 - 31/08/2019	184	Univariate OR Multivariate	*BTC* Price Data	1d	Ensemble using CNN-LSTM or CNN-BiLSTM	Ensemble using CNN-BiLSTM	64.51	-	-	-	N/A
...	[54]	19/08/2013 - 19/07/2016 01/04/2013 - 01/04/2017	107 146	Multivariate	*BTC* OHLCV *BTC* Blockchain Data Macroeconomic Data	1d	DNN RNN SVM Ensemble	Ensemble	62.91	-	-	-	N/A
...	[236]	30/10/2013 - 06/07/2021	-	Multivariate	Technical Indicators	1d	DNN	DNN	62.5	-	-	-	N/A
...	[226]	01/01/2021 - 30/06/2021	36	Multivariate	*BTC* OHLCV *Twitter* Sentiment *Google Trends* Index	1d 3ds 5ds	SVM	SVM	61	65	61	60	N/A
...	[57]	24/09/2017 - 30/11/2020	233	Multivariate	*Twitter* Sentiment Technical Indicators	1d	LSTM GRU Stacking Ensemble Averaging Ensemble Blending Ensemble	Stacking Ensemble	59.23	-	-	-	N/A
...	[76]	12/12/2014 - 25/12/2018	148	Multivariate	*BTC* OHLC *Twitter* Volume *Twitter* Sentiment *Google Trends* Index	1d	GB	GB	57.84	-	-	-	N/A
...	[46]	01/01/2017 - 31/12/2020	153	Multivariate	*BTC* OHLCV	1d	CNN-LSTM CNN-LSTM-Att	CNN-LSTM CNN-LSTM-Att	57.24	-	-	-	N/A

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	cAcc. (%)	Prec. (%)	Rec. (%)	F1 (%)	Code
...	[41]	01/01/2017 - 31/10/2020	152	Univariate AND Multi-variate	*BTC* Price *ETH* Price *XRP* Price	1d	CNN-LSTM MI-CNN-LSTM	CNN-LSTM	55.03	-	-	-	N/A
...	[20]	01/01/2018 - 31/08/2019	184	Univariate	*BTC* Price	1d	Averaging Ensemble or Bagging Ensemble or Stacking Ensemble using CNN-LSTM or CNN-BiLSTM	Stacking Ensemble (KNN) using CNN-BiLSTM	54.66	-	-	-	N/A
...	[55]	29/11/2011 - 31/12/2018	518	Multivariate	*BTC* Market Cap. *BTC* Blockchain Data	1d	DNN LSTM CNN ResNet CNN-LSTM Ensemble SVM	DNN	53.06	52.9	69.7	60	N/A
...	[70]	19/08/2013 - 19/07/2016	214	Multivariate	*BTC* OHLC *BTC* Blockchain Data Technical Indicators	1d	RNN LSTM ARIMA	LSTM	52.78	35.5	-	-	N/A
...	[148]	31/03/2015 – 30/09/2018 01/10/2018 – 01/04/2022	- 183 - 182	Multivariate	*BTC* OHLCV *BTC* Blockchain Data *LTC* Price *ETH* Price *XRP* Price *DASH* Price *DOGE* Price Macroeconomic Data *Twitter* Data *Google Trends* Index	1d	RF LSTM	RF	52.49	-	-	-	N/A
ETH	[224]	01/12/2017 - 30/06/2018	64	Multivariate	*ETH* Price Data *Google Trends* Index *Telegram* Sentiment	1d 4ds 5ds 7ds	LSTM	LSTM	85	83	-	83	N/A
...	[162]	16/09/2018 - 16/04/2020	58	Multivariate	*ETH* Volume *ETH* Blockchain Data *BTC* Price *USD* Volume Technical Indicators *Google Trends* Index	1d 1w	LSTM GRU TCN LSTM-GRU LSTM-TCN GRU-TCN Ensemble	Ensemble	84.2	85.2	82.1	-	N/A
...	[40]	23/07/2017 - 15/07/2020	217	Multivariate	*ETH* Close Price Other Crypto Prices	1d	ARIMA SVR RF XGBoost MLP LSTM GRU CNN CNN-LSTM CNN-GRU WAMC	WAMC	75.23	76.58	78.7	77.6	N/A

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	cAcc. (%)	Prec. (%)	Rec. (%)	F1 (%)	Code
...	[233]	07/08/2015 - 08/02/2016	22	Multivariate	*ETH* Price *ETH* Transaction Count *ETH* Forum Data	1d	AODE	AODE	71.82	-	-	71.7	N/A
...	[21]	01/01/2018 - 31/08/2019	184	Univariate OR Multivariate	*ETH* Price Data	1d	Ensemble using CNN-LSTM or CNN-BiLSTM	Ensemble using CNN-LSTM	63.45	-	-	-	N/A
...	[226]	01/01/2021 - 30/06/2021	36	Multivariate	*ETH* OHLCV *Twitter* Sentiment *Google Trends* Index	1d 3ds 5ds	SVM	SVM	63	63	62	61	N/A
...	[236]	07/05/2017 - 06/07/2021	-	Multivariate	Technical Indicators	1d	DNN	DNN	61.33	-	-	-	N/A
...	[20]	01/01/2018 - 31/08/2019	184	Univariate	*ETH* Price	1d	Averaging Ensemble or Bagging Ensemble or Stacking Ensemble using CNN-LSTM or CNN-BiLSTM	Stacking Ensemble (KNN) using CNN-BiLSTM	54.14	-	-	-	N/A
...	[41]	01/01/2017 - 31/10/2020	152	Univariate AND Multivariate	*ETH* Price *BTC* Price *XRP* Price	1d	CNN-LSTM MI-CNN-LSTM	CNN-LSTM	51.51	-	-	-	N/A
...	[234]	16/02/2018 - 21/04/2018	18	Multivariate	*ETH* OHLCV *Twitter* Sentiment	1d	MLP SVM RF	MLP	44	56	44	39	LINK
LTC	[226]	01/01/2021 - 30/06/2021	36	Multivariate	*LTC* OHLCV *Twitter* Sentiment *Google Trends* Index	1d 3ds 5ds	SVM	SVM	75	75	75	75	N/A
...	[234]	16/02/2018 - 21/04/2018	18	Multivariate	*LTC* OHLCV *Twitter* Sentiment	1d	MLP SVM RF	MLP	66	80	67	62	LINK
XRP	[226]	01/01/2021 - 30/06/2021	36	Multivariate	*XRP* OHLCV *Twitter* Sentiment *Google Trends* Index	1d 3ds 5ds	SVM	SVM	75	81	75	75	N/A
...	[233]	07/09/2015 - 08/02/2016	16	Multivariate	*XRP* Price *XRP* Forum Data	1d	AODE	AODE	71.82	-	-	71.7	N/A
...	[21]	01/01/2018 - 31/08/2019	184	Univariate OR Multivariate	*XRP* Price Data	1d	Ensemble using CNN-LSTM or CNN-BiLSTM	Ensemble using CNN-LSTM	65.4	-	-	-	N/A
...	[234]	16/02/2018 - 21/04/2018	18	Multivariate	*XRP* OHLCV *Twitter* Sentiment	1d	MLP SVM RF	MLP	64	68	67	66	LINK

Crypto	Ref.	Period	Obs. (#)	Type	Features	Freq.	Models	Top	cAcc. (%)	Prec. (%)	Rec. (%)	F1 (%)	Code
...	[20]	01/01/2018 - 31/08/2019	184	Univariate	*XRP* Price	1d	Averaging Ensemble or Bagging Ensemble or Stacking Ensemble using CNN-LSTM or CNN-BiLSTM	Bagging Ensemble using CNN-BiLSTM	55.64	-	-	-	N/A
...	[41]	01/01/2017 - 31/10/2020	152	Univariate AND Multi-variate	*XRP* Price *BTC* Price *ETH* Price	1d	CNN-LSTM MI-CNN-LSTM	CNN-LSTM	49.61	-	-	-	N/A
ADA	[236]	14/12/2017 - 06/07/2021	-	Multivariate	Technical Indicators	1d	DNN	DNN	64.4	-	-	-	N/A
...	[226]	01/01/2021 - 30/06/2021	36	Multivariate	*ADA* OHLCV *Twitter* Sentiment *Google* Trends Index	1d 3ds 5ds	SVM	SVM	59	73	59	60	N/A
DOGE	[226]	01/01/2021 - 30/06/2021	36	Multivariate	*DOGE* OHLCV *Twitter* Sentiment *Google Trends* Index	1d 3ds 5ds	SVM	SVM	72	81	72	72	N/A
BCH	[40]	23/07/2017 - 15/07/2020	217	Multivariate	*BCH* Close Price Other Crypto Prices	1d	ARIMA SVR RF XGBoost MLP LSTM GRU CNN CNN-LSTM CNN-GRU WAMC	WAMC	75.23	74.31	75.7	75	N/A
DOT	[226]	01/01/2021 - 30/06/2021	36	Multivariate	*DOT* OHLCV *Twitter* Sentiment *Google Trends* Index	1d 3ds 5ds	SVM	SVM	68	80	68	64	N/A

Table 24: Studies on *cryptocurrency price movement prediction* at daily intervals sorted by the reported classification accuracy, where the definitions of the utilized abbreviations with respect to the columns, cryptocurrencies, time granularities, and models can be found in Tables 8, 9, 10, and 11.

A.3.2 Overview Statistics

Model	Count	Papers
SVM / SVR	14	[40, 54, 55, 68, 75, 169, 222, 225, 226, 228–231, 234]
LSTM	12	[40, 55, 57, 70, 75, 77, 148, 155, 162, 169, 224, 235]
RF	8	[40, 75, 148, 169, 222, 228, 229, 234]
CNN	7	[40, 55, 56, 77, 155, 169, 225]
CNN-LSTM	7	[20, 21, 40, 41, 46, 55, 56]
Ensemble	6	[20, 21, 54, 55, 57, 162]
GRU	6	[40, 57, 155, 162, 169, 235]
LR	5	[68, 75, 222, 229, 230]
DNN	4	[54, 55, 68, 236]
MLP	4	[40, 56, 232, 234]
RNN	4	[54, 70, 169, 232]
XGBoost	4	[40, 75, 222, 229]
KNN	3	[222, 229, 231]
LDA	3	[75, 222, 231]
NB	3	[229–231]
ARIMA	2	[40, 70]
Averaging Ensemble	2	[20, 57]
BiLSTM	2	[155, 235]
CNN-BiLSTM	2	[20, 21]
DT	2	[222, 231]
GB	2	[76, 169]
QDA	2	[75, 222]
Stacking Ensemble	2	[20, 57]
AODE	1	[233]
Bagging Ensemble	1	[20]
BiGRU	1	[235]
Blending Ensemble	1	[57]
CNN-GRU	1	[40]
CNN-LSTM-AM	1	[46]
DNDT	1	[59]
DRCNN	1	[59]
DSVR	1	[59]
GLM	1	[228]
GRU-AM	1	[169]

Model	Count	Papers
GRU-TCN	1	[162]
LSTM-AM	1	[169]
LSTM-GRU	1	[162]
LSTM-TCN	1	[162]
MI-CNN-LSTM	1	[41]
PCA	1	[231]
RBFNN	1	[56]
ResNet	1	[55]
RT	1	[231]
SVM+CNN-SVM	1	[225]
TCN	1	[162]
WAMC	1	[40]

Table 25: Application count of models in *cryptocurrency price movement prediction* studies.

Cryptocurrency	Count	Papers
BTC	29	[20, 21, 41, 46, 54–57, 59, 68, 70, 75, 76, 148, 169, 222, 224–226, 228–236]
ETH	12	[20, 21, 40, 41, 56, 155, 162, 224, 226, 233, 234, 236]
XRP	7	[20, 21, 41, 56, 226, 233, 234]
LTC	3	[56, 226, 234]
ADA	2	[226, 236]
BCH	1	[40]
DASH	1	[56]
DOGE	1	[226]
DOT	1	[226]
XMR	1	[56]

Table 26: Application count of cryptocurrencies in *cryptocurrency price movement prediction* studies.

Data Type	Count	Papers
Multivariate	26	[40, 46, 54–57, 59, 68, 70, 75–77, 148, 155, 162, 169, 222, 224–226, 228, 232–236]
Univariate	2	[20, 229]
Univariate & Multivariate	2	[41, 231]
Univariate or Multivariate	2	[21, 230]

Table 27: Application count of data types in *cryptocurrency price movement prediction* studies.

Feature Category	Count	Papers
Market Data	25	[20, 21, 40, 41, 46, 54, 55, 68, 70, 76, 77, 148, 155, 162, 169, 222, 224–226, 228, 229, 232–235]
Blockchain Data	12	[54, 55, 59, 68, 70, 75, 77, 148, 162, 222, 228, 232]
Technical Indicators	8	[56, 57, 70, 77, 162, 169, 225, 236]
Twitter Data & Sentiment	9	[57, 76, 77, 148, 225, 226, 230, 231, 234]
Google Trends Index	7	[75, 76, 148, 162, 222, 224, 226]
Macroeconomic Data	6	[54, 59, 75, 148, 222, 225]
Market Data of Other Crypto	5	[40, 41, 148, 162, 225]
Forum Data	2	[59, 233]
Baidu Index	1	[75]
News Data & Sentiment	1	[235]
Telegram Data & Sentiment	1	[224]

Table 28: Application count of feature categories in *cryptocurrency price movement prediction* studies.

Publically Available Code?	Count	Papers
Yes	3	[222, 225, 234]
No	30	[20, 21, 40, 41, 46, 54–57, 59, 68, 70, 75–77, 148, 155, 162, 169, 224, 226, 228–233, 235, 236]

Table 29: Source code availability count in *cryptocurrency price movement prediction* studies.

B Fundamentals

B.1 Variational Mode Decomposition

B.1.1 Mode Definition

In the literature [182], the modes as a result of the decomposition are defined as follows:

$$u_k(t) = A_k(t)\cos(\phi_k(t)), \quad \phi_k'(t) \geq 0, \quad A_k(t) \geq 0 \tag{60}$$

with $\phi_k(t)$ representing the phase, $A_k(t)$ the envelope, and t time. The definition, as shown, defines each mode as an amplitude-modulated–frequency-modulated (AM–FM) signal, meaning that both its amplitude and frequency change over time, with $A_k(t)$ representing amplitude modulation (AM) as $A_k(t)$ corresponds to the instantaneous amplitude of the signal, while the frequency modulation (FM) is represented by $\phi_k(t)$, whose derivative corresponds to the instantaneous frequency, $\phi_k'(t)$ [182].

B.1.2 Formulation

For evaluating the bandwidth of each mode, VMD employs a 3-step process:

1. Apply the Hilbert transform to the signal of each mode to construct the corresponding analytic signal, yielding a one-sided frequency spectrum, with each analytic signal defined as:

   $$u_k^{\text{analytic}}(t) = j\left(\frac{1}{\pi t} * u_k(t)\right) + u_k(t), \quad \mathcal{H}(u_k(t)) = \frac{1}{\pi t} * u_k(t) \tag{61}$$

   where $*$ denotes the convolution operator, j denotes the imaginary unit, and the part of the equation within the brackets is the Hilbert transform, $\mathcal{H}(u_k(t))$ [57, 237].
   Under the consideration that $u_k(t)$ can alternatively be expressed as $u_k(t) = \delta(t) * u_k(t)$, each analytic signal, $u_k^{\text{analytic}}(t)$, can alternatively be defined as follows:

   $$u_k^{\text{analytic}}(t) = \left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t) \tag{62}$$

   with $\delta(t)$ denoting the Dirac delta function [81].

2. Shift each mode's frequency spectrum to the fundamental frequency band, i.e., baseband, through the mixing of the signal with an exponential tuned to the estimated value of the central frequency of the corresponding mode, $e^{-j\omega_k t}$ [182, 238].

3. After following the previous two steps, the squared L2-norm of the gradient of the corresponding baseband signal is used to compute the bandwidth of each mode [182].

The described 3-step process for bandwidth evaluation leads to the following formulation of the constrained variational optimization problem, that minimizes the bandwidth of each mode u_k around a corresponding center frequency ω_k, while constrained to the summation of the modes reconstructing the original signal $f(t)$ [182]:

$$\min_{\{u_k\},\{\omega_k\}} \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \quad \text{subject to} \quad \sum_{k=1}^{K} u_k(t) = f(t) \tag{63}$$

To solve the shown constrained optimization problem, Dragomiretskiy and Zosso [182] transform the constrained problem into an unconstrained problem by adding a quadratic penalty term:

$$\left\| f(t) - \sum_{k=1}^{K} u_k(t) \right\|_2^2 \tag{64}$$

and a Lagrangian multiplier term:

$$\left\langle \lambda(t), f(t) - \sum_{k=1}^{K} u_k(t) \right\rangle \tag{65}$$

for guaranteeing finite convergence and enforcing the constraint [81, 182]. This results in the unconstrained optimization problem being formulated as:

$$\begin{aligned} \mathcal{L}(\{u_k\}, \{\omega_k\}, \lambda) = \alpha \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t)\, e^{-j\omega_k t} \right] \right\|_2^2 \\ + \left\| f(t) - \sum_{k=1}^{K} u_k(t) \right\|_2^2 \\ + \left\langle \lambda(t), f(t) - \sum_{k=1}^{K} u_k(t) \right\rangle \end{aligned} \tag{66}$$

where α is a user-defined penalty factor that controls the bandwidth of the modes, while $\lambda(t)$ denotes the Lagrange multiplier imposing the reconstruction constraint [238]. Larger values of α enforce narrower bandwidth modes at the risk of inaccurate center frequency estimation, whereas smaller values allow wider bandwidth modes that may be more susceptible to noise [182, 184]. Moreover, the value of α also indirectly influences the accuracy of the reconstruction by directly affecting the quality of the estimated modes [185].

B.1.3 Optimization

To attain the optimal solution to the unconstrained variational optimization problem defined in (66), VMD employs the alternating direction method of multipliers (ADMM) [81, 82]. ADMM iteratively solves optimization problems when the objective functions are divisible with respect to the variables by decomposing them into simpler subproblems [183]. At each iteration, the variables are updated in an alternating manner, with the others held fixed, followed by a dual update that enforces the constraint [183]. The variables updated in VMD are the modes and the center frequencies, whereas the dual update updates the Lagrange multiplier [182]. More specifically, the following updates are performed within each ADMM iteration:

1. For each mode:

   (a) Update u_k:

$$\hat{u}_k^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i<k} \hat{u}_i^{n+1}(\omega) - \sum_{i>k} \hat{u}_i^{n}(\omega) + \frac{\hat{\lambda}^n(\omega)}{2}}{1 + 2\alpha\left(\omega - \omega_k^n\right)^2}, \quad \omega \geq 0 \tag{67}$$

with n denoting the iteration index, i the mode index, and ω the angular frequency, while $\hat{f}(\omega)$, $\hat{u}_k^{n+1}(\omega)$, $\hat{u}_i^{n}(\omega)$, $\hat{u}_i^{n+1}(\omega)$, and $\hat{\lambda}^n(\omega)$ correspond to the Fourier transforms of $f(t)$, $u_k^{n+1}(t)$, $u_i^n(t)$, $u_i^{n+1}(t)$, and $\lambda(t)$, respectively [82, 182].

(b) Update ω_k:

$$\omega_k^{n+1} \leftarrow \frac{\int_0^\infty \omega \left|\hat{u}_k^{n+1}(\omega)\right|^2 d\omega}{\int_0^\infty \left|\hat{u}_k^{n+1}(\omega)\right|^2 d\omega} \tag{68}$$

2. Update λ:

$$\hat{\lambda}^{n+1}(\omega) = \hat{\lambda}^n(\omega) + \tau\left(\hat{f}(\omega) - \sum_k \hat{u}_k^{n+1}(\omega)\right), \quad \omega \geq 0 \tag{69}$$

where τ is a user-defined step size parameter that influences the convergence of the ADMM algorithm and its sensitivity to noise [186]. An appropriate choice of τ can improve the convergence of the ADMM algorithm, where larger values increase sensitivity to noise, while smaller values reduce this sensitivity and typically result in more stable but slower convergence [183, 186].

The ADMM algorithm iterates until the change in each mode between successive iterations falls below a user-defined convergence tolerance ϵ, formulated as [97, 182]:

$$\sum_{k=1}^{K} \frac{\left\|\hat{u}_k^{n+1} - \hat{u}_k^n\right\|_2^2}{\left\|\hat{u}_k^n\right\|_2^2} < \epsilon \tag{70}$$

B.2 Temporal Convolutional Network

B.2.1 Convolutional Layer

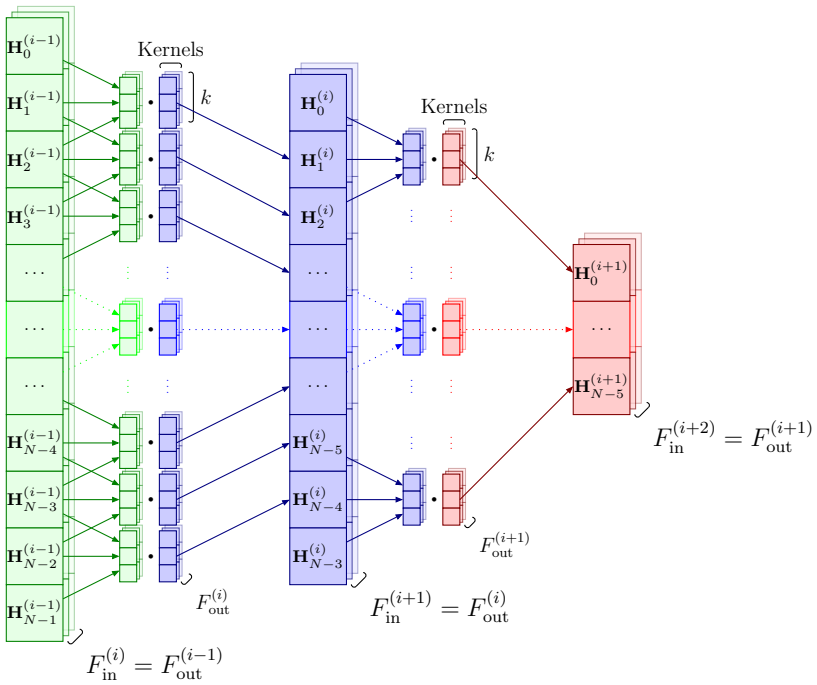


Figure 13: The application of 1D convolutional layers using a kernel of size $k = 3$ to a single sample $\mathbf{H}^{(i-1)}$ from a batch with a sequence length N, where i denotes the layer index, F_{in} the number of input features, and F_{out} the number of output features, i.e., the number of kernels applied to $\mathbf{H}^{(i-1)}$.

At the foundation of Convolutional Neural Networks (CNNs) are convolutional layers, which apply convolution operations to an input by sliding a set of learnable weights—referred to as kernels or filters—across the input and computing the dot product between each segment and the kernel. The TCN architecture introduced by Bai et al. [131] specifically utilizes 1-dimensional (1D) convolutional layers. An example of the application of 1D convolutional layers is illustrated in Figure 13.

The inputs of a 1D convolutional layer are of shape $\mathbf{X} \in \mathbb{R}^{B \times F_{\text{in}} \times L_{\text{in}}}$, where B is the batch size, F_{in} is the number of input features, and L_{in} is the sequence length of the input. The outputs, on the other hand, are of shape $\hat{\mathbf{Y}} \in \mathbb{R}^{B \times F_{\text{out}} \times L_{\text{out}}}$, with F_{out} denoting the number of output features and L_{out} the sequence length of the output. F_{out} is a tunable hyperparameter of a convolutional layer that determines how many kernels are applied to the input. Another important tunable hyperparameter of a convolutional layer is the size of the kernels, k. Given k, each kernel, f, has learnable weights of shape $\mathbf{W}_f \in \mathbb{R}^{F_{\text{in}} \times k}$ and is slid across the input of each sample in a batch, computing a dot product between it and a corresponding patch of the input with the same shape resulting in a scalar to which a learnable bias $b_f \in \mathbb{R}$ is added. Thus, the full set of weights and biases with respect to a convolutional layer are of shape $\mathbf{W} \in \mathbb{R}^{F_{\text{out}} \times F_{\text{in}} \times k}$ and $\mathbf{b} \in \mathbb{R}^{F_{\text{out}}}$, respectively. Based on the preceding definitions and assuming all other hyperparameters of a convolutional layer are set to default values, the output $\hat{Y}_{n,f,l}$ of a 1D convolutional layer corresponding to kernel f applied to an input $\mathbf{X}$ can be expressed

as:

$$\hat{Y}_{n,f,l} = \mathbf{W}_f \cdot \mathbf{X}_{n,:,l:l+k} + b_f \tag{71}$$

with $\cdot$ denoting the dot product operation and $\mathbf{X}_{n,:,l:l+k} \in \mathbb{R}^{F_{\text{in}} \times k}$ denoting a subsequence of the input of the n-th batch consisting of all F_{in} input features and sequence indices from l to $l+k-1$. Under the same conditions, L_{out} is given by:

$$L_{\text{out}} = L_{\text{in}} - (k-1) \tag{72}$$

In Figure 13, the process of applying 1D convolutional layers with a kernel size $k = 3$ to a single sample $\mathbf{H}^{(i-1)} \in \mathbb{R}^{F_{\text{out}}^{(i-1)} \times N}$ from a batch is illustrated, where $\mathbf{H}^{(i-1)}$ represents the intermediate representation serving as input to the i-th layer with a sequence length N. As shown in Figure 13, applying $F_{\text{out}}^{(i)}$ convolutional kernels of size $k = 3$ to $\mathbf{H}^{(i-1)}$, results in the next intermediate representation $\mathbf{H}^{(i)} \in \mathbb{R}^{F_{\text{out}}^{(i)} \times N-2}$. Subsequently, applying $F_{\text{out}}^{(i+1)}$ kernels of size $k = 3$ to $\mathbf{H}^{(i)}$ results in $\mathbf{H}^{(i+1)} \in \mathbb{R}^{F_{\text{out}}^{(i+1)} \times N-4}$.

B.2.2 Dilated Causal Convolutional Layer

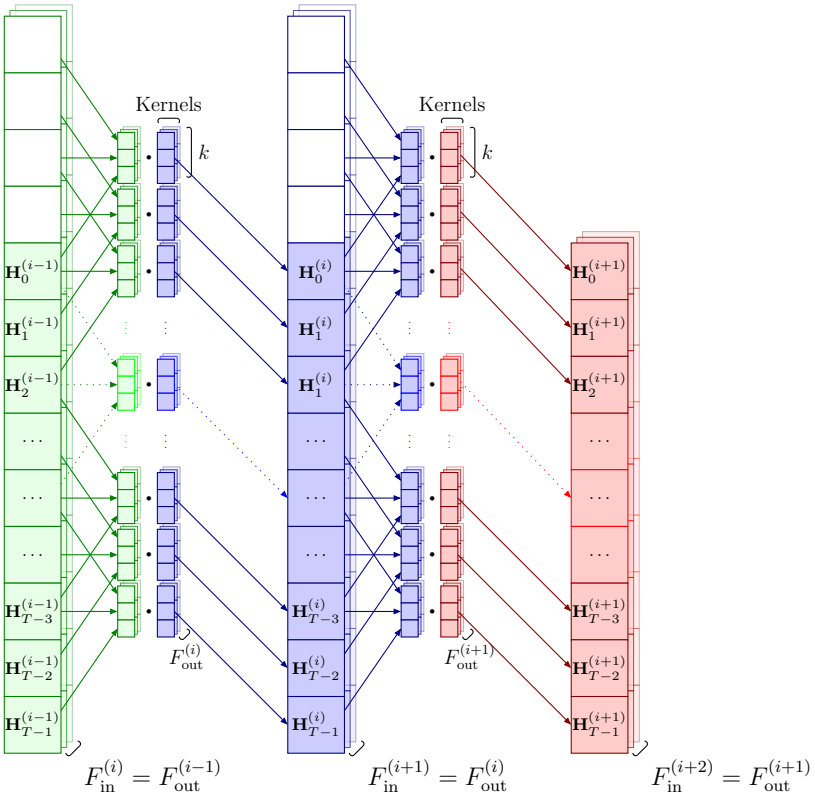


Figure 14: The application of 1D dilated causal convolutional layers using a kernel of size $k = 3$ and a dilation rate of $r = 2$ to a single sample $\mathbf{H}^{(i-1)}$ from a batch with a sequence length T, where i denotes the layer index, F_{in} the number of input features, and F_{out} the number of output features, i.e., the number of kernels applied to $\mathbf{H}^{(i-1)}$. Causality and the sequence length T are maintained throughout subsequent layers by padding 4 zeros at the beginning of each input sequence.

The TCN proposed by Bai et al. [131] and TCNs in general are based on a special type of 1D convolutional layer, namely 1D dilated causal convolutional layers, depicted in Figure 14. 1D dilated causal convolutional layers are designed such that:

- The output sequence is of the same length as the input sequence.
- The input sequence is processed in a manner that respects the causality of the sequence.
- Dilated convolutions are applied, allowing for the capture of dependencies over a longer distance.

Causality and Sequence Length Preservation
Given an input $\mathbf{X} \in \mathbb{R}^{B \times F_{\text{in}} \times T}$, 1D dilated causal convolutional layers ensure that the corresponding output is given by $\hat{\mathbf{Y}} \in \mathbb{R}^{B \times F_{\text{out}} \times T}$, whilst ensuring that each output at time step t only depends on the input at t or preceding time steps.
1D dilated causal convolutional layers achieve both by padding the input and the intermediate inputs with zeros before applying 1D convolutional layers, as described in Section 13. If all other hyperparameters of a 1D convolutional layer are set to their default values, except for the number of output features F_{out} and the kernel size k, then $k-1$ zeros are padded to each sequence. Per the definition of the output sequence length, L_{out}, of a 1D convolutional layer formulated in (72), the padding ensures that L_{out} is equal to the original input sequence length without padding, L_{in}. The zero-padding is added at the beginning of the sequences.
Since the convolutional kernels are applied along T in a temporal order, padding at the beginning of the sequence ensures that the output at time step t depends only on inputs from time steps 0 to t. The necessity of the padding for maintaining causality is illustrated in Figure 13. Without padding at the beginning of the input, the output $\mathbf{H}_0^i$ of the i-th 1D convolutional layer, for example, depends on $\mathbf{H}_0^{i-1}$, $\mathbf{H}_1^{i-1}$, and $\mathbf{H}_2^{i-1}$, thus violating causality.

Dilation
Using 1D convolutional layers that are solely causal limits the range of temporal dependencies that can be captured for a given output. In other words, it limits the size of the receptive field [131]. In the case of 1D causal convolutional layers, the receptive field grows linearly with the number of 1D convolutional layers, where the receptive field R of a single 1D causal convolutional layer is expressed as:

$$R = 1 + (k-1) \tag{73}$$

This may limit the effectiveness of modeling sequences that require larger receptive fields [131]. To address this, 1D dilated causal convolutional layers use dilation in addition to zero-padding to ensure causality.
The extent of this dilation is controlled by the dilation rate parameter r. This parameter is a hyperparameter of a convolutional layer, set to 1 by default, which corresponds to applying the convolution without dilation. The dilation rate specifies the spacing between the time steps of the subsequence over which the convolutional kernel is applied. Therefore, based on the formulation previously provided in for the output $\hat{Y}_{n,f,l}$ of a 1D convolutional layer corresponding to a kernel f applied to an input $\mathbf{X}$, the output $\hat{Y}_{n,f,t}$ of a 1D dilated causal convolutional layer can be expressed as:

$$\hat{Y}_{n,f,t} = \mathbf{W}_f \cdot \mathbf{X}_{n,:,\,t:t+r(k-1):r} + b_f \tag{74}$$

where $\cdot$ denotes the dot product operation and $\mathbf{X}_{n,:,t:t+r(k-1):r} \in \mathbb{R}^{F_{\text{in}} \times k}$ denotes a subsequence of the input of the n-th batch consisting of all F_{in} input features and time steps $t, t+r, \ldots, t+(k-1)r$.
The larger r, the wider the range of temporal dependencies that can be captured [131]. Given r, the receptive field of a single 1D dilated causal convolutional layer can be expressed as:

$$R = 1 + (k-1)r \tag{75}$$

Dilation also affects the length of the output sequence of a convolutional layer. Without padding, L_{out} of a 1D dilated causal convolutional layer is given by:

$$L_{\text{out}} = L_{\text{in}} - (k-1)r \tag{76}$$

Thus, to ensure that the input and output sequences are of an equal length T, $(k-1)r$ zeros are padded to the input sequence of the dilated causal convolutional layer.
In Figure 14, the process of applying 1D dilated causal convolutional layers with a kernel size $k = 3$ and a dilation rate $r = 2$ to a single sample $\mathbf{H}^{(i-1)} \in \mathbb{R}^{F_{\text{out}}^{(i-1)} \times T}$ from a batch is displayed, where $\mathbf{H}^{(i-1)}$ represents the intermediate representation serving as input to the i-th layer with a sequence length T. Unlike the default convolutional layers shown in Figure 13, each intermediate input sequence is padded with 4 zeros at the beginning to maintain causality and an equal sequence length across subsequent layers. Consequently, as depicted in Figure 14, the application a dilated causal convolutional layer with a kernel size of 3 and a dilation rate of 2 to $\mathbf{H}^{(i-1)}$, results in intermediate representation $\mathbf{H}^{(i)} \in \mathbb{R}^{F_{\text{out}}^{(i)} \times T}$. The subsequent application of another layer with the same kernel size and dilation rate to $\mathbf{H}^{(i)} \in \mathbb{R}^{F_{\text{out}}^{(i)} \times T}$ results in $\mathbf{H}^{(i+1)} \in \mathbb{R}^{F_{\text{out}}^{(i+1)} \times T}$.

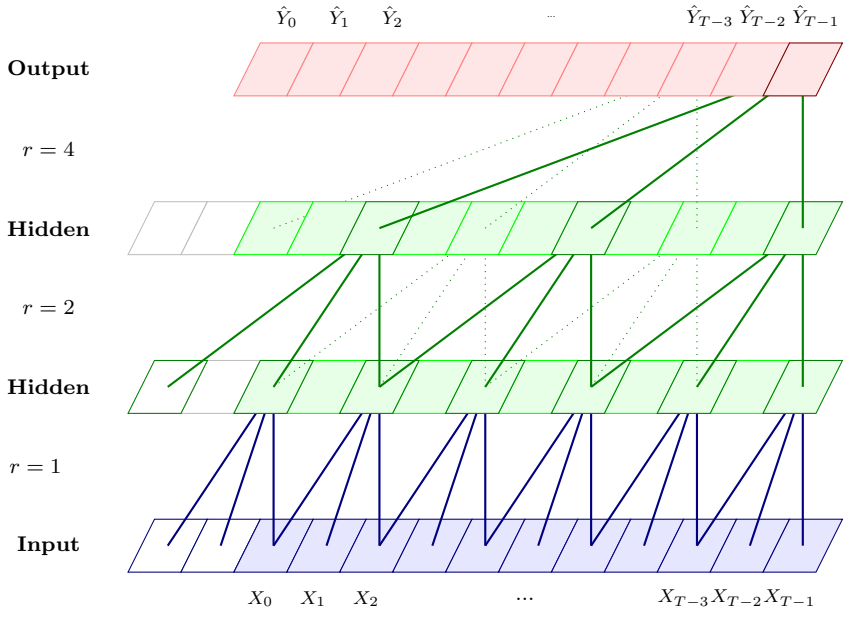


Figure 15: The application of 1D dilated causal convolutional layers with kernel size $k = 3$ and exponentially increasing dilation rate r, using a dilation base of $a = 2$, to an input sequence $\mathbf{X}$ resulting in an output sequence $\hat{\mathbf{Y}}$.

Dilation in TCN
Although r is technically a tunable hyperparameter, it is typically not tuned for the TCN

introduced by Bai et al. [131]. Instead, it increases exponentially with the number of TCN layers. In other words, the dilation rate r of the ith TCN layer is defined as $r = a^i$, where a is the dilation base. As such, given (75), the receptive field of a single 1D dilated causal convolutional layer part of TCN layer i is defined as:

$$R = 1 + (k - 1)a^i \tag{77}$$

Consequently, based on (76), L_{out} of a 1D dilated causal convolutional layer part of TCN layer i can be formulated as:

$$L_{\text{out}} = L_{\text{in}} - (k - 1)a^i \tag{78}$$

The dilation base a can be considered a tunable hyperparameter; however, in alignment with the architecture proposed by Bai et al. [131], it is typically fixed to $a = 2$. Exponentially increasing r with network depth ensures coverage of all time steps within the receptive field, while enabling the model to capture large receptive fields as the network becomes deeper [131]. The application of 1D dilated causal convolutional layers with kernel size $k = 3$ and an exponentially increasing dilation rate r with dilation base $a = 2$ to an input sequence X is depicted in Figure 14. The illustration demonstrates that the sequential application of a sufficient number of dilated causal convolutional layers, depending on k, with exponentially increasing dilation rates enables full historical coverage such that the receptive field spans all time steps.

C Supplementary Data Analysis

C.1 Dataset Statistics

Crypto	Feature	O.C.	Mean	S.D.	Min.	5%	25%	Median	75%	95%	Max.
BTC/USD	$\mathbf{S}_{\text{Open}}$	1826	18605.68	17629.62	1914.10	3473.07	6631.30	9465.04	33686.38	56111.74	67525.82
	$\mathbf{S}_{\text{High}}$	1826	19146.42	18116.83	2044.40	3580.50	6784.88	9689.83	34879.50	57766.50	69000.00
	$\mathbf{S}_{\text{Low}}$	1826	17988.79	17063.75	1809.00	3403.35	6508.91	9212.90	32194.60	53932.25	66222.40
	$\mathbf{S}_{\text{Close}}$	1826	18621.99	17628.20	1914.10	3483.80	6634.85	9469.24	33687.12	56111.74	67525.83
ETH/USD	$\mathbf{S}_{\text{Open}}$	1826	1020.83	1220.38	83.75	129.06	206.47	362.66	1727.06	3738.20	4807.98
	$\mathbf{S}_{\text{High}}$	1826	1057.67	1259.45	85.00	134.69	214.05	376.15	1808.61	3851.82	4868.00
	$\mathbf{S}_{\text{Low}}$	1826	977.58	1173.91	81.79	124.12	197.75	347.28	1659.97	3585.78	4713.89
	$\mathbf{S}_{\text{Close}}$	1826	1021.77	1220.45	83.76	129.06	206.48	363.68	1737.40	3738.20	4807.98
LTC/USD	$\mathbf{S}_{\text{Open}}$	1826	101.34	64.22	23.06	34.34	51.45	76.54	140.28	225.52	387.77
	$\mathbf{S}_{\text{High}}$	1826	106.03	68.53	23.76	36.43	53.17	79.47	145.92	235.54	420.00
	$\mathbf{S}_{\text{Low}}$	1826	96.19	59.63	22.32	32.73	49.58	73.04	133.67	212.25	345.00
	$\mathbf{S}_{\text{Close}}$	1826	101.41	64.35	23.08	34.36	51.47	76.55	140.28	225.51	387.80
XMR/USD	$\mathbf{S}_{\text{Open}}$	1826	142.31	90.49	29.20	45.61	66.02	113.49	208.59	314.16	484.29
	$\mathbf{S}_{\text{High}}$	1826	148.66	95.57	32.76	46.80	68.30	117.52	217.75	328.68	519.13
	$\mathbf{S}_{\text{Low}}$	1826	135.44	84.71	25.08	43.96	64.07	108.63	199.02	290.13	451.24
	$\mathbf{S}_{\text{Close}}$	1826	142.39	90.46	29.20	45.61	66.01	113.64	208.74	314.00	484.00
XRP/USD	$\mathbf{S}_{\text{Open}}$	1826	0.509	0.363	0.135	0.188	0.251	0.352	0.687	1.188	2.780
	$\mathbf{S}_{\text{High}}$	1826	0.534	0.391	0.149	0.193	0.259	0.370	0.722	1.253	3.290
	$\mathbf{S}_{\text{Low}}$	1826	0.481	0.333	0.101	0.179	0.242	0.334	0.648	1.116	2.580
	$\mathbf{S}_{\text{Close}}$	1826	0.509	0.363	0.135	0.188	0.251	0.353	0.689	1.188	2.780

Table 30: Statistics of $\mathbf{S}_{\text{Open}}$, $\mathbf{S}_{\text{High}}$, $\mathbf{S}_{\text{Low}}$, and $\mathbf{S}_{\text{Close}}$ with respect to *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* in the *benchmark dataset*.

Crypto	Feature	O.C.	Mean	S.D.	Min.	5%	25%	Median	75%	95%	Max.
BTC/USD	$\mathbf{S}_{\text{Open}}$	2922	29820.58	26285.22	1914.10	3803.33	8332.50	20996.50	44536.46	88613.19	111696.21
	$\mathbf{S}_{\text{High}}$	2922	30518.37	26814.84	2044.40	3893.88	8594.33	21574.47	45996.98	91763.176	111980.00
	$\mathbf{S}_{\text{Low}}$	2922	29076.57	25738.53	1809.00	3658.51	8089.06	20512.50	43334.98	86124.14	109177.37
	$\mathbf{S}_{\text{Close}}$	2922	29855.68	26316.62	1914.10	3807.82	8342.49	21054.83	44565.62	88678.78	111696.21
ETH/USD	$\mathbf{S}_{\text{Open}}$	2922	1470.97	1219.75	83.75	137.85	279.04	1336.69	2412.30	3646.19	4807.98
	$\mathbf{S}_{\text{High}}$	2922	1514.50	1252.76	85.00	142.34	288.72	1388.50	2488.75	3746.70	4868.00
	$\mathbf{S}_{\text{Low}}$	2922	1421.93	1181.94	81.79	134.01	265.18	1297.54	2310.00	3529.07	4713.89
	$\mathbf{S}_{\text{Close}}$	2922	1471.76	1219.70	83.76	137.86	279.64	1337.93	2413.85	3646.61	4807.98
LTC/USD	$\mathbf{S}_{\text{Open}}$	2922	92.86	53.08	23.06	40.80	57.56	76.12	110.65	202.23	387.77
	$\mathbf{S}_{\text{High}}$	2922	96.66	56.70	23.76	42.16	59.36	78.14	114.92	214.69	420.00
	$\mathbf{S}_{\text{Low}}$	2922	88.68	49.22	22.32	39.42	55.50	73.31	105.38	191.47	345.00
	$\mathbf{S}_{\text{Close}}$	2922	92.90	53.18	23.08	40.83	57.56	76.12	110.68	202.20	387.80
XMR/USD	$\mathbf{S}_{\text{Open}}$	2922	150.86	76.31	29.20	48.17	90.93	147.80	188.50	287.95	484.29
	$\mathbf{S}_{\text{High}}$	2922	156.35	80.27	32.76	49.83	94.50	151.60	196.63	303.46	519.13
	$\mathbf{S}_{\text{Low}}$	2922	145.08	72.04	25.08	46.44	87.50	144.45	178.83	273.51	451.24
	$\mathbf{S}_{\text{Close}}$	2922	150.95	76.34	29.20	48.31	91.07	147.80	188.77	289.23	484.00
XRP/USD	$\mathbf{S}_{\text{Open}}$	2922	0.627	0.551	0.135	0.195	0.302	0.475	0.646	2.190	3.292
	$\mathbf{S}_{\text{High}}$	2922	0.653	0.578	0.149	0.200	0.312	0.489	0.679	2.252	3.400
	$\mathbf{S}_{\text{Low}}$	2922	0.598	0.522	0.101	0.190	0.292	0.458	0.622	2.107	3.176
	$\mathbf{S}_{\text{Close}}$	2922	0.628	0.552	0.135	0.195	0.303	0.475	0.648	2.190	3.292

Table 31: Statistics of $\mathbf{S}_{\text{Open}}$, $\mathbf{S}_{\text{High}}$, $\mathbf{S}_{\text{Low}}$, and $\mathbf{S}_{\text{Close}}$ with respect to *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* in the extended dataset.

C.2 Price Visualization

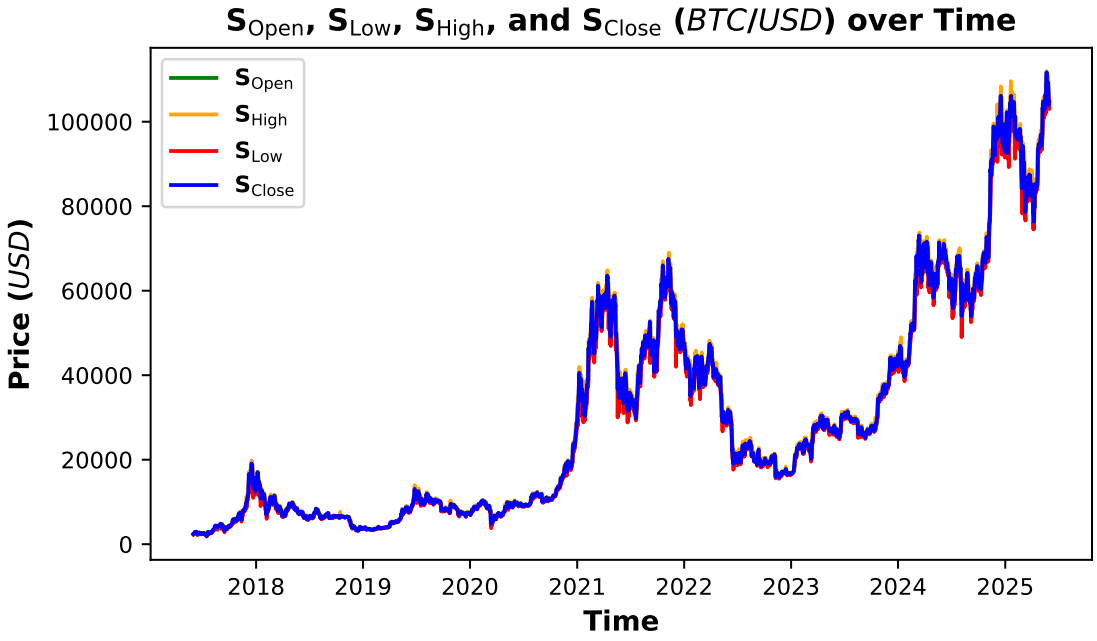


Figure 16: $\mathbf{S}_{\text{Open}}$, $\mathbf{S}_{\text{High}}$, $\mathbf{S}_{\text{Low}}$, and $\mathbf{S}_{\text{Close}}$ with respect to BTC/USD from 1 June 2017 to 31 May 2025.

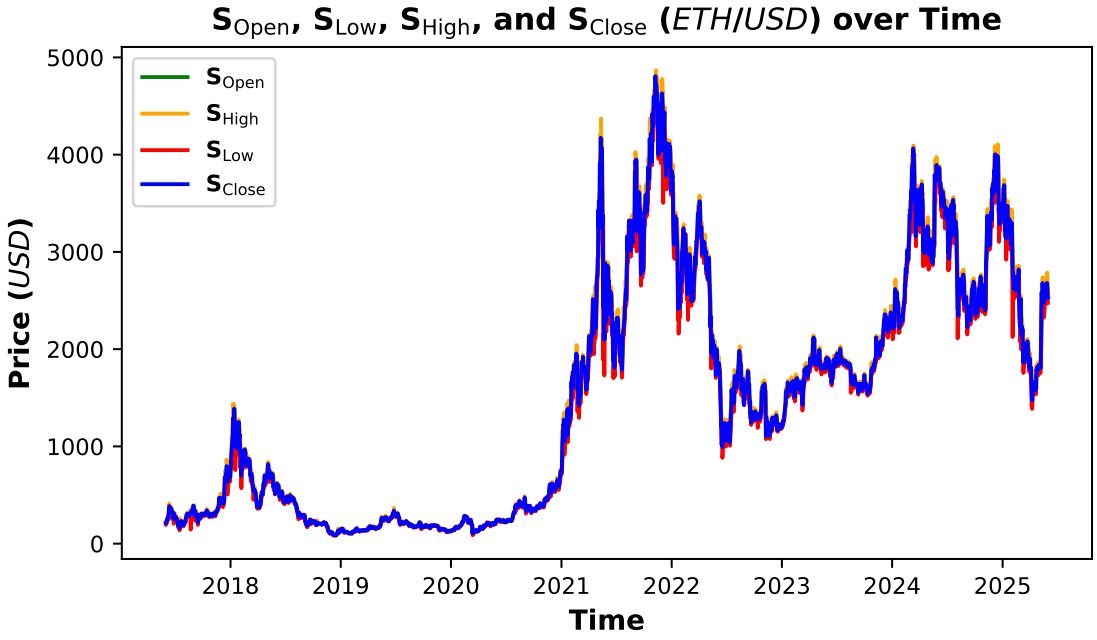


Figure 17: $\mathbf{S}_{\text{Open}}$, $\mathbf{S}_{\text{High}}$, $\mathbf{S}_{\text{Low}}$, and $\mathbf{S}_{\text{Close}}$ with respect to ETH/USD from 1 June 2017 to 31 May 2025.

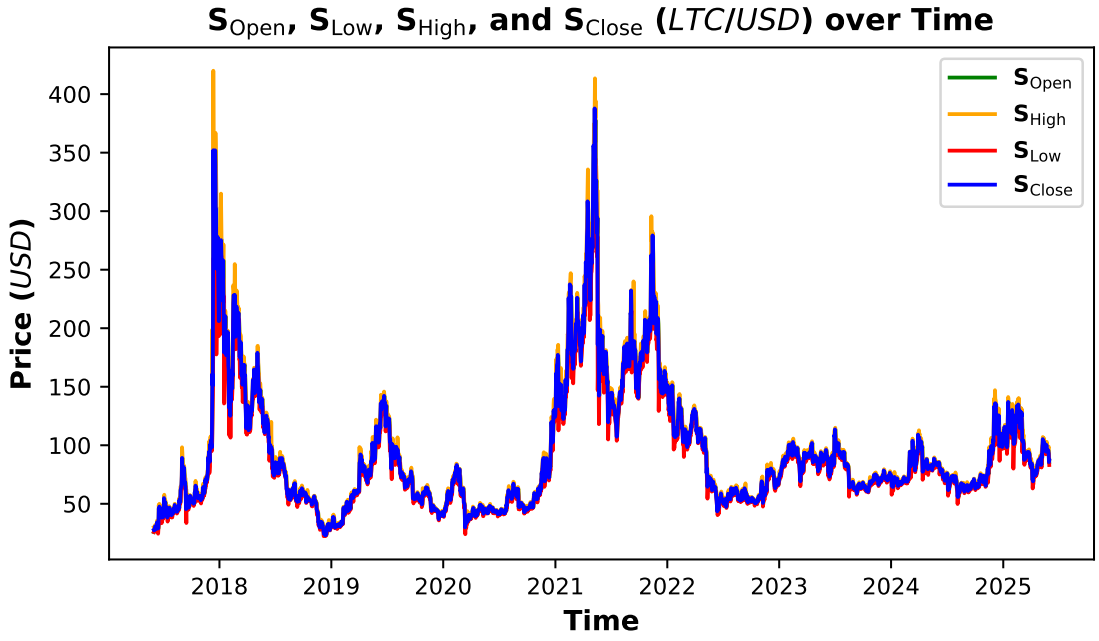


Figure 18: $\mathbf{S}_{\text{Open}}$, $\mathbf{S}_{\text{High}}$, $\mathbf{S}_{\text{Low}}$, and $\mathbf{S}_{\text{Close}}$ with respect to LTC/USD from 1 June 2017 to 31 May 2025.

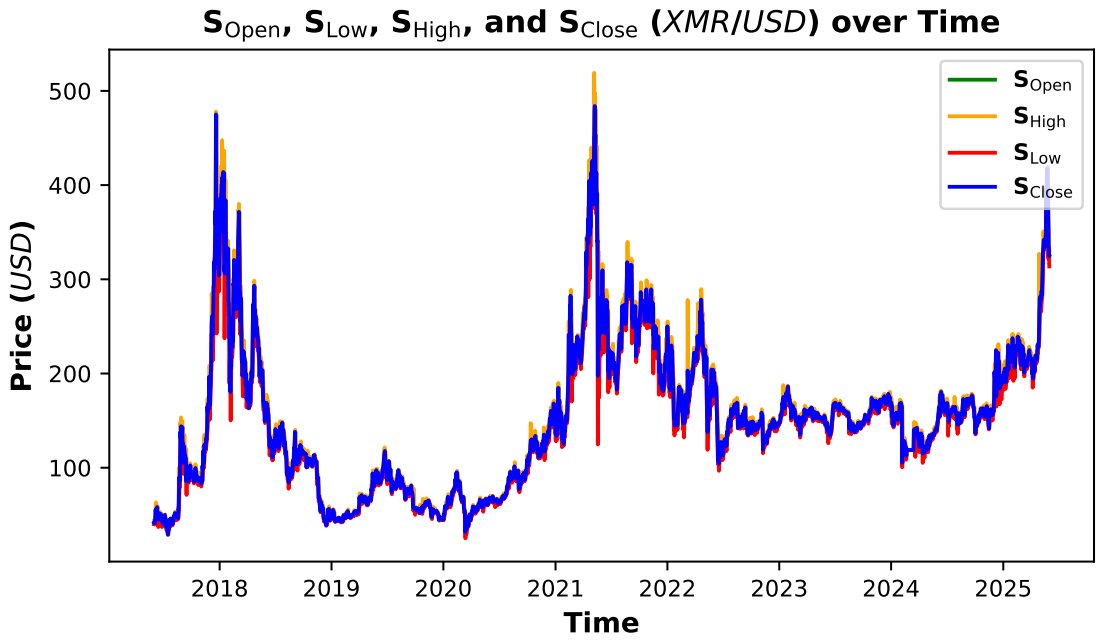


Figure 19: $\mathbf{S}_{\text{Open}}$, $\mathbf{S}_{\text{High}}$, $\mathbf{S}_{\text{Low}}$, and $\mathbf{S}_{\text{Close}}$ with respect to XMR/USD from 1 June 2017 to 31 May 2025.

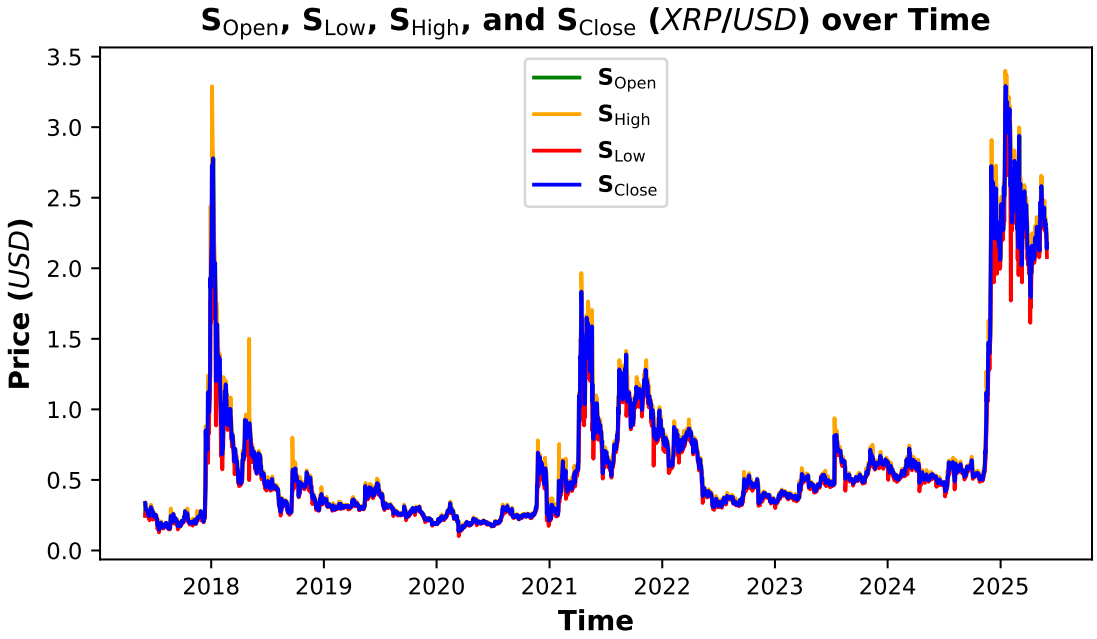


Figure 20: $\mathbf{S}_{\text{Open}}$, $\mathbf{S}_{\text{High}}$, $\mathbf{S}_{\text{Low}}$, and $\mathbf{S}_{\text{Close}}$ with respect to XRP/USD from 1 June 2017 to 31 May 2025.

C.3 Returns Visualization

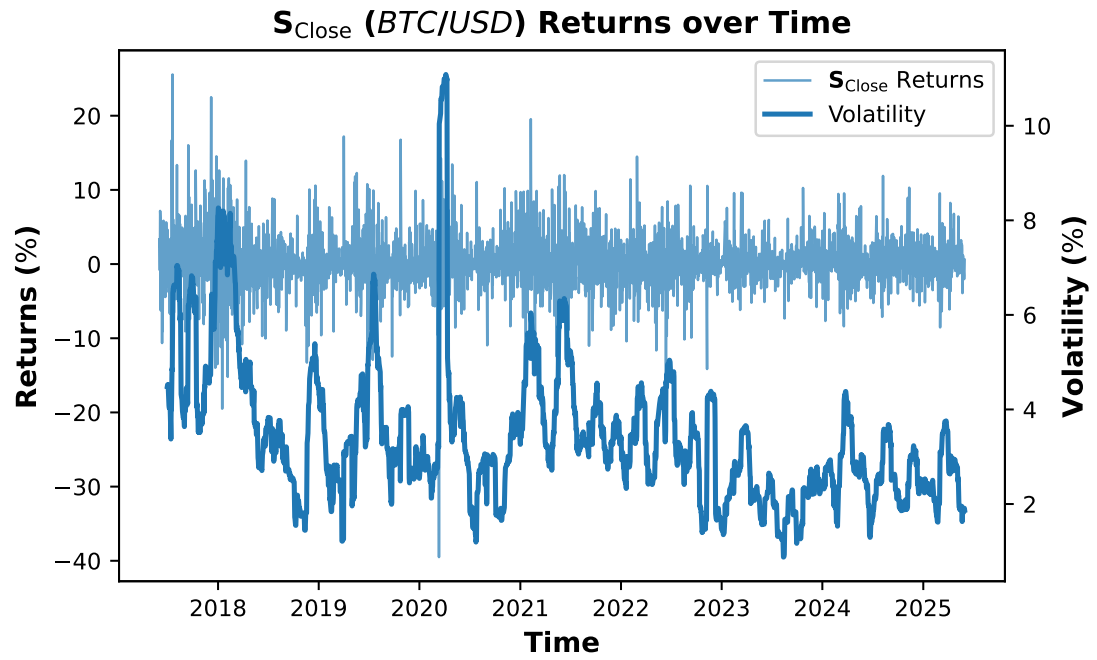


Figure 21: $\mathbf{S}_{\text{Close}}$ returns with respect to BTC/USD from 1 June 2017 to 31 May 2025 with volatility over 30-day rolling window.

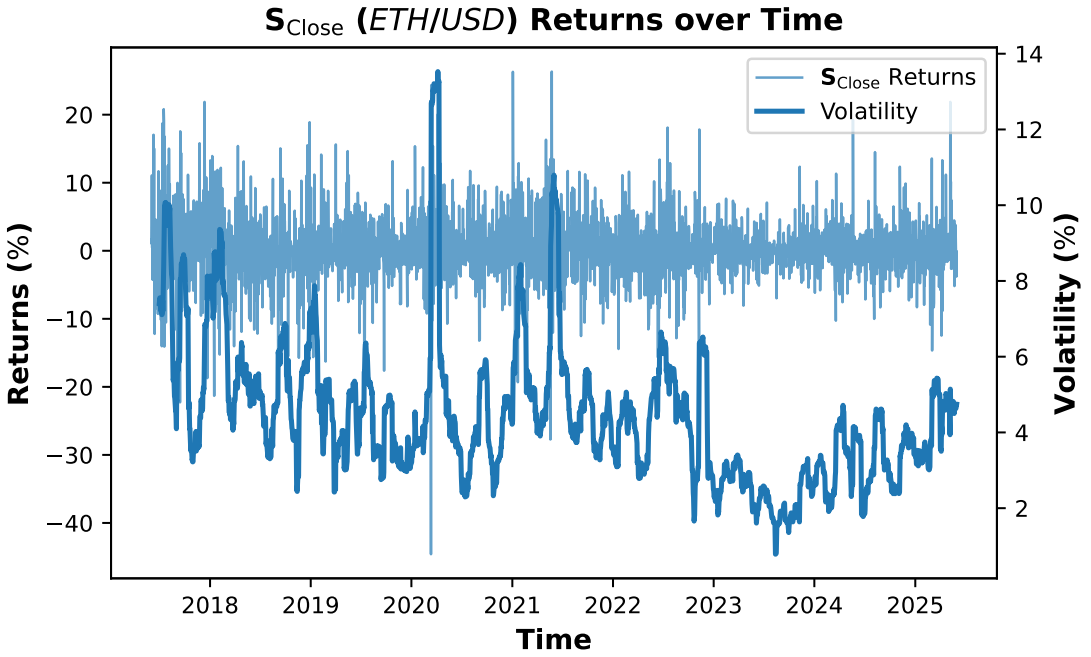


Figure 22: S_{Close} returns with respect to *ETH / USD* from 1 June 2017 to 31 May 2025 with volatility over 30-day rolling window

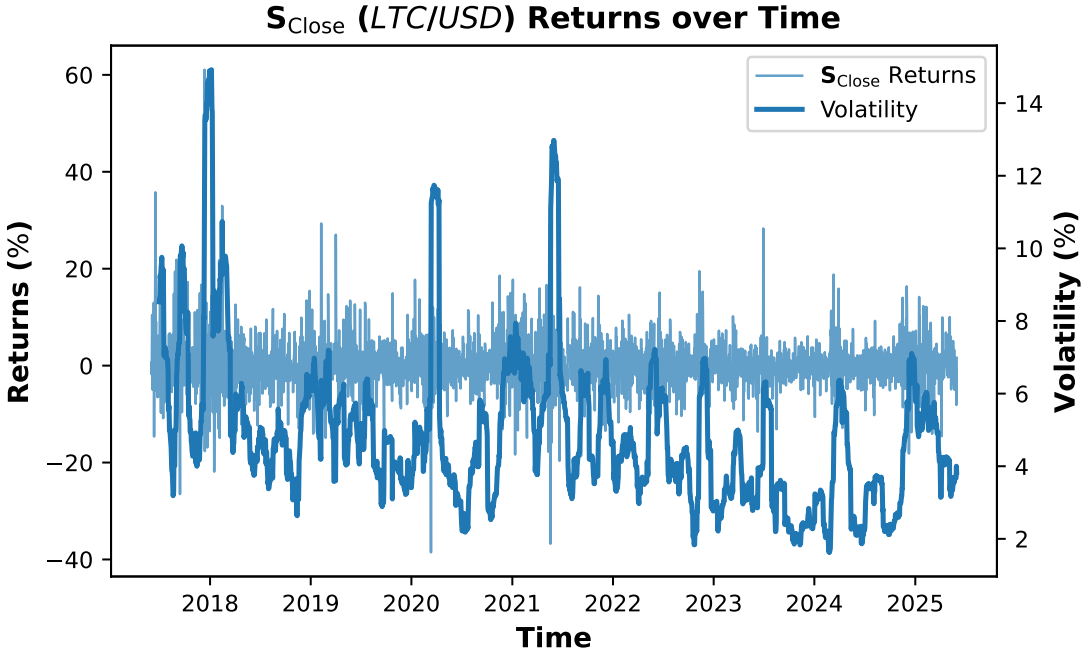


Figure 23: S_{Close} returns with respect to *LTC / USD* from 1 June 2017 to 31 May 2025 with volatility over 30-day rolling window.

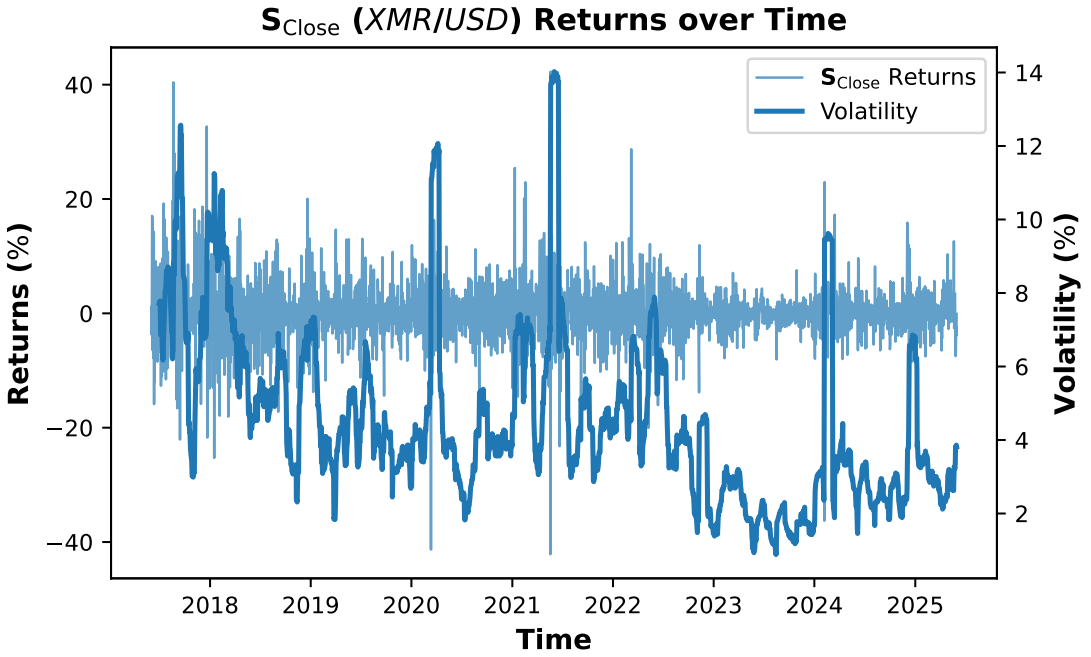


Figure 24: S_{Close} returns with respect to XMR/USD from 1 June 2017 to 31 May 2025 with volatility over 30-day rolling window.

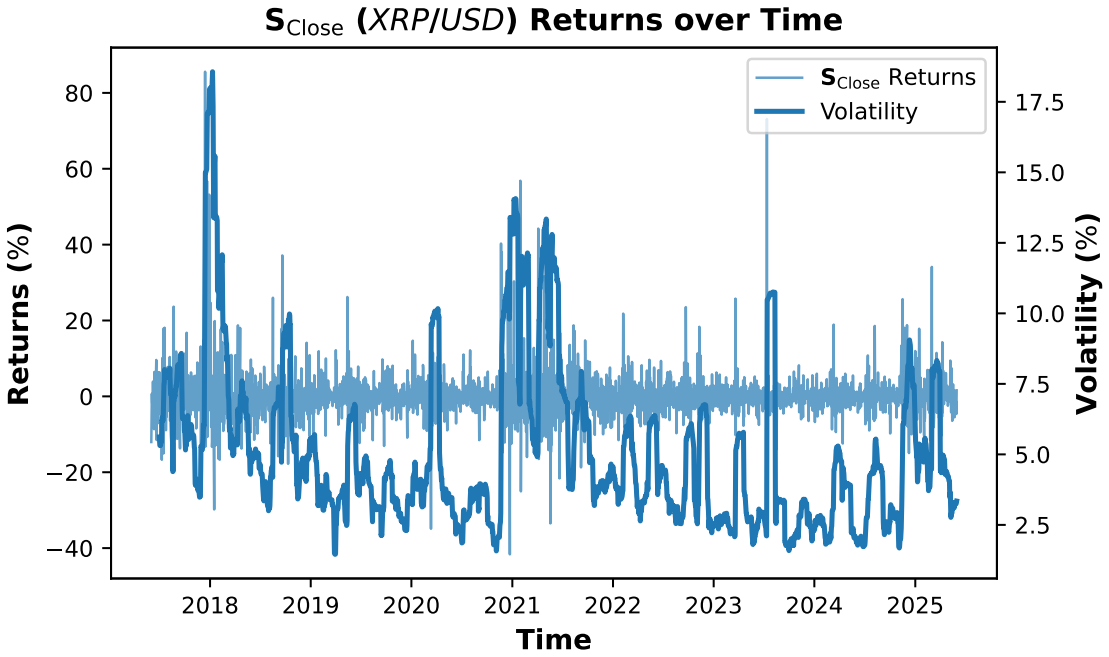


Figure 25: S_{Close} returns with respect to XRP/USD from 1 June 2017 to 31 May 2025 with volatility over 30-day rolling window.

C.4 Autocorrelation Visualization

C.4.1 ACF Plots

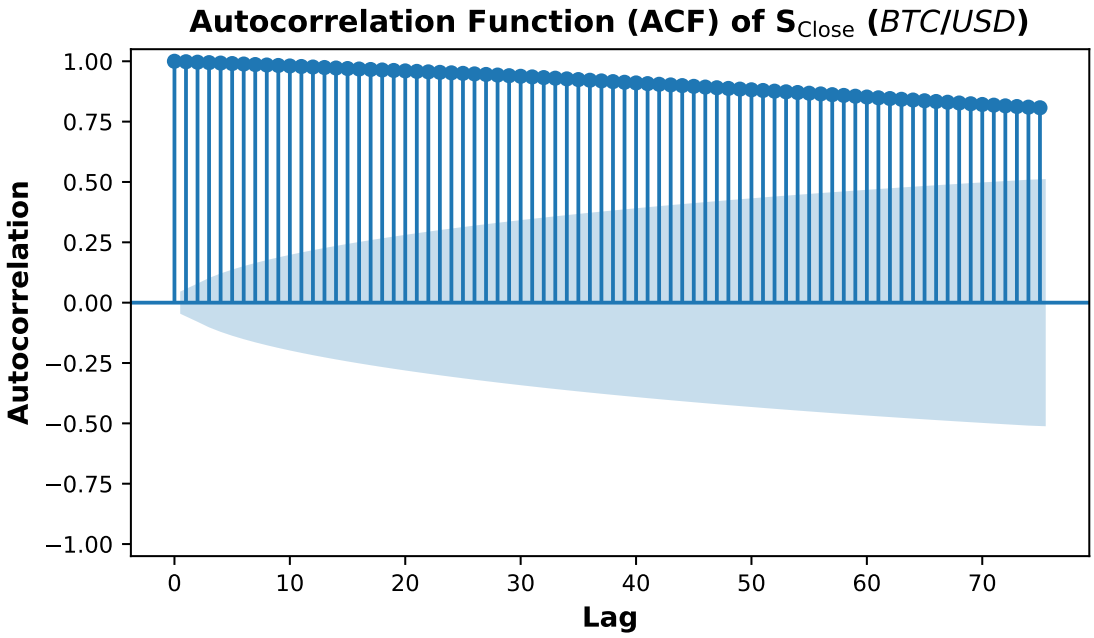


Figure 26: Autocorrelation Function (ACF) of $\mathbf{S}_{\text{Close}}$ with respect to BTC/USD in the *benchmark dataset*.

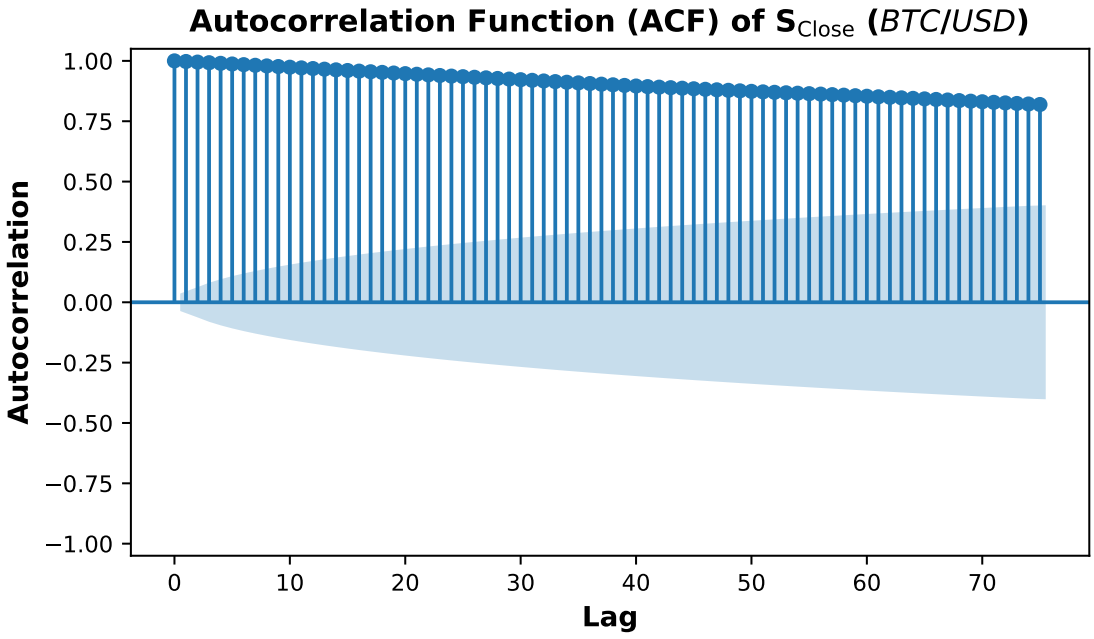


Figure 27: Autocorrelation Function (ACF) of $\mathbf{S}_{\text{Close}}$ with respect to BTC/USD in the *extended dataset*.

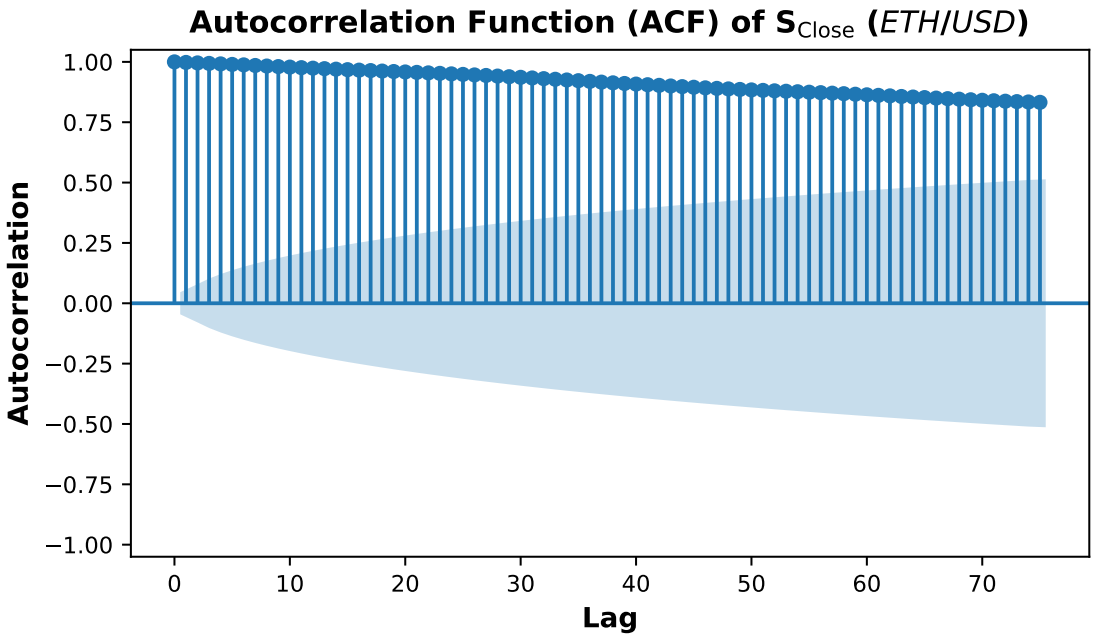


Figure 28: Autocorrelation Function (ACF) of $\mathbf{S}_{\text{Close}}$ with respect to ETH/USD in the *benchmark dataset*.

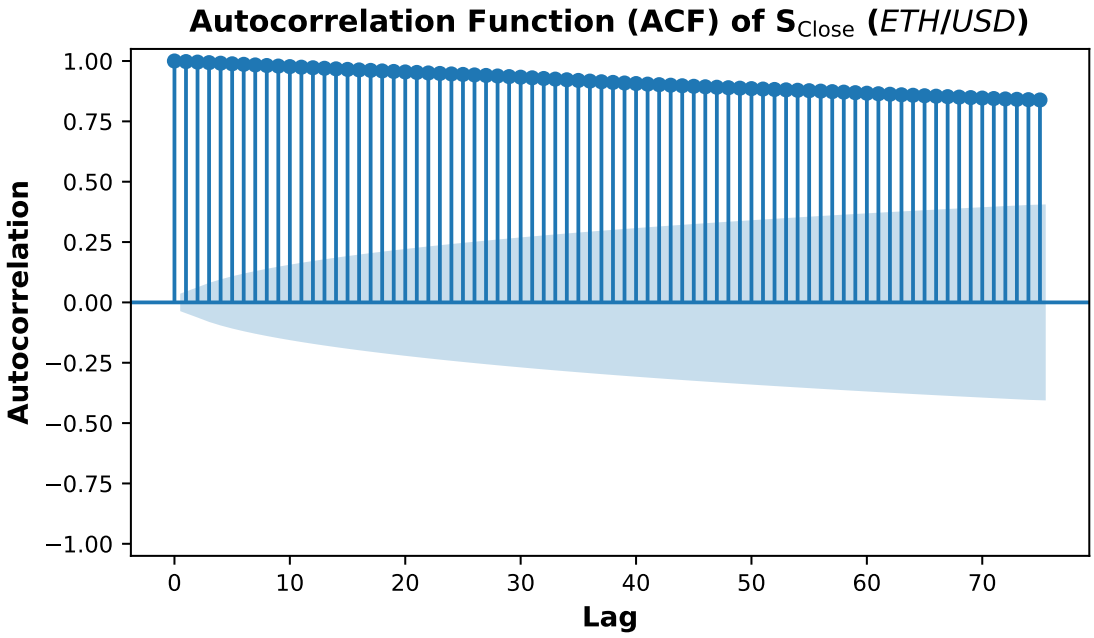


Figure 29: Autocorrelation Function (ACF) of $\mathbf{S}_{\text{Close}}$ with respect to ETH/USD in the *extended dataset*.

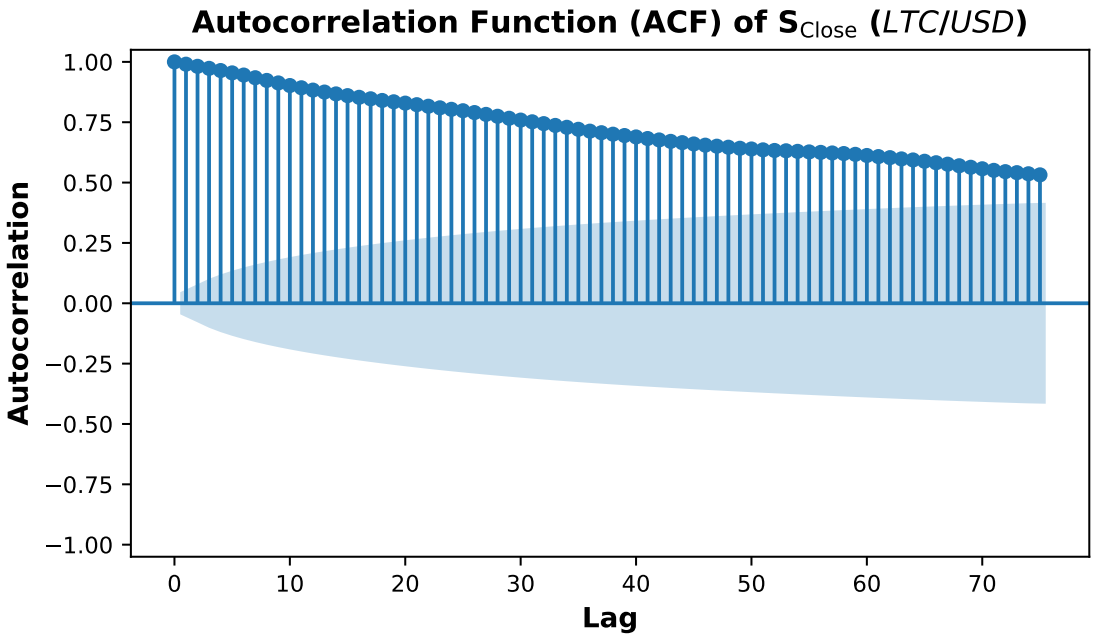


Figure 30: Autocorrelation Function (ACF) of $\mathbf{S}_{\text{Close}}$ with respect to LTC/USD in the *benchmark dataset*.

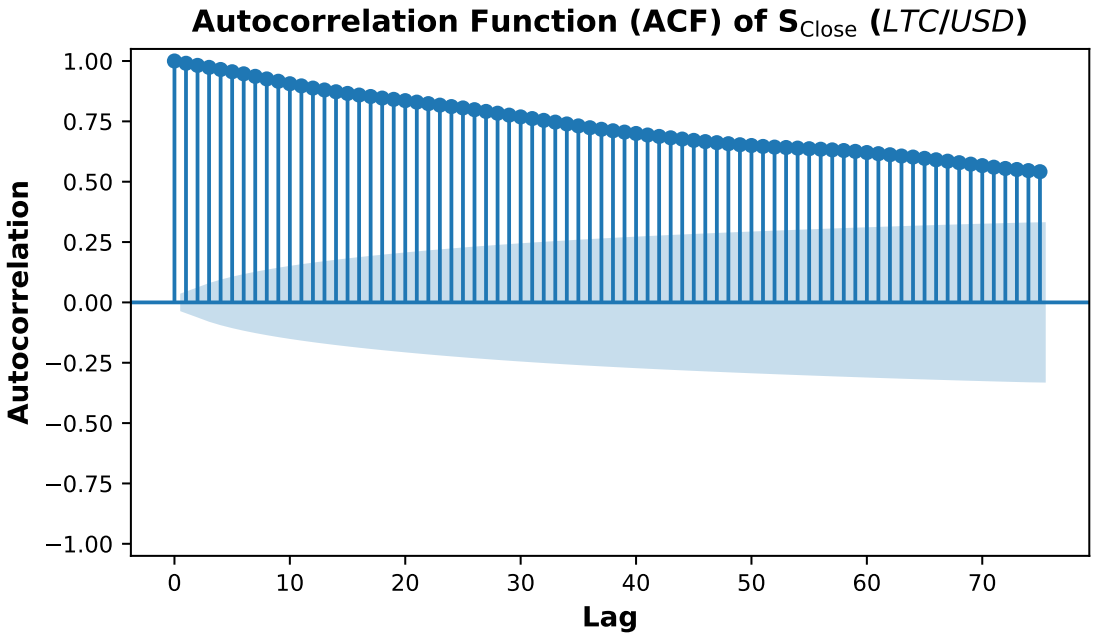


Figure 31: Autocorrelation Function (ACF) of $\mathbf{S}_{\text{Close}}$ with respect to LTC/USD in the *extended dataset*.

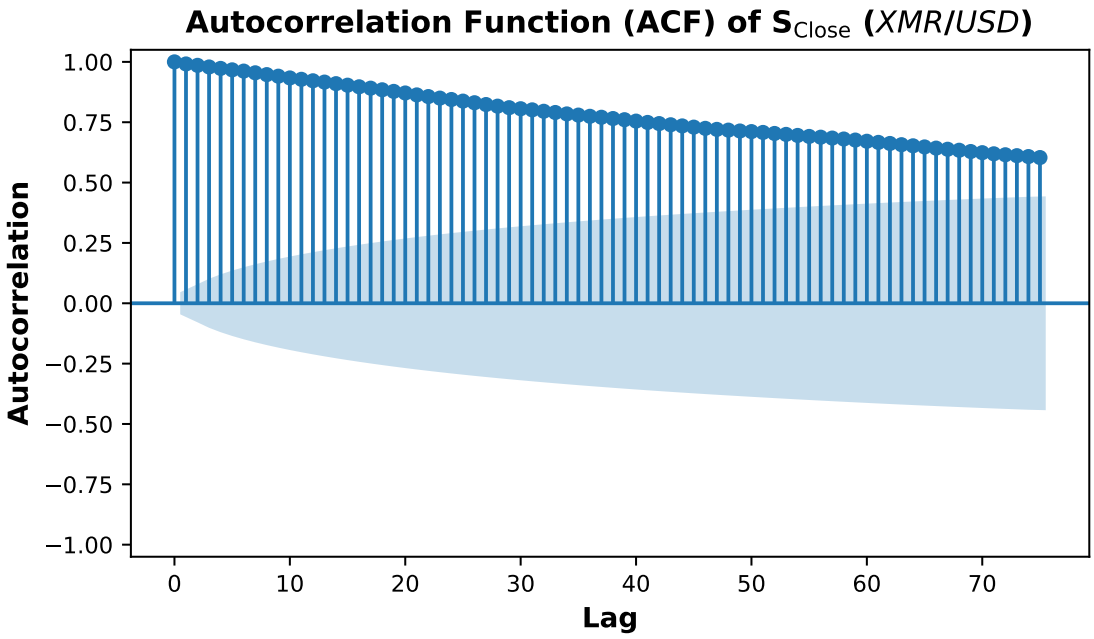


Figure 32: Autocorrelation Function (ACF) of $\mathbf{S}_{\text{Close}}$ with respect to *XMR/USD* in the *benchmark dataset*.

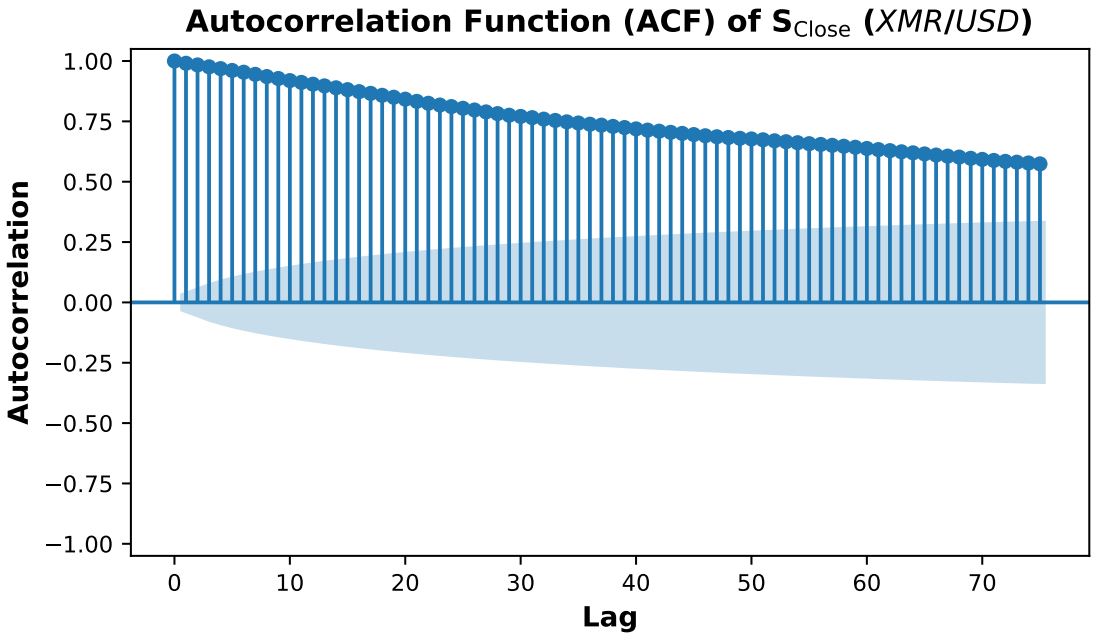


Figure 33: Autocorrelation Function (ACF) of $\mathbf{S}_{\text{Close}}$ with respect to *XMR/USD* in the *extended dataset*.

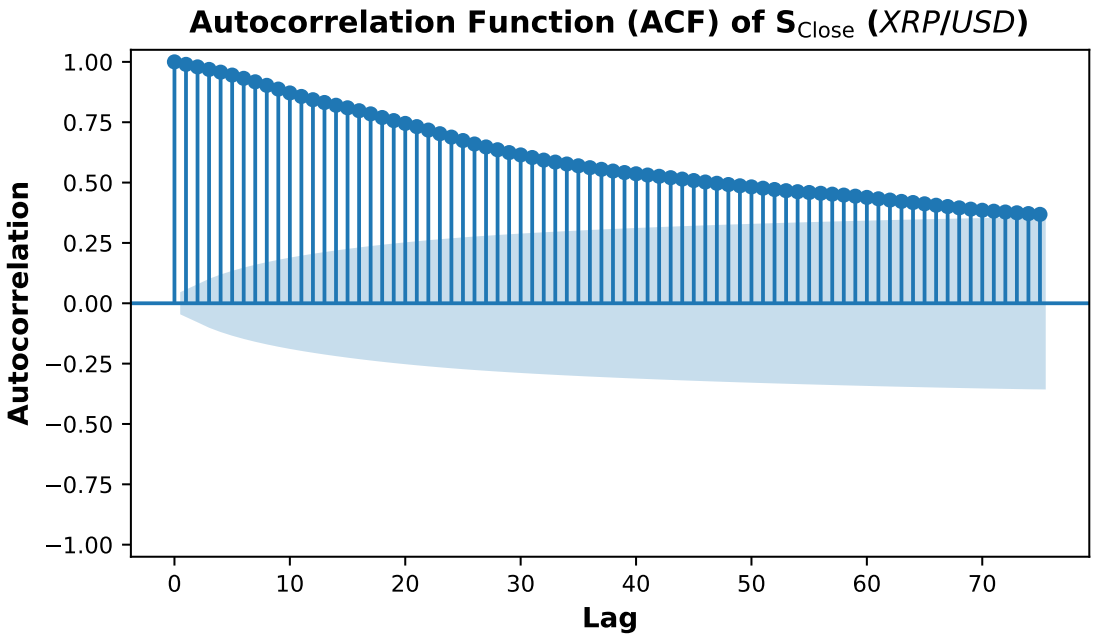


Figure 34: Autocorrelation Function (ACF) of $\mathbf{S}_{\text{Close}}$ with respect to XRP/USD in the *benchmark dataset*.

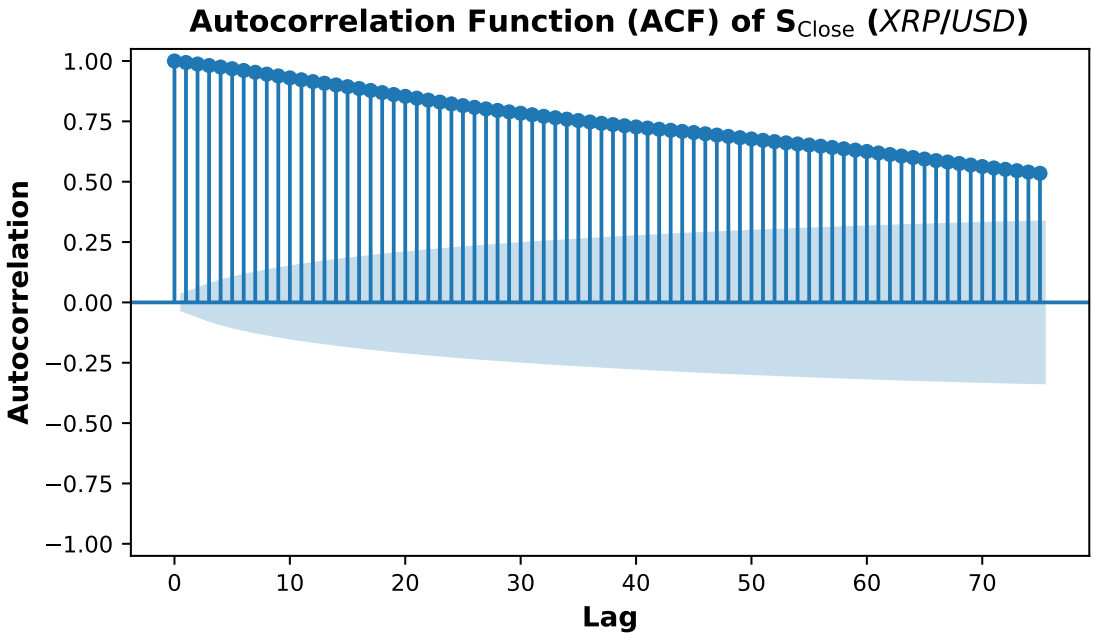


Figure 35: Autocorrelation Function (ACF) of $\mathbf{S}_{\text{Close}}$ with respect to XRP/USD in the *extended dataset*.

C.4.2 PACF Plots

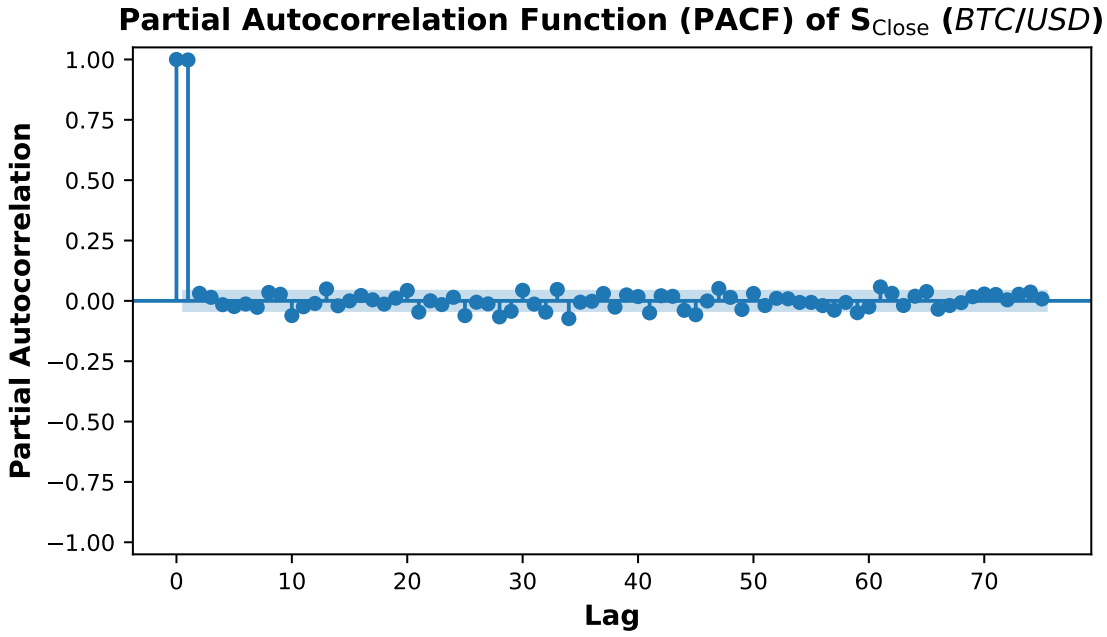


Figure 36: Partial Autocorrelation Function (PACF) of $\mathbf{S}_{\text{Close}}$ with respect to BTC/USD in the *benchmark dataset*.

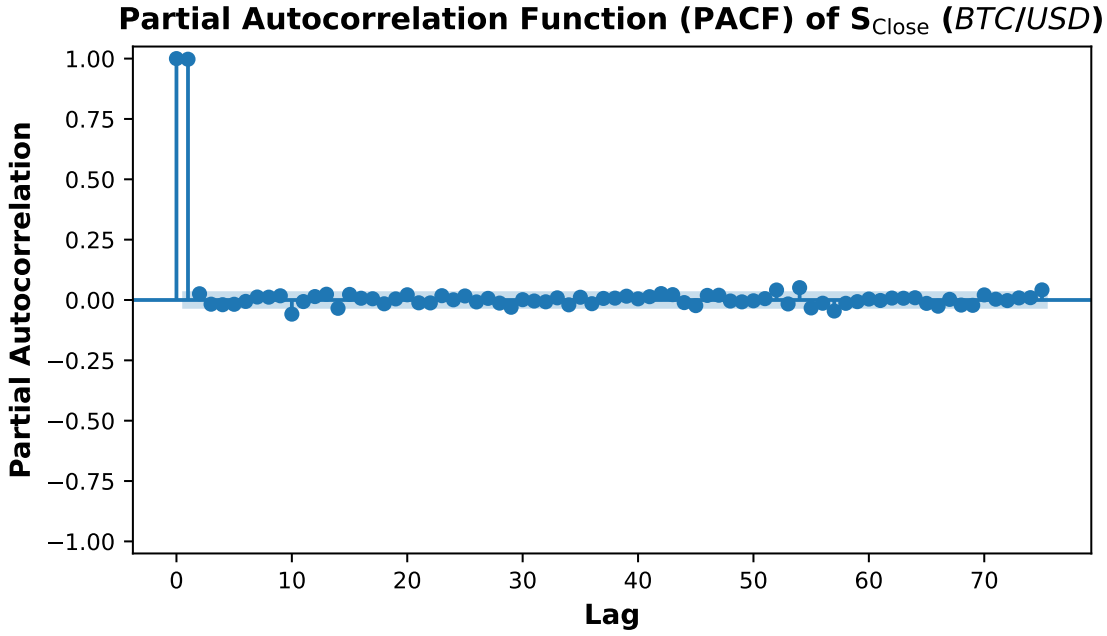


Figure 37: Partial Autocorrelation Function (PACF) of $\mathbf{S}_{\text{Close}}$ with respect to BTC/USD in the *extended dataset*.

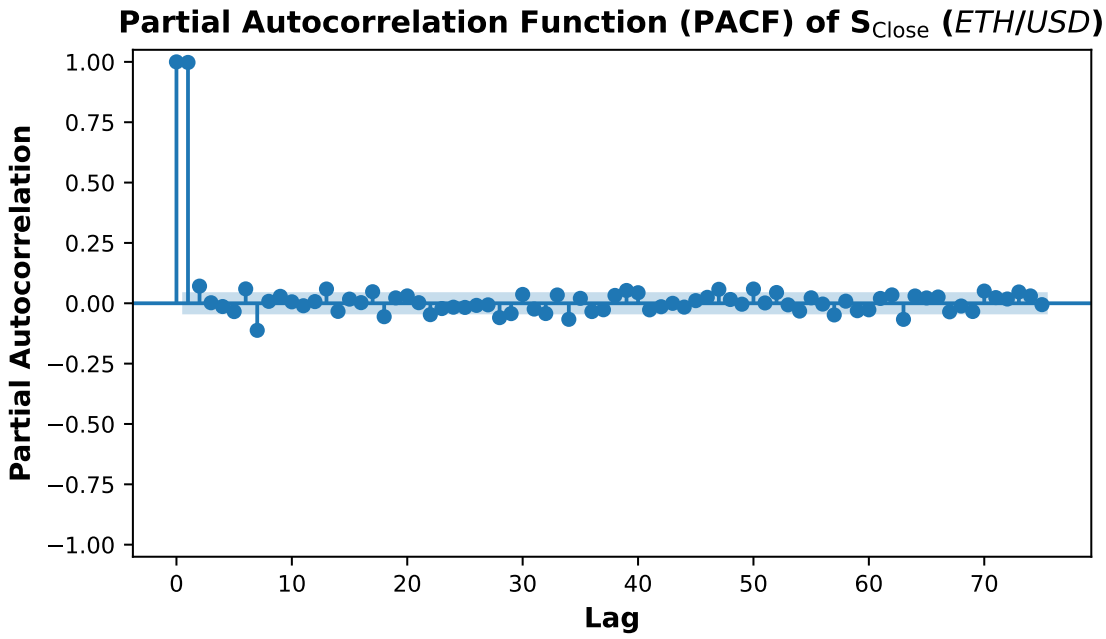


Figure 38: Partial Autocorrelation Function (PACF) of $\mathbf{S}_{\text{Close}}$ with respect to *ETH / USD* in the *benchmark dataset*.

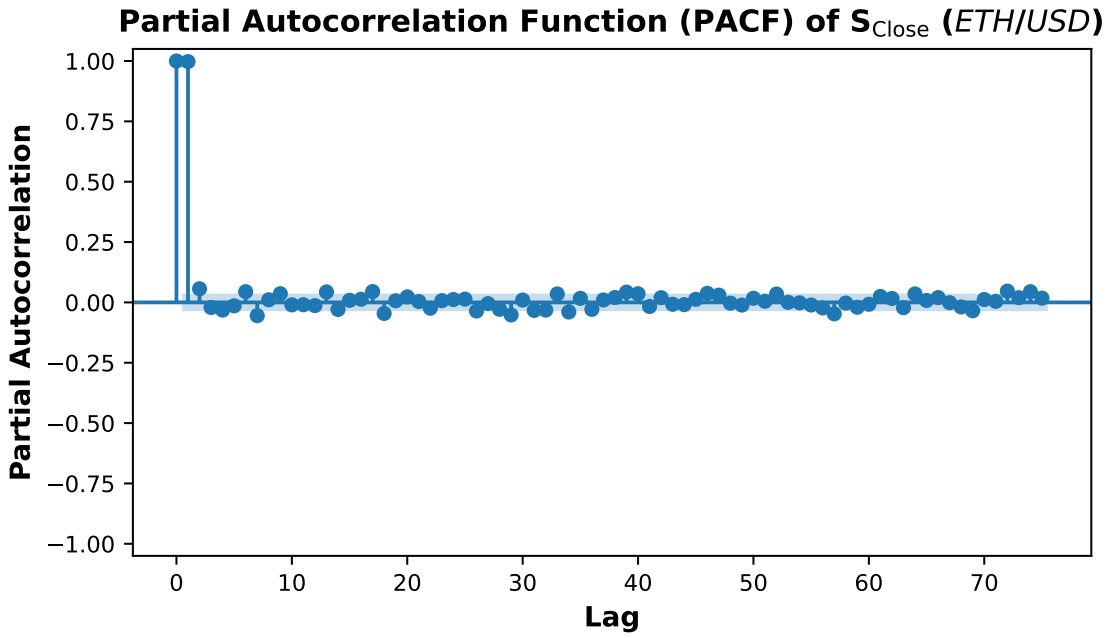


Figure 39: Partial Autocorrelation Function (PACF) of $\mathbf{S}_{\text{Close}}$ with respect to *ETH / USD* in the *extended dataset*.

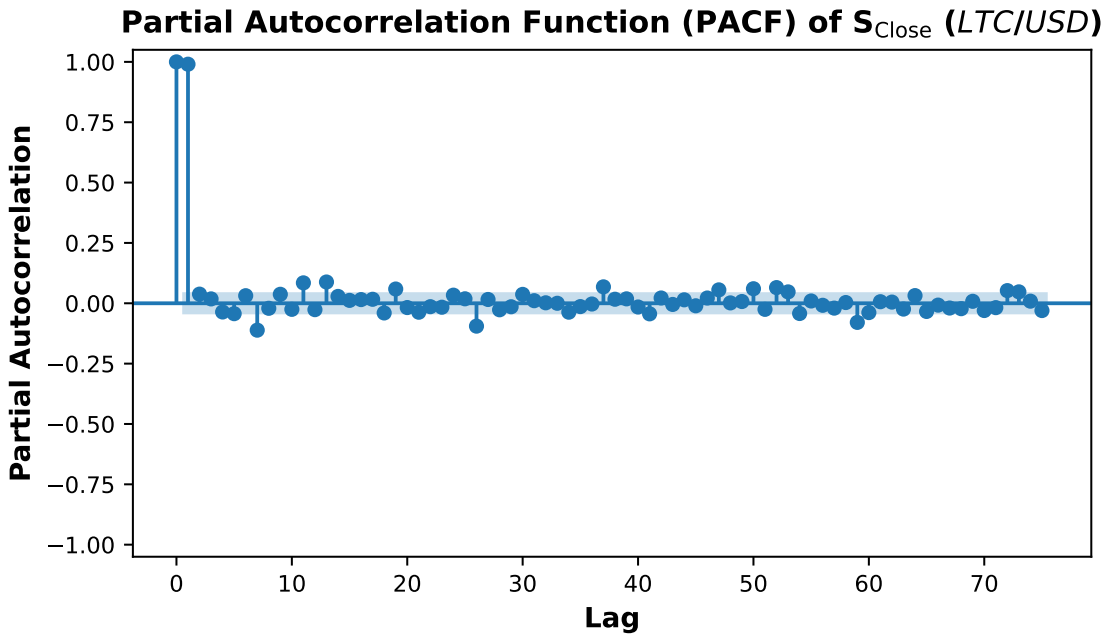


Figure 40: Partial Autocorrelation Function (PACF) of $\mathbf{S}_{\text{Close}}$ with respect to *LTC / USD* in the *benchmark dataset*.

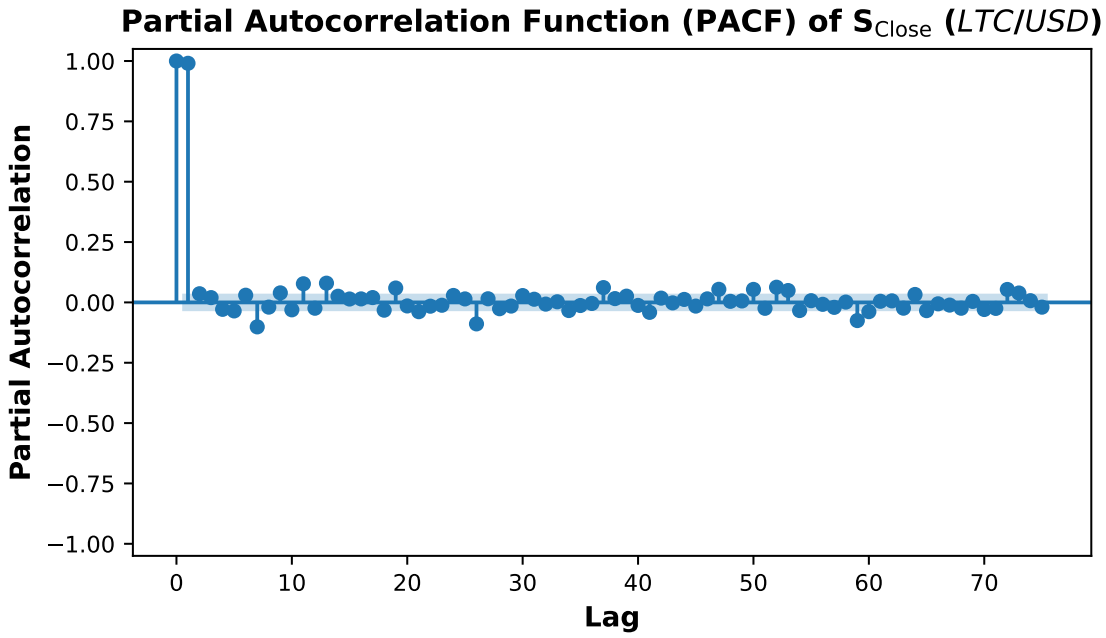


Figure 41: Partial Autocorrelation Function (PACF) of $\mathbf{S}_{\text{Close}}$ with respect to *LTC / USD* in the *extended dataset*.

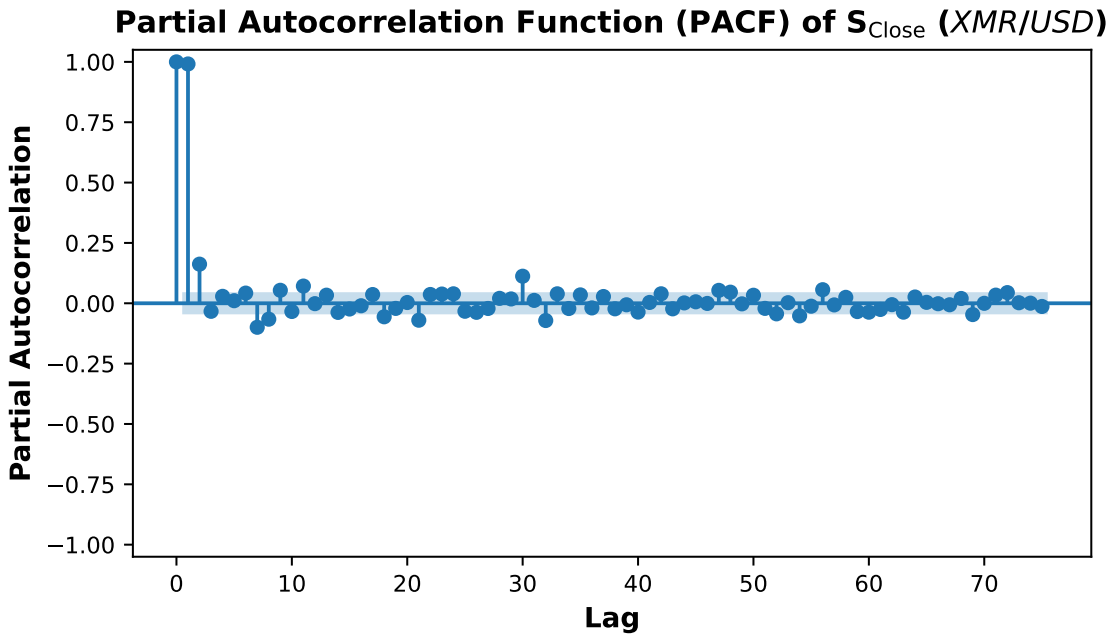


Figure 42: Partial Autocorrelation Function (PACF) of $\mathbf{S}_{\text{Close}}$ with respect to *XMR/USD* in the *benchmark dataset*.

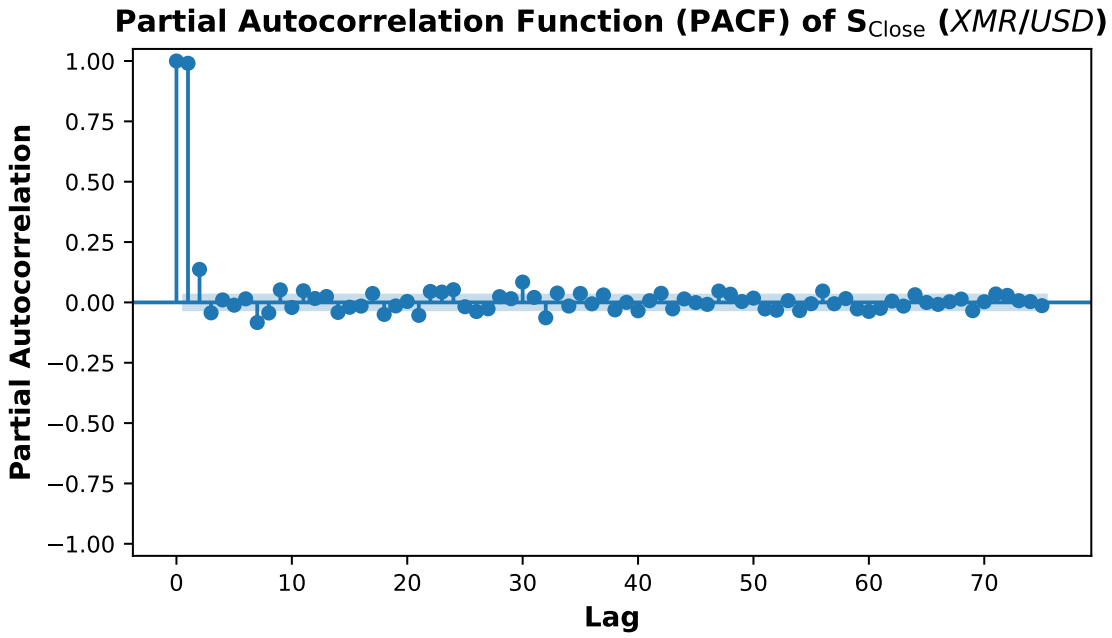


Figure 43: Partial Autocorrelation Function (PACF) of $\mathbf{S}_{\text{Close}}$ with respect to *XMR/USD* in the *extended dataset*.

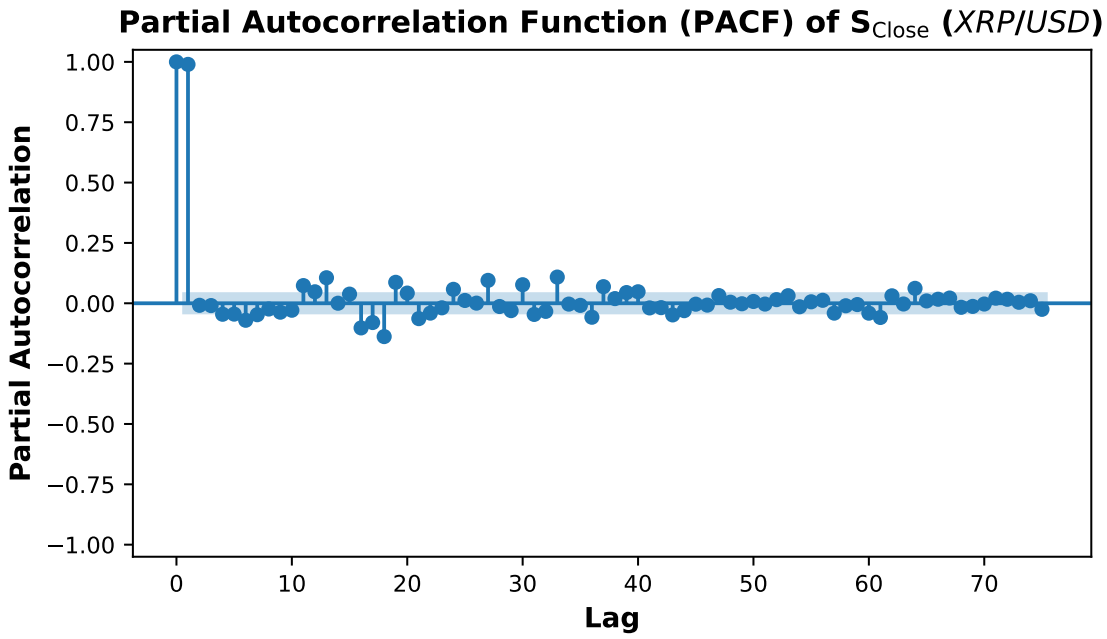


Figure 44: Partial Autocorrelation Function (PACF) of $\mathbf{S}_{\text{Close}}$ with respect to *XRP / USD* in the *benchmark dataset*.

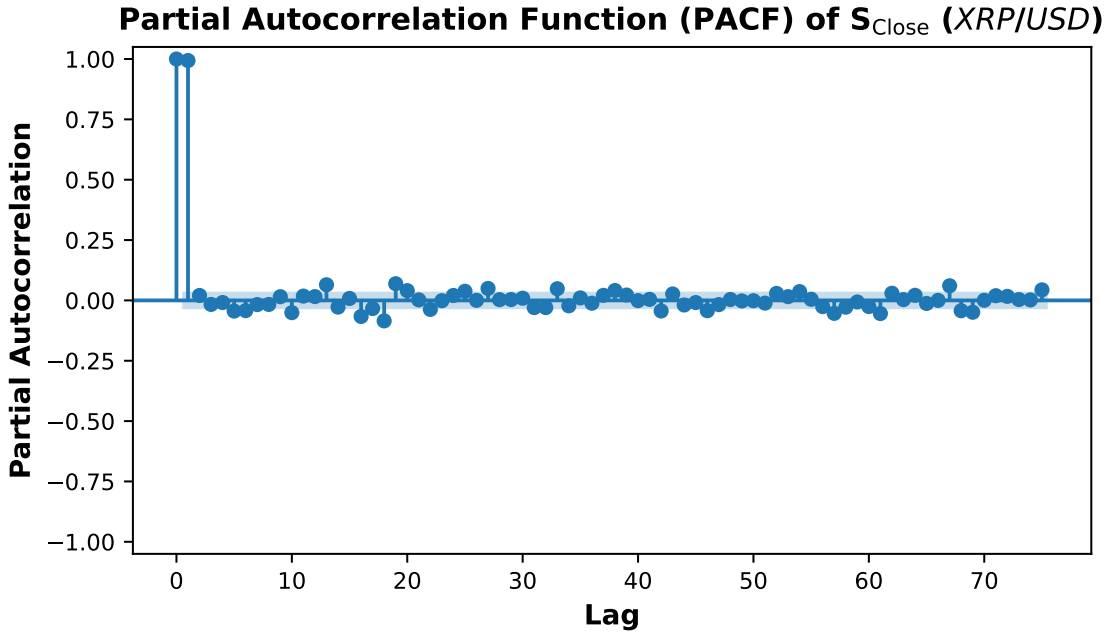


Figure 45: Partial Autocorrelation Function (PACF) of $\mathbf{S}_{\text{Close}}$ with respect to *XRP / USD* in the *extended dataset*.

C.5 Interrelationships

C.5.1 Pearson Correlation

	BTC/USD	***ETH/USD***	***LTC/USD***	***XMR/USD***	***XRP/USD***
BTC/USD	1.000	0.837	0.328	0.554	0.744
ETH/USD	0.837	1.000	0.451	0.613	0.524
LTC/USD	0.328	0.451	1.000	0.824	0.465
XMR/USD	0.554	0.613	0.824	1.000	0.663
XRP/USD	0.744	0.524	0.465	0.663	1.000

Table 32: Pearson Correlation between $\mathbf{S}_{\text{Close}}$ with respect to *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* in the *extended dataset*.

	BTC/USD	***ETH/USD***	***LTC/USD***	***XMR/USD***	***XRP/USD***
BTC/USD	1.000	0.765	0.695	0.641	0.514
ETH/USD	0.765	1.000	0.744	0.645	0.593
LTC/USD	0.695	0.744	1.000	0.602	0.568
XMR/USD	0.641	0.645	0.602	1.000	0.483
XRP/USD	0.514	0.593	0.568	0.483	1.000

Table 33: Pearson Correlation between $\mathbf{S}_{\text{Close}}$ returns with respect to *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* in the *extended dataset*.

C.5.2 Spearman Correlation

	BTC/USD	***ETH/USD***	***LTC/USD***	***XMR/USD***	***XRP/USD***
BTC/USD	1.000	0.910	0.556	0.714	0.719
ETH/USD	0.910	1.000	0.615	0.770	0.771
LTC/USD	0.556	0.615	1.000	0.804	0.736
XMR/USD	0.714	0.770	0.804	1.000	0.837
XRP/USD	0.719	0.771	0.736	0.837	1.000

Table 34: Spearman Correlation between $\mathbf{S}_{\text{Close}}$ with respect to *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* in the *extended dataset*.

	BTC/USD	***ETH/USD***	***LTC/USD***	***XMR/USD***	***XRP/USD***
BTC/USD	1.000	0.772	0.720	0.625	0.651
ETH/USD	0.772	1.000	0.765	0.629	0.716
LTC/USD	0.720	0.765	1.000	0.610	0.698
XMR/USD	0.625	0.629	0.610	1.000	0.573
XRP/USD	0.651	0.716	0.698	0.573	1.000

Table 35: Spearman Correlation between $\mathbf{S}_{\text{Close}}$ returns with respect to *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* in the *extended dataset*.

C.5.3 Granger Causality

Lag	*ETH/USD*	*LTC/USD*	*XMR/USD*	*XRP/USD*
1	0.002075	0.000379	0.002593	0.001774
2	0.000027	0.000132	0.008022	0.000015
3	0.000105	0.000305	0.013370	0.000025
4	0.000322	0.000875	0.017242	0.000053
5	0.000186	0.000062	0.015724	0.000136
6	0.000014	0.000160	0.000937	0.000337
7	0.000000	0.000190	0.001241	0.000034
8	0.000000	0.000243	0.002563	0.000063
9	0.000000	0.000133	0.001853	0.000010
10	0.000000	0.000192	0.003132	0.000000
11	0.000000	0.000091	0.005046	0.000000
12	0.000000	0.000143	0.007777	0.000000
13	0.000000	0.000130	0.014133	0.000000
14	0.000001	0.000022	0.027937	0.000000
15	0.000001	0.000016	0.039358	0.000000
16	0.000002	0.000023	0.033918	0.000000
17	0.000002	0.000059	0.042943	0.000000
18	0.000005	0.000067	0.066012	0.000000
19	0.000010	0.000112	0.078727	0.000000
20	0.000013	0.000211	0.083538	0.000000
21	0.000021	0.000019	0.061674	0.000000
22	0.000009	0.000017	0.033739	0.000000
23	0.000013	0.000023	0.042262	0.000000
24	0.000015	0.000019	0.012344	0.000000
25	0.000011	0.000032	0.019798	0.000000
26	0.000018	0.000058	0.009172	0.000000
27	0.000019	0.000035	0.012745	0.000000
28	0.000003	0.000040	0.004088	0.000000
29	0.000005	0.000038	0.004133	0.000000
30	0.000009	0.000051	0.003403	0.000000

Table 36: Granger Causality between $\mathbf{S}_{\text{Close}}$ with respect to *BTC/USD* and $\mathbf{S}_{\text{Close}}$ with respect to *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* in the *extended dataset*.

Lag	*ETH/USD*	*LTC/USD*	*XMR/USD*	*XRP/USD*
1	0.000005	0.002950	0.026182	0.000052
2	0.000017	0.010193	0.088143	0.000082
3	0.000030	0.021209	0.037246	0.000273
4	0.000009	0.000407	0.008752	0.000528
5	0.000016	0.000738	0.005718	0.000963
6	0.000007	0.000620	0.004296	0.000263
7	0.000007	0.000277	0.002604	0.000382
8	0.000003	0.000139	0.001288	0.000008
9	0.000000	0.000283	0.002692	0.000001
10	0.000000	0.000004	0.004844	0.000000
11	0.000001	0.000009	0.009127	0.000000
12	0.000001	0.000016	0.012845	0.000000
13	0.000000	0.000023	0.028121	0.000000
14	0.000000	0.000014	0.037000	0.000000
15	0.000000	0.000028	0.046082	0.000000
16	0.000000	0.000045	0.020497	0.000000
17	0.000001	0.000102	0.016912	0.000000
18	0.000000	0.000101	0.020768	0.000000
19	0.000000	0.000173	0.026283	0.000000
20	0.000001	0.000166	0.029437	0.000000
21	0.000001	0.000226	0.038361	0.000000
22	0.000002	0.000184	0.052656	0.000000
23	0.000005	0.000478	0.038347	0.000000
24	0.000005	0.000684	0.055991	0.000001
25	0.000005	0.000868	0.055166	0.000001
26	0.000009	0.000628	0.079078	0.000000
27	0.000001	0.000695	0.033553	0.000000
28	0.000000	0.000811	0.040556	0.000001
29	0.000000	0.000893	0.023872	0.000002
30	0.000001	0.000681	0.017986	0.000002

Table 37: Granger Causality between $\mathbf{S}_{\text{Close}}$ returns with respect to *BTC/USD* and $\mathbf{S}_{\text{Close}}$ returns with respect to *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* in the *extended dataset*.

Lag	*BTC/USD*	*LTC/USD*	*XMR/USD*	*XRP/USD*
1	0.043805	0.919133	0.570338	0.469786
2	0.085341	0.641858	0.767828	0.037134
3	0.154377	0.801462	0.883495	0.082628
4	0.065256	0.878397	0.819411	0.054456
5	0.039024	0.948635	0.535337	0.053767
6	0.001322	0.799376	0.725133	0.018529
7	0.000000	0.780959	0.505360	0.026111
8	0.000000	0.544214	0.536760	0.005742
9	0.000000	0.044308	0.195229	0.001561
10	0.000000	0.002935	0.058098	0.000000
11	0.000000	0.001013	0.063535	0.000000
12	0.000000	0.002172	0.072012	0.000000
13	0.000000	0.000203	0.073888	0.000000
14	0.000000	0.000308	0.114589	0.000000
15	0.000000	0.000411	0.143746	0.000000
16	0.000000	0.000381	0.176822	0.000000
17	0.000000	0.001301	0.197822	0.000000
18	0.000000	0.003309	0.103002	0.000001
19	0.000000	0.002983	0.044229	0.000000
20	0.000000	0.004084	0.047099	0.000000
21	0.000000	0.001113	0.013476	0.000000
22	0.000000	0.000874	0.009910	0.000000
23	0.000000	0.000321	0.014475	0.000000
24	0.000000	0.000473	0.002591	0.000000
25	0.000000	0.000709	0.000162	0.000000
26	0.000000	0.000785	0.000097	0.000000
27	0.000000	0.000859	0.000129	0.000000
28	0.000000	0.000281	0.000116	0.000001
29	0.000000	0.000031	0.000146	0.000000
30	0.000000	0.000044	0.000014	0.000000

Table 38: Granger Causality between $\mathbf{S}_{\text{Close}}$ with respect to *ETH/USD* and $\mathbf{S}_{\text{Close}}$ with respect to *BTC/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* in the *extended dataset*.

Lag	*BTC/USD*	*LTC/USD*	*XMR/USD*	*XRP/USD*
1	0.710977	0.585986	0.110551	0.001741
2	0.701778	0.348076	0.260465	0.006128
3	0.711823	0.383601	0.396676	0.004443
4	0.843802	0.310694	0.046809	0.009734
5	0.386468	0.377900	0.066447	0.017888
6	0.112902	0.290982	0.118501	0.032306
7	0.091511	0.382313	0.150414	0.031219
8	0.122313	0.240022	0.191348	0.002531
9	0.134749	0.041083	0.319054	0.000002
10	0.115249	0.008355	0.452401	0.000002
11	0.130224	0.016827	0.370560	0.000002
12	0.127402	0.018057	0.245454	0.000005
13	0.171527	0.024571	0.397818	0.000010
14	0.166884	0.022408	0.350601	0.000015
15	0.201124	0.037223	0.347811	0.000016
16	0.178357	0.043274	0.448851	0.000027
17	0.021950	0.034936	0.493372	0.000053
18	0.011344	0.048728	0.570198	0.000055
19	0.008935	0.050827	0.397366	0.000072
20	0.009627	0.086861	0.480186	0.000247
21	0.001216	0.104716	0.486664	0.000304
22	0.000306	0.097220	0.432160	0.000444
23	0.000629	0.122245	0.527797	0.000651
24	0.000191	0.145597	0.564163	0.001064
25	0.000312	0.133299	0.629218	0.001526
26	0.000442	0.082374	0.643126	0.002221
27	0.000222	0.061502	0.686904	0.002299
28	0.000052	0.017559	0.617111	0.000873
29	0.000054	0.024528	0.425936	0.000770
30	0.000067	0.018232	0.265106	0.000478

Table 39: Granger Causality between $\mathbf{S}_{\text{Close}}$ returns with respect to *ETH/USD* and $\mathbf{S}_{\text{Close}}$ returns with respect to *BTC/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* in the *extended dataset*.

Lag	*BTC/USD*	*ETH/USD*	*XMR/USD*	*XRP/USD*
1	0.339336	0.945705	0.360693	0.614041
2	0.058390	0.957315	0.334396	0.003010
3	0.038558	0.060893	0.487952	0.000502
4	0.074483	0.095494	0.003201	0.000160
5	0.128914	0.130721	0.001514	0.000342
6	0.058497	0.003340	0.001643	0.000616
7	0.041783	0.001284	0.000431	0.000976
8	0.060585	0.000393	0.000488	0.002335
9	0.104535	0.000391	0.000606	0.002548
10	0.097447	0.000007	0.000759	0.002062
11	0.024669	0.000000	0.000551	0.004188
12	0.011451	0.000001	0.000007	0.001802
13	0.015753	0.000000	0.000006	0.001238
14	0.007406	0.000000	0.000003	0.002021
15	0.003742	0.000000	0.000005	0.003021
16	0.004333	0.000001	0.000007	0.001078
17	0.007336	0.000001	0.000014	0.001822
18	0.009145	0.000003	0.000000	0.001646
19	0.016376	0.000010	0.000000	0.000029
20	0.007298	0.000009	0.000000	0.000006
21	0.006920	0.000017	0.000000	0.000018
22	0.008343	0.000030	0.000000	0.000017
23	0.011526	0.000049	0.000000	0.000003
24	0.015191	0.000052	0.000000	0.000007
25	0.005856	0.000072	0.000000	0.000009
26	0.011127	0.000097	0.000000	0.000075
27	0.010242	0.000116	0.000000	0.000031
28	0.009972	0.000101	0.000000	0.000020
29	0.006712	0.000162	0.000000	0.000012
30	0.006569	0.000139	0.000000	0.000017

Table 40: Granger Causality between $\mathbf{S}_{\text{Close}}$ with respect to *LTC/USD* and $\mathbf{S}_{\text{Close}}$ with respect to *BTC/USD*, *ETH/USD*, *XMR/USD*, and *XRP/USD* in the *extended dataset*.

Lag	*BTC/USD*	*ETH/USD*	*XMR/USD*	*XRP/USD*
1	0.401083	0.001951	0.001901	0.001077
2	0.266066	0.004626	0.008525	0.003819
3	0.424098	0.004721	0.003816	0.008133
4	0.588205	0.007752	0.002466	0.011421
5	0.004839	0.016588	0.006825	0.023952
6	0.005025	0.011851	0.000149	0.033337
7	0.009208	0.016235	0.000364	0.056575
8	0.007224	0.024416	0.000518	0.035636
9	0.010754	0.000880	0.000226	0.005033
10	0.003368	0.000024	0.000067	0.006696
11	0.001262	0.000026	0.000001	0.004419
12	0.001588	0.000014	0.000001	0.006061
13	0.002293	0.000021	0.000002	0.010620
14	0.003338	0.000018	0.000002	0.014169
15	0.005590	0.000093	0.000006	0.023978
16	0.005171	0.000152	0.000037	0.040502
17	0.004512	0.000192	0.000040	0.032214
18	0.002038	0.000255	0.000070	0.022178
19	0.003131	0.000219	0.000149	0.031724
20	0.005126	0.000441	0.000247	0.040367
21	0.004986	0.000942	0.000364	0.062011
22	0.004541	0.001161	0.000557	0.057110
23	0.008233	0.001843	0.000331	0.082272
24	0.009039	0.002296	0.000519	0.080942
25	0.009824	0.000364	0.000746	0.090836
26	0.007711	0.000500	0.000747	0.068817
27	0.007920	0.000878	0.000890	0.094409
28	0.011406	0.001110	0.001025	0.085076
29	0.004624	0.000296	0.000171	0.101047
30	0.002058	0.000181	0.000157	0.072812

Table 41: Granger Causality between $\mathbf{S}_{\text{Close}}$ returns with respect to *LTC/USD* and $\mathbf{S}_{\text{Close}}$ returns with respect to *BTC/USD*, *ETH/USD*, *XMR/USD*, and *XRP/USD* in the *extended dataset*.

Lag	*BTC/USD*	*ETH/USD*	*LTC/USD*	*XRP/USD*
1	0.006406	0.415075	0.104943	0.032435
2	0.017992	0.876424	0.336730	0.055157
3	0.042914	0.466273	0.000000	0.010285
4	0.039185	0.461799	0.000000	0.001761
5	0.048644	0.533930	0.000000	0.000437
6	0.055123	0.271799	0.000000	0.000207
7	0.062488	0.221997	0.000000	0.000000
8	0.053394	0.198803	0.000000	0.000000
9	0.075343	0.335460	0.000000	0.000000
10	0.097358	0.043694	0.000000	0.000000
11	0.057802	0.003569	0.000000	0.000000
12	0.036545	0.005753	0.000000	0.000000
13	0.022058	0.008902	0.000000	0.000000
14	0.031428	0.012132	0.000000	0.000000
15	0.017119	0.004604	0.000000	0.000000
16	0.020732	0.006563	0.000000	0.000000
17	0.029273	0.003914	0.000000	0.000000
18	0.030274	0.003925	0.000000	0.000000
19	0.031374	0.001861	0.000000	0.000000
20	0.017603	0.001190	0.000000	0.000000
21	0.027223	0.002493	0.000000	0.000000
22	0.027284	0.002528	0.000000	0.000000
23	0.039142	0.003098	0.000000	0.000000
24	0.048436	0.004747	0.000000	0.000000
25	0.045683	0.007415	0.000000	0.000000
26	0.007562	0.000742	0.000000	0.000000
27	0.010200	0.001288	0.000000	0.000000
28	0.012192	0.001527	0.000000	0.000000
29	0.007910	0.001466	0.000000	0.000000
30	0.003182	0.002816	0.000000	0.000000

Table 42: Granger Causality between $\mathbf{S}_{\text{Close}}$ with respect to *XMR/USD* and $\mathbf{S}_{\text{Close}}$ with respect to *BTC/USD*, *ETH/USD*, *LTC/USD*, and *XRP/USD* in the *extended dataset*.

Lag	*BTC/USD*	*ETH/USD*	*LTC/USD*	*XRP/USD*
1	0.866715	0.966651	0.327344	0.150295
2	0.345915	0.824710	0.050861	0.260589
3	0.543444	0.848578	0.089087	0.155005
4	0.589622	0.502051	0.148067	0.217937
5	0.456714	0.639113	0.113295	0.117134
6	0.610606	0.690133	0.194630	0.000245
7	0.478035	0.751313	0.246837	0.000314
8	0.477839	0.757436	0.266597	0.000027
9	0.361892	0.789922	0.128526	0.000002
10	0.376816	0.590859	0.092882	0.000002
11	0.435050	0.633781	0.095285	0.000003
12	0.518014	0.665949	0.131894	0.000006
13	0.613078	0.636021	0.055732	0.000011
14	0.673523	0.566805	0.066125	0.000022
15	0.604321	0.541023	0.101993	0.000021
16	0.644500	0.598275	0.129845	0.000034
17	0.557574	0.587201	0.133766	0.000051
18	0.588438	0.553416	0.065399	0.000044
19	0.629332	0.589373	0.023922	0.000076
20	0.538175	0.432615	0.032977	0.000116
21	0.509541	0.449725	0.038273	0.000187
22	0.578012	0.400876	0.050462	0.000282
23	0.699918	0.502744	0.046479	0.000284
24	0.743687	0.571255	0.051300	0.000397
25	0.591792	0.373785	0.023609	0.000492
26	0.656361	0.389528	0.032046	0.000350
27	0.717175	0.238346	0.039770	0.000451
28	0.726875	0.119153	0.057336	0.000602
29	0.668033	0.117562	0.066739	0.000285
30	0.545066	0.119573	0.094306	0.000195

Table 43: Granger Causality between $\mathbf{S}_{\text{Close}}$ returns with respect to *XMR/USD* and $\mathbf{S}_{\text{Close}}$ returns with respect to *BTC/USD*, *ETH/USD*, *LTC/USD*, and *XRP/USD* in the *extended dataset*.

Lag	*BTC/USD*	*ETH/USD*	*LTC/USD*	*XMR/USD*
1	0.000149	0.391375	0.722082	0.793092
2	0.000544	0.033867	0.005936	0.123179
3	0.001754	0.075403	0.000131	0.201612
4	0.004367	0.134163	0.000345	0.313274
5	0.003073	0.100500	0.000741	0.422012
6	0.001665	0.011710	0.000753	0.012866
7	0.000030	0.024642	0.001911	0.024148
8	0.000034	0.012767	0.000017	0.000281
9	0.000044	0.016071	0.000000	0.000008
10	0.000082	0.034577	0.000000	0.000000
11	0.000000	0.000698	0.000000	0.000000
12	0.000000	0.000424	0.000000	0.000000
13	0.000000	0.000887	0.000000	0.000000
14	0.000000	0.001914	0.000000	0.000000
15	0.000000	0.001943	0.000000	0.000000
16	0.000000	0.000368	0.000000	0.000000
17	0.000000	0.000363	0.000000	0.000000
18	0.000000	0.000625	0.000000	0.000000
19	0.000000	0.000972	0.000000	0.000000
20	0.000000	0.001115	0.000000	0.000000
21	0.000000	0.001872	0.000000	0.000000
22	0.000000	0.002716	0.000000	0.000000
23	0.000000	0.003788	0.000000	0.000000
24	0.000000	0.005219	0.000000	0.000000
25	0.000000	0.006297	0.000000	0.000000
26	0.000000	0.004835	0.000000	0.000000
27	0.000000	0.013995	0.000000	0.000000
28	0.000000	0.014185	0.000000	0.000000
29	0.000000	0.020286	0.000000	0.000000
30	0.000000	0.025864	0.000000	0.000000

Table 44: Granger Causality between $\mathbf{S}_{\text{Close}}$ with respect to *XRP/USD* and $\mathbf{S}_{\text{Close}}$ with respect to *BTC/USD*, *ETH/USD*, *LTC/USD*, and *XMR/USD* in the *extended dataset*.

Lag	*BTC/USD*	*ETH/USD*	*LTC/USD*	*XMR/USD*
1	0.004390	0.023668	0.007793	0.010474
2	0.026316	0.069436	0.000000	0.037324
3	0.016466	0.077238	0.000000	0.056258
4	0.015954	0.103986	0.000000	0.094216
5	0.039733	0.115086	0.000000	0.017916
6	0.067173	0.184230	0.000001	0.047451
7	0.114393	0.008328	0.000000	0.010063
8	0.162261	0.012047	0.000000	0.013841
9	0.077977	0.011840	0.000000	0.019408
10	0.041035	0.000062	0.000000	0.009046
11	0.030790	0.000021	0.000000	0.004802
12	0.040395	0.000049	0.000000	0.007019
13	0.038131	0.000056	0.000000	0.006027
14	0.053589	0.000052	0.000000	0.007516
15	0.067725	0.000120	0.000000	0.018234
16	0.077907	0.000152	0.000000	0.027276
17	0.038153	0.000125	0.000000	0.025847
18	0.012124	0.000284	0.000000	0.041795
19	0.021543	0.000636	0.000000	0.046138
20	0.024892	0.000380	0.000000	0.050566
21	0.008304	0.000627	0.000000	0.064695
22	0.008208	0.000816	0.000000	0.081108
23	0.011023	0.000658	0.000000	0.040950
24	0.004775	0.001079	0.000000	0.028707
25	0.002124	0.000442	0.000000	0.024544
26	0.002322	0.000837	0.000000	0.023526
27	0.002367	0.001073	0.000000	0.031828
28	0.000274	0.001426	0.000000	0.042267
29	0.000505	0.000755	0.000000	0.036658
30	0.000768	0.000840	0.000000	0.044078

Table 45: Granger Causality between $\mathbf{S}_{\text{Close}}$ returns with respect to *XRP/USD* and $\mathbf{S}_{\text{Close}}$ returns with respect to *BTC/USD*, *ETH/USD*, *LTC/USD*, and *XMR/USD* at a daily frequency from 1 June 2017 to 31 May 2025.

D Hyperparameters

D.1 Benchmark Framework

Model	Python Library	Hyperparameter	Value
ARIMA	*StatsModels* [239]	p	1
		d	0
		q	2
CNN-LSTM	*TensorFlow* [204]	1D-Convolutional N Layers	1
		1D-Convolutional Layer N Kernels	64
		1D-Convolutional Layer Kernel Size	5
		1D-Convolutional Layer Activation	ReLU
		LSTM N Layers	1
		LSTM N Units	75
		Dense N Layers	1
		Dense N Units	16
		Dense Layer Activation	ReLU
		Learning Rate	1×10^{-4}
		Weight Decay	1×10^{-3}
GRU	*TensorFlow* [204]	GRU N Layers	1
		GRU N Units	75
		GRU Layer Activation	ReLU
		Dense N Layers	1
		Dense N Units	100
		Dense Layer Activation	ReLU
		Learning Rate	1×10^{-3}
		Weight Decay	1×10^{-3}
KNN	*Scikit-Learn* [240]	N Neighbours	28
		Weights	Uniform
		Algorithm	Brute
		p	2
LSTM-GRU	*TensorFlow* [204]	LSTM Layers	2
		LSTM N Units First Layer	75
		LSTM N Units Second Layer	50
		LSTM Layer Activation	ReLU
		Dropout Rate between LSTM Layers	0.05
		Dense N Units of Layer after LSTM	32
		Dense Layer Activation after LSTM	ReLU
		GRU N Layers	1
		GRU N Units	50
		GRU Layer Activation	ReLU
		Dropout Rate between GRU and Dense	0.0
		Dense N Layers after GRU	1
		Dense N Units Layer after GRU	64
		Dense Layer Activation after GRU	ReLU
		Learning Rate	1×10^{-3}
		Weight Decay	1×10^{-3}
RF	*Scikit-Learn* [240]	N Estimators	200
		Criterion	Squared Error
		Max Depth	100
		Max Features	Square Root

Model	Python Library	Hyperparameters	Values
		Bootstrap	True
SVR	*Scikit-Learn* [240]	Kernel	Polynomial
		Degree	5
		Gamma	Auto
		Tolerance	0.001
		C	100
TCN	*TensorFlow* [204]	1D-Convolutional N Layers	4
		1D-Convolutional Layer N Kernels	32
		1D-Convolutional Layer Kernel Size	16
		1D-Convolutional Layer Dilation Rate	8
		1D-Convolutional Layer Activation	ReLU
		Dropout Rate after 1D-Convolutional Layers	0.05
		Dense N Layers	1
		Dense N Units	64
		Dense Layer Activation	ReLU
		Learning Rate	1×10^{-4}
		Weight Decay	1×10^{-3}
TFT	*Darts* [241]	Input Length	30
		Output Length	1
		LSTM N Layers	3
		Hidden Size	64
		Attention N Heads	7
		Feed Forward Network	Gated Residual Network
		Dropout Rate	0.05
		Learning Rate	1×10^{-3}

Table 46: The hyperparameters of each model applied as part of the benchmark framework adopted by Murray et al. [27].

D.2 Novel Framework

Crypto	K	α	τ
BTC/USD	6	213	0.065
ETH/USD	4	480	0.204
LTC/USD	3	285	0.142
XMR/USD	8	1266	0.166
XRP/USD	4	326	0.016

Table 47: The VMD hyperparameters per cryptocurrency for the leakage-free VMD application method EVMD determined through the hyperparameter tuning process detailed in Section 5.5.

Crypto	K	α	τ
BTC/USD	4	397	0.135
ETH/USD	4	462	0.166
LTC/USD	3	226	0.197
XMR/USD	3	273	0.300
XRP/USD	4	254	0.054

Table 48: The VMD hyperparameters per cryptocurrency for the leakage-free VMD application method SVMD determined through the hyperparameter tuning process detailed in Section 5.5.

Model	D	k	F_{out}	r	p	Act.	N_{head}	p_{MHA}	u
TCN [27]	4	16	32	8	0.05	ReLU	-	-	64
Differenced-TCN [27]	4	16	32	8	0.05	ReLU	-	-	64
TCN	2	6	64	-	0.213	SiLU	-	-	-
Differenced-TCN	2	2	96	-	0.046	SiLU	-	-	-
CMHA-TCN	2	5	48	-	0.284	SiLU	4	0.185	-
Differenced-CMHA-TCN	2	2	96	-	0.097	SiLU	4	0.157	-
EVMD-TCN	2	2	48	-	0.227	ELU	-	-	-
EVMD-CMHA-TCN	3	2	32	-	0.299	GELU	2	0.156	-
EVMD-PMB-TCN	2	5	16	-	0.226	SiLU	-	-	-
EVMD-PMB-CMHA-TCN	2	2	32	-	0.051	SiLU	4	0.065	-
SVMD-TCN	3	3	32	-	0.238	ELU	-	-	-
SVMD-CMHA-TCN	4	5	16	-	0.268	GELU	2	0.233	-
SVMD-PMB-TCN	2	4	16	-	0.281	GELU	-	-	-
SVMD-PMB-CMHA-TCN	2	2	32	-	0.149	SiLU	2	0.079	-

Table 49: The architectural hyperparameters of each model determined through the hyperparameter tuning process detailed in Section 5.5, with the exception of the hyperparameters of TCN [27] and Differenced-TCN [27].

Model	η	λ	c
TCN [27]	1.0×10^{-4}	1.0×10^{-3}	-
Differenced-TCN [27]	1.0×10^{-4}	1.0×10^{-3}	-
TCN	2.691×10^{-3}	2.005×10^{-4}	2.208
Differenced-TCN	3.013×10^{-3}	2.521×10^{-3}	2.914
CMHA-TCN	2.372×10^{-3}	4.153×10^{-4}	2.943
Differenced-CMHA-TCN	4.240×10^{-3}	1.037×10^{-5}	4.107
EVMD-TCN	3.274×10^{-3}	1.430×10^{-5}	0.730
EVMD-CMHA-TCN	4.510×10^{-3}	7.436×10^{-5}	0.825
EVMD-PMB-TCN	1.263×10^{-3}	2.031×10^{-5}	3.827
EVMD-PMB-CMHA-TCN	3.301×10^{-3}	1.407×10^{-5}	4.277
SVMD-TCN	4.978×10^{-3}	1.468×10^{-5}	2.530
SVMD-CMHA-TCN	3.611×10^{-3}	2.286×10^{-5}	0.785
SVMD-PMB-TCN	2.414×10^{-3}	1.648×10^{-5}	4.088
SVMD-PMB-CMHA-TCN	3.403×10^{-3}	1.336×10^{-5}	4.102

Table 50: The training hyperparameters of each model determined through the hyperparameter tuning process detailed in Section 5.5, with the exception of the hyperparameters of TCN [27] and Differenced-TCN [27].

E Supplementary Benchmark Experimental Results

E.1 *BTC/USD* Results

Type	Model	NRMSE	NMAE	NMAPE (%)	RMSE	MAE	MAPE (%)	R^2
Reported	ARIMA	0.0251	-	-	-	-	-	-
	CNN-LSTM	**0.0239**	-	-	-	-	-	-
	GRU	0.0245	-	-	-	-	-	-
	KNN	0.0249	-	-	-	-	-	-
	LSTM-GRU	0.0246	-	-	-	-	-	-
	RF	0.0266	-	-	-	-	-	-
	SVR	0.0248	-	-	-	-	-	-
	TCN	0.0250	-	-	-	-	-	-
	TFT	0.0249	-	-	-	-	-	-
Original	ARIMA	0.0251	0.0190	2.855	1549.809	1173.462	2.723	0.723
	CNN-LSTM	**0.0239**	**0.0185**	**2.779**	**1471.549**	**1141.633**	**2.650**	**0.750**
	GRU	0.0243	0.0187	2.797	1500.678	1151.110	2.667	0.740
	KNN	0.0250	0.0191	2.859	1538.779	1171.908	2.726	0.727
	LSTM-GRU	0.0243	0.0187	2.796	1500.376	1150.648	2.667	0.740
	RF	0.0261	0.0198	2.988	1606.387	1222.086	2.849	0.699
	SVR	0.0248	0.0191	2.869	1530.912	1175.267	2.735	0.730
	TCN	0.0250	0.0190	2.860	1541.757	1174.335	2.728	0.728
	TFT	0.0251	0.0191	2.872	1550.430	1177.979	2.738	0.725
Revised	ARIMA	0.0641	0.0492	2.870	1560.229	1180.500	2.737	0.717
	CNN-LSTM	0.0617	0.0485	2.950	1559.230	1209.701	2.813	0.718
	GRU	0.0618	0.0480	2.912	1563.429	1198.962	2.777	0.719
	KNN	**0.0607**	**0.0471**	2.860	**1537.183**	1174.424	2.728	**0.727**
	LSTM-GRU	0.0624	0.0484	2.932	1582.806	1209.201	2.797	0.713
	RF	0.0621	0.0483	2.955	1583.614	1213.536	2.818	0.710
	SVR	0.0625	0.0482	2.906	1575.853	1193.543	2.771	0.713
	TCN	0.0611	**0.0471**	**2.856**	1542.733	**1173.482**	**2.724**	0.726
	TFT	0.0613	0.0474	2.934	1557.251	1195.408	2.797	0.722

Table 51: Average results of the *benchmark experiments* across 3 repetitions and splits $M_1, \ldots, M_{12}$ in relation to forecasting $\mathbf{S}_{\text{Close}}$ with respect to BTC/USD using the benchmark framework proposed by Murray et al. [27].

E.2 *ETH / USD* Results

Type	Model	NRMSE	NMAE	NMAPE (%)	RMSE	MAE	MAPE (%)	R^2
Reported	ARIMA	0.0320	-	-	-	-	-	-
	CNN-LSTM	**0.030**	-	-	-	-	-	-
	GRU	0.0309	-	-	-	-	-	-
	KNN	0.0319	-	-	-	-	-	-
	LSTM-GRU	0.0309	-	-	-	-	-	-
	RF	0.0332	-	-	-	-	-	-
	SVR	0.0342	-	-	-	-	-	-
	TCN	0.0319	-	-	-	-	-	-
	TFT	0.0319	-	-	-	-	-	-
Original	ARIMA	0.0320	0.0253	3.534	130.735	103.435	3.429	0.726
	CNN-LSTM	**0.0303**	**0.0243**	**3.390**	**123.993**	**99.446**	**3.289**	**0.749**
	GRU	0.0309	0.0245	3.412	126.224	100.340	3.311	0.740
	KNN	0.0319	0.0254	3.547	130.371	104.007	3.443	0.727
	LSTM-GRU	0.0309	0.0245	3.413	126.181	100.392	3.312	0.740
	RF	0.0333	0.0260	3.629	136.073	106.224	3.522	0.703
	SVR	0.0342	0.0275	3.838	139.823	112.386	3.725	0.686
	TCN	0.0319	0.0254	3.546	130.276	103.880	3.441	0.728
	TFT	0.0319	0.0253	3.536	130.396	103.526	3.431	0.728
Revised	ARIMA	0.0886	0.0702	3.537	130.437	103.575	3.433	0.727
	CNN-LSTM	0.0902	0.0730	3.741	136.254	110.313	3.631	0.702
	GRU	0.0881	0.0690	3.592	134.175	105.055	3.485	0.715
	KNN	0.0860	0.0686	3.570	130.680	104.434	3.464	0.726
	LSTM-GRU	0.0883	0.0695	3.627	134.651	105.926	3.519	0.715
	RF	0.0866	0.0684	3.591	132.077	104.457	3.484	0.727
	SVR	0.0939	0.0752	3.859	139.073	107.089	3.565	0.701
	TCN	0.0858	0.0681	3.539	130.313	103.567	3.434	0.728
	TFT	**0.0856**	**0.0679**	**3.529**	**130.012**	**103.253**	**3.424**	**0.729**

Table 52: Average results of the *benchmark experiments* across 3 repetitions and splits $M_1, \ldots, M_{12}$ in relation to forecasting $\mathbf{S}_{\text{Close}}$ with respect to *ETH / USD* using the benchmark framework proposed by Murray et al. [27].

E.3 *LTC / USD* Results

Type	Model	NRMSE	NMAE	NMAPE (%)	RMSE	MAE	MAPE (%)	R^2
Reported	ARIMA	0.0198	-	-	-	-	-	-
	CNN-LSTM	**0.0189**	-	-	-	-	-	-
	GRU	0.0193	-	-	-	-	-	-
	KNN	0.0197	-	-	-	-	-	-
	LSTM-GRU	0.0195	-	-	-	-	-	-
	RF	0.0199	-	-	-	-	-	-
	SVR	0.0207	-	-	-	-	-	-
	TCN	0.0198	-	-	-	-	-	-
	TFT	0.0199	-	-	-	-	-	-
Original	ARIMA	0.0198	0.0149	4.564	7.218	5.442	3.732	0.752
	CNN-LSTM	**0.0187**	**0.0143**	**4.401**	**6.837**	**5.230**	**3.595**	**0.774**
	GRU	0.0194	0.0146	4.475	7.064	5.329	3.657	0.761
	KNN	0.0197	0.0148	4.543	7.203	5.381	3.710	0.752
	LSTM-GRU	0.0194	0.0147	4.493	7.092	5.354	3.671	0.760
	RF	0.0199	0.0150	4.626	7.265	5.481	3.778	0.749
	SVR	0.0208	0.0155	4.818	7.569	5.637	3.924	0.726
	TCN	0.0198	0.0149	4.584	7.204	5.432	3.744	0.751
	TFT	0.0199	0.0149	4.603	7.267	5.431	3.755	0.746
Revised	ARIMA	0.0220	0.0166	4.594	7.251	5.472	3.759	0.746
	CNN-LSTM	0.0220	0.0167	4.641	7.284	5.536	3.797	0.746
	GRU	0.0217	0.0164	4.547	7.198	5.417	3.718	0.752
	KNN	0.0219	0.0165	4.578	7.256	5.454	3.744	0.748
	LSTM-GRU	**0.0217**	**0.0164**	4.552	**7.173**	5.439	3.723	**0.754**
	RF	0.0226	0.0172	4.739	7.489	5.680	3.875	0.737
	SVR	0.0219	0.0164	4.598	7.263	5.413	3.748	0.747
	TCN	**0.0217**	**0.0164**	**4.522**	7.179	**5.380**	**3.696**	0.753
	TFT	0.0217	0.0164	4.591	7.176	5.437	3.751	0.754

Table 53: Average results of the *benchmark experiments* across 3 repetitions and splits $M_1, \ldots, M_{12}$ in relation to forecasting $\mathbf{S}_{\text{Close}}$ with respect to *LTC / USD* using the benchmark framework proposed by Murray et al. [27].

E.4 *XMR/USD* Results

Type	Model	NRMSE	NMAE	NMAPE (%)	RMSE	MAE	MAPE (%)	R^2
Reported	ARIMA	0.0244	-	-	-	-	-	-
	CNN-LSTM	**0.0236**	-	-	-	-	-	-
	GRU	0.0243	-	-	-	-	-	-
	KNN	0.0245	-	-	-	-	-	-
	LSTM-GRU	0.0244	-	-	-	-	-	-
	RF	0.0251	-	-	-	-	-	-
	SVR	0.0268	-	-	-	-	-	-
	TCN	0.0245	-	-	-	-	-	-
	TFT	0.0250	-	-	-	-	-	-
Original	ARIMA	0.0244	0.0188	4.536	11.119	8.569	3.905	0.649
	CNN-LSTM	**0.0234**	**0.0184**	**4.422**	**10.662**	**8.347**	**3.806**	**0.681**
	GRU	0.0241	0.0187	4.500	10.940	8.495	3.873	0.664
	KNN	0.0245	0.0188	4.551	11.128	8.568	3.915	0.657
	LSTM-GRU	0.0240	0.0187	4.503	10.918	8.511	3.877	0.665
	RF	0.0251	0.0193	4.646	11.423	8.770	3.999	0.640
	SVR	0.0268	0.0205	4.941	12.191	9.334	4.254	0.577
	TCN	0.0245	0.0191	4.603	11.164	8.672	3.961	0.652
	TFT	0.0246	0.0190	4.587	11.196	8.624	3.945	0.650
Revised	ARIMA	0.0249	0.0193	4.548	11.113	8.583	3.914	0.650
	GRU	0.0253	0.0197	4.638	11.306	8.780	3.994	0.642
	CNN-LSTM	0.0254	0.0201	4.744	11.361	8.960	4.084	0.635
	KNN	0.0250	0.0192	4.548	11.154	8.593	3.916	0.646
	LSTM-GRU	0.0252	0.0196	4.639	11.268	8.772	3.994	0.642
	RF	0.0256	0.0198	4.668	11.458	8.845	4.020	0.627
	SVR	**0.0248**	**0.0192**	4.560	**11.081**	8.568	3.922	**0.652**
	TCN	0.0249	0.0192	4.547	11.109	8.591	3.914	0.650
	TFT	0.0250	**0.0192**	**4.542**	11.164	**8.567**	**3.909**	0.648

Table 54: Average results of the *benchmark experiments* across 3 repetitions and splits $M_1, \ldots, M_{12}$ in relation to forecasting $\mathbf{S}_{\text{Close}}$ with respect to *XMR/USD* using the benchmark framework proposed by Murray et al. [27].

E.5 *XRP/USD* Results

Type	Model	NRMSE	NMAE	NMAPE (%)	RMSE	MAE	MAPE (%)	R^2
Reported	ARIMA	0.0158	-	-	-	-	-	-
	CNN-LSTM	**0.0148**	-	-	-	-	-	-
	GRU	0.0153	-	-	-	-	-	-
	KNN	0.0155	-	-	-	-	-	-
	LSTM-GRU	0.0154	-	-	-	-	-	-
	RF	0.0157	-	-	-	-	-	-
	SVR	0.0160	-	-	-	-	-	-
	TCN	0.0156	-	-	-	-	-	-
	TFT	0.0159	-	-	-	-	-	-
Original	ARIMA	0.0158	0.0118	4.562	0.0417	0.0311	3.736	0.689
	CNN-LSTM	**0.0149**	**0.0112**	**4.347**	**0.0394**	**0.0296**	**3.559**	**0.717**
	GRU	0.0152	0.0114	4.414	0.0420	0.0316	3.784	0.681
	KNN	0.0156	0.0115	4.515	0.0411	0.0305	3.690	0.694
	LSTM-GRU	0.0153	0.0114	4.429	0.0404	0.0302	3.625	0.705
	RF	0.0158	0.0118	4.585	0.0418	0.0311	3.752	0.686
	SVR	0.0160	0.0120	4.736	0.0424	0.0318	3.865	0.683
	TCN	0.0156	0.0116	4.530	0.0413	0.0307	3.706	0.693
	TFT	0.0159	0.0118	4.622	0.0422	0.0312	3.778	0.687
Revised	ARIMA	0.0159	0.0117	4.560	0.0420	0.0310	3.731	0.686
	CNN-LSTM	0.0158	0.0118	4.606	0.0417	0.0313	3.770	0.685
	GRU	0.0159	0.0119	4.617	0.0420	0.0316	3.784	0.681
	KNN	0.0157	0.0117	4.538	0.0416	0.0310	3.715	0.691
	LSTM-GRU	0.0158	0.0119	4.594	0.0417	0.0314	3.764	0.685
	RF	0.0161	0.0121	4.699	0.0426	0.0320	3.845	0.671
	SVR	0.0159	0.0119	4.662	0.0420	0.0313	3.804	0.692
	TCN	**0.0156**	**0.0116**	**4.491**	**0.0412**	**0.0306**	**3.677**	**0.694**
	TFT	0.0162	0.0121	4.723	0.0428	0.0319	3.859	0.664

Table 55: Average results of the *benchmark experiments* across 6 repetitions and splits $M_1, \ldots, M_{12}$ with respect to forecasting $\mathbf{S}_{\text{Close}}$ in *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* using the novel framework.

F Supplementary Novel Experimental Results

F.1 Overall Results

F.1.1 DLVMD Results

Crypto	Model	RMSE	MAE	MAPE (%)	R^2	DA (%)
BTC/USD	EVMD-TCN	1545.067 ± 4.061	1169.630 ± 1.618	2.714 ± 0.004	0.726 ± 0.002	52.988 ± 1.208
	DLVMD-TCN with EVMD-TCN Params	**309.818** ± 10.450	**246.724** ± 8.565	**0.579** ± 0.021	**0.988** ± 0.001	**95.083** ± 0.464
	SVMD-TCN	1554.311 ± 3.203	1192.961 ± 4.597	2.769 ± 0.009	0.719 ± 0.001	54.775 ± 0.899
	DLVMD-TCN with SVMD-TCN Params	402.917 ± 6.168	326.924 ± 4.963	0.762 ± 0.009	0.979 ± 0.001	91.024 ± 0.190
ETH/USD	EVMD-TCN	133.939 ± 0.403	104.889 ± 0.214	3.481 ± 0.008	0.713 ± 0.002	54.393 ± 1.021
	DLVMD-TCN with EVMD-TCN Params	36.519 ± 0.771	29.290 ± 0.553	**0.983** ± 0.021	**0.980** ± 0.001	**93.414** ± 0.531
	SVMD-TCN	132.156 ± 0.437	103.358 ± 0.149	3.441 ± 0.007	0.723 ± 0.002	53.390 ± 1.007
	DLVMD-TCN with SVMD-TCN Params	**36.156** ± 0.609	**29.161** ± 0.408	0.989 ± 0.011	**0.980** ± 0.001	92.847 ± 0.921
LTC/USD	EVMD-TCN	7.371 ± 0.011	5.532 ± 0.020	3.824 ± 0.016	0.741 ± 0.001	48.579 ± 0.741
	DLVMD-TCN with EVMD-TCN Parameters	2.094 ± 0.016	1.671 ± 0.018	1.176 ± 0.013	0.978 ± 0.000	89.400 ± 0.442
	SVMD-TCN	7.360 ± 0.043	5.522 ± 0.034	3.816 ± 0.030	0.743 ± 0.003	50.887 ± 1.737
	DLVMD-TCN with SVMD-TCN Params	**1.601** ± 0.042	**1.276** ± 0.047	**0.899** ± 0.037	**0.987** ± 0.001	**92.589** ± 0.549
XMR/USD	EVMD-TCN	11.654 ± 0.063	9.028 ± 0.036	4.150 ± 0.018	0.621 ± 0.004	53.557 ± 0.916
	DLVMD-TCN with EVMD-TCN Params	**3.070** ± 0.062	**2.496** ± 0.056	**1.145** ± 0.028	**0.972** ± 0.001	92.217 ± 0.812
	SVMD-TCN	11.614 ± 0.015	8.947 ± 0.020	4.111 ± 0.008	0.627 ± 0.002	51.263 ± 1.372
	DLVMD-TCN with SVMD-TCN Params	3.694 ± 0.043	2.939 ± 0.042	1.355 ± 0.018	0.956 ± 0.001	**92.456** ± 0.596
XRP/USD	EVMD-TCN	0.0423 ± 0.0002	0.0314 ± 0.0002	3.792 ± 0.021	0.678 ± 0.002	54.323 ± 1.301
	DLVMD-TCN with EVMD-TCN Params	0.0115 ± 0.0002	0.0092 ± 0.0002	1.075 ± 0.026	0.974 ± 0.001	90.725 ± 0.619
	SVMD-TCN	0.0420 ± 0.0001	0.0313 ± 0.0001	3.780 ± 0.015	0.683 ± 0.003	50.121 ± 1.572
	DLVMD-TCN with SVMD-TCN Params	**0.0101** ± 0.0002	**0.0082** ± 0.0002	**0.967** ± 0.021	**0.980** ± 0.002	**90.785** ± 0.577

Table 56: Average results of the DLVMD-based models in relation to the *benchmark experiments* across 6 repetitions and splits $M_1, \ldots, M_{12}$ in relation to forecasting $\mathbf{S}_{\text{Close}}$ with respect to *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD* using the *novel framework*.

F.1.2 Overfitting

Crypto	Model	Train Loss	Val Loss	Gap	Loss Ratio
BTC / USD	TCN [27]	0.0113 ± 0.0003	0.1368 ± 0.0192	0.1255	12.106
	Diff-TCN [27]	0.0338 ± 0.0000	0.1670 ± 0.0000	0.1332	4.941
	TCN	0.0096 ± 0.0000	0.0476 ± 0.0000	0.0380	4.958
	Diff-TCN	0.0339 ± 0.0000	0.1689 ± 0.0004	0.1350	4.982
	CMHA-TCN	0.0096 ± 0.0000	0.0475 ± 0.0000	0.0379	4.948
	Diff-CMHA-TCN	0.0328 ± 0.0001	0.1692 ± 0.0009	0.1364	5.159
	EVMD-TCN	0.0096 ± 0.0000	0.0476 ± 0.0001	0.0380	4.958
	EVMD-CMHA-TCN	0.0096 ± 0.0000	0.0477 ± 0.0000	0.0381	4.969
	EVMD-PMB-TCN	0.0102 ± 0.0001	0.0479 ± 0.0000	0.0377	4.696
	EVMD-PMB-CMHA-TCN	0.0107 ± 0.0001	0.0484 ± 0.0006	0.0377	**4.523**
	SVMD-TCN	0.0098 ± 0.0000	0.0476 ± 0.0000	0.0378	4.857
	SVMD-CMHA-TCN	0.0096 ± 0.0000	0.0477 ± 0.0000	0.0381	4.969
	SVMD-PMB-TCN	0.0099 ± 0.0001	0.0476 ± 0.0001	0.0377	4.808
	SVMD-PMB-CMHA-TCN	0.0102 ± 0.0001	0.0477 ± 0.0001	**0.0375**	4.676
ETH / USD	TCN [27]	0.0106 ± 0.0002	0.1646 ± 0.0100	0.1540	15.528
	Diff-TCN [27]	0.0314 ± 0.0000	0.2059 ± 0.0001	0.1745	6.557
	TCN	0.0091 ± 0.0000	0.0599 ± 0.0001	0.0508	6.582
	Diff-TCN	0.0308 ± 0.0001	0.2067 ± 0.0002	0.1759	6.711
	CMHA-TCN	0.0092 ± 0.0000	0.0598 ± 0.0000	0.0506	6.500
	Diff-CMHA-TCN	0.0288 ± 0.0002	0.2070 ± 0.0003	0.1782	7.188
	EVMD-TCN	0.0090 ± 0.0000	0.0593 ± 0.0001	0.0503	6.589
	EVMD-CMHA-TCN	0.0091 ± 0.0000	0.0594 ± 0.0001	0.0503	6.527
	EVMD-PMB-TCN	0.0092 ± 0.0000	0.0594 ± 0.0001	0.0502	6.457
	EVMD-PMB-CMHA-TCN	0.0099 ± 0.0001	0.0596 ± 0.0001	0.0497	6.020
	SVMD-TCN	0.0096 ± 0.0001	0.0588 ± 0.0000	0.0492	6.125
	SVMD-CMHA-TCN	0.0091 ± 0.0000	0.0587 ± 0.0000	0.0496	6.451
	SVMD-PMB-TCN	0.0094 ± 0.0000	0.0587 ± 0.0001	0.0493	6.245
	SVMD-PMB-CMHA-TCN	0.0098 ± 0.0001	0.0588 ± 0.0001	**0.0490**	**6.000**
LTC / USD	TCN [27]	0.0110 ± 0.0000	0.0276 ± 0.0003	0.0166	2.509
	Diff-TCN [27]	0.0187 ± 0.0000	0.0400 ± 0.0000	0.0213	2.139
	TCN	0.0108 ± 0.0000	0.0235 ± 0.0000	0.0127	2.176
	Diff-TCN	0.0185 ± 0.0000	0.0398 ± 0.0000	0.0213	2.151
	CMHA-TCN	0.0108 ± 0.0000	0.0235 ± 0.0000	0.0127	2.176
	Diff-CMHA-TCN	0.0184 ± 0.0000	0.0398 ± 0.0000	0.0214	2.163
	EVMD-TCN	0.0108 ± 0.0000	0.0232 ± 0.0000	0.0124	2.148
	EVMD-CMHA-TCN	0.0108 ± 0.0000	0.0232 ± 0.0000	0.0124	2.148
	EVMD-PMB-TCN	0.0110 ± 0.0000	0.0234 ± 0.0000	0.0124	2.127
	EVMD-PMB-CMHA-TCN	0.0109 ± 0.0000	0.0233 ± 0.0000	0.0124	2.138
	SVMD-TCN	0.0110 ± 0.0000	0.0233 ± 0.0000	0.0123	2.118
	SVMD-CMHA-TCN	0.0107 ± 0.0000	0.0233 ± 0.0000	0.0126	2.178
	SVMD-PMB-TCN	0.0110 ± 0.0001	0.0232 ± 0.0000	0.0122	2.109
	SVMD-PMB-CMHA-TCN	0.0111 ± 0.0000	0.0232 ± 0.0000	**0.0121**	**2.090**
XMR / USD	TCN [27]	0.0112 ± 0.0000	0.0240 ± 0.0000	0.0128	2.143
	Diff-TCN [27]	0.0234 ± 0.0000	0.0465 ± 0.0000	0.0231	1.987
	TCN	0.0114 ± 0.0000	0.0229 ± 0.0000	0.0115	2.009
	Diff-TCN	0.0227 ± 0.0000	0.0457 ± 0.0000	0.0230	2.013
	CMHA-TCN	0.0114 ± 0.0000	0.0228 ± 0.0000	0.0114	2.000
	Diff-CMHA-TCN	0.0227 ± 0.0000	0.0460 ± 0.0001	0.0233	2.026
	EVMD-TCN	0.0112 ± 0.0000	0.0226 ± 0.0000	0.0114	2.018
	EVMD-CMHA-TCN	0.0114 ± 0.0001	0.0228 ± 0.0000	0.0114	2.000
	EVMD-PMB-TCN	0.0116 ± 0.0001	0.0228 ± 0.0000	0.0112	1.966
	EVMD-PMB-CMHA-TCN	0.0131 ± 0.0002	0.0230 ± 0.0000	**0.0099**	**1.756**
	SVMD-TCN	0.0114 ± 0.0000	0.0224 ± 0.0000	0.0110	1.965
	SVMD-CMHA-TCN	0.0112 ± 0.0000	0.0224 ± 0.0000	0.0112	2.000
	SVMD-PMB-TCN	0.0114 ± 0.0000	0.0224 ± 0.0000	0.0110	1.965
	SVMD-PMB-CMHA-TCN	0.0118 ± 0.0000	0.0223 ± 0.0000	0.0105	1.890
XRP / USD	TCN [27]	0.0067 ± 0.0000	0.0194 ± 0.0003	0.0127	2.896
	Diff-TCN [27]	0.0165 ± 0.0001	0.0373 ± 0.0000	0.0208	2.261
	TCN	0.0072 ± 0.0000	0.0165 ± 0.0000	0.0093	2.292
	Diff-TCN	0.0159 ± 0.0000	0.0372 ± 0.0000	0.0213	2.340
	CMHA-TCN	0.0071 ± 0.0000	0.0165 ± 0.0000	0.0094	2.324
	Diff-CMHA-TCN	0.0160 ± 0.0000	0.0373 ± 0.0000	0.0213	2.331
	EVMD-TCN	0.0071 ± 0.0000	0.0162 ± 0.0000	0.0091	2.282
	EVMD-CMHA-TCN	0.0071 ± 0.0000	0.0165 ± 0.0000	0.0094	2.324
	EVMD-PMB-TCN	0.0072 ± 0.0000	0.0165 ± 0.0000	0.0093	2.292
	EVMD-PMB-CMHA-TCN	0.0076 ± 0.0001	0.0165 ± 0.0000	0.0089	2.171
	SVMD-TCN	0.0073 ± 0.0000	0.0164 ± 0.0000	0.0091	2.247
	SVMD-CMHA-TCN	0.0069 ± 0.0000	0.0163 ± 0.0000	0.0094	2.362
	SVMD-PMB-TCN	0.0071 ± 0.0000	0.0163 ± 0.0000	0.0092	2.296
	SVMD-PMB-CMHA-TCN	0.0077 ± 0.0001	0.0165 ± 0.0000	**0.0088**	**2.143**

Table 57: Average overfitting-related metrics in relation to the *benchmark experiments* across 6 repetitions and splits $M_1, \ldots, M_{12}$ with respect to forecasting $\mathbf{S}_{\text{Close}}$ in *BTC / USD*, *ETH / USD*, *LTC / USD*, *XMR / USD*, and *XRP / USD* using the *novel framework*.

F.2 Monthly Results

F.2.1 *BTC/USD*

Month	Model	RMSE	MAE	MAPE	R2	DA
June 2021	**TCN** [27]	2876.558 ± 1153.367	2475.228 ± 1165.722	6.866 ± 3.164	−0.749 ± 1.563	**57.222** ± 5.241
	Diff-TCN [27]	1808.020 ± 1.423	1422.856 ± 0.479	4.011 ± 0.001	0.405 ± 0.001	46.667 ± 0.000
	TCN	**1795.779** ± 9.437	1408.798 ± 8.808	3.972 ± 0.026	**0.413** ± 0.006	50.000 ± 3.849
	Diff-TCN	1802.198 ± 4.967	**1402.780** ± 7.897	**3.949** ± 0.025	0.408 ± 0.003	52.778 ± 2.291
	CMHA-TCN	1802.129 ± 3.340	1410.657 ± 3.547	3.978 ± 0.010	0.408 ± 0.002	46.667 ± 0.000
	Diff-CMHA-TCN	1805.858 ± 4.671	1403.371 ± 8.091	3.950 ± 0.025	0.406 ± 0.003	55.556 ± 4.969
	EVMD-TCN	1813.609 ± 11.544	1418.193 ± 9.960	3.995 ± 0.029	0.401 ± 0.008	47.778 ± 4.157
	EVMD-CMHA-TCN	1805.413 ± 6.541	1408.471 ± 4.883	3.964 ± 0.014	0.406 ± 0.004	46.111 ± 3.557
	EVMD-PMB-TCN	1813.732 ± 8.192	1412.887 ± 11.593	3.977 ± 0.035	0.401 ± 0.005	51.111 ± 3.685
	EVMD-PMB-CMHA-TCN	1825.252 ± 10.288	1423.148 ± 17.037	4.002 ± 0.046	0.393 ± 0.007	48.333 ± 5.693
	SVMD-TCN	1873.576 ± 4.195	1512.884 ± 3.732	4.249 ± 0.012	0.361 ± 0.003	45.000 ± 2.546
	SVMD-CMHA-TCN	1835.304 ± 8.491	1487.646 ± 10.232	4.180 ± 0.030	0.387 ± 0.006	44.444 ± 3.685
	SVMD-PMB-TCN	1854.958 ± 17.455	1498.419 ± 15.938	4.208 ± 0.043	0.373 ± 0.012	46.111 ± 1.242
	SVMD-PMB-CMHA-TCN	1859.659 ± 15.264	1500.499 ± 9.121	4.214 ± 0.025	0.370 ± 0.010	45.556 ± 4.581
July 2021	TCN [27]	2926.635 ± 1418.963	2592.355 ± 1389.282	7.378 ± 3.920	−0.106 ± 1.022	48.925 ± 5.403
	Diff-TCN [27]	1080.371 ± 0.555	873.881 ± 0.752	2.522 ± 0.002	0.878 ± 0.000	58.065 ± 0.000
	TCN	1078.166 ± 8.182	871.260 ± 7.448	2.518 ± 0.021	0.878 ± 0.002	**58.602** ± 2.895
	Diff-TCN	1075.945 ± 4.988	872.440 ± 3.179	2.521 ± 0.009	0.879 ± 0.001	51.075 ± 1.202
	CMHA-TCN	1082.114 ± 3.741	870.335 ± 2.217	2.518 ± 0.005	0.878 ± 0.001	58.065 ± 1.862
	Diff-CMHA-TCN	1084.381 ± 6.545	881.343 ± 5.501	2.543 ± 0.015	0.877 ± 0.002	51.613 ± 3.725
	EVMD-TCN	1075.465 ± 7.163	871.005 ± 8.112	2.519 ± 0.020	0.879 ± 0.002	56.989 ± 5.157
	EVMD-CMHA-TCN	1083.936 ± 3.372	883.484 ± 5.632	2.552 ± 0.015	0.877 ± 0.001	51.613 ± 4.165
	EVMD-PMB-TCN	1077.582 ± 8.514	871.730 ± 6.353	2.523 ± 0.015	0.879 ± 0.002	55.376 ± 3.914
	EVMD-PMB-CMHA-TCN	1095.312 ± 22.084	886.188 ± 17.079	2.568 ± 0.053	0.875 ± 0.005	54.839 ± 6.715
	SVMD-TCN	1081.115 ± 9.204	876.464 ± 2.242	2.526 ± 0.005	0.878 ± 0.002	52.151 ± 3.442
	SVMD-CMHA-TCN	1074.947 ± 8.033	**869.984** ± 5.125	**2.508** ± 0.014	0.879 ± 0.002	55.914 ± 5.157
	SVMD-PMB-TCN	**1072.129** ± 8.055	875.378 ± 5.535	2.525 ± 0.019	**0.880** ± 0.002	53.763 ± 3.566
	SVMD-PMB-CMHA-TCN	1075.689 ± 9.137	877.402 ± 4.201	2.527 ± 0.012	0.879 ± 0.002	52.688 ± 5.790
August 2021	TCN [27]	5253.832 ± 1590.167	4965.087 ± 1679.863	10.811 ± 3.671	−1.929 ± 1.829	55.376 ± 1.202
	Diff-TCN [27]	1457.103 ± 1.748	1197.457 ± 4.592	2.638 ± 0.011	0.794 ± 0.001	45.161 ± 0.000
	TCN	1458.140 ± 7.110	1192.881 ± 10.183	2.628 ± 0.024	0.793 ± 0.002	46.237 ± 2.404
	Diff-TCN	1457.914 ± 14.650	1197.249 ± 13.547	2.647 ± 0.031	0.793 ± 0.004	48.925 ± 5.072
	CMHA-TCN	1448.095 ± 5.217	1168.913 ± 10.422	2.575 ± 0.025	0.796 ± 0.002	**61.290** ± 5.889
	Diff-CMHA-TCN	1449.296 ± 4.101	1191.903 ± 7.729	2.630 ± 0.018	0.796 ± 0.001	51.613 ± 3.725
	EVMD-TCN	1437.434 ± 4.613	**1164.271** ± 7.067	**2.569** ± 0.017	0.799 ± 0.001	58.602 ± 3.442
	EVMD-CMHA-TCN	1449.249 ± 6.129	1166.014 ± 9.436	2.574 ± 0.023	0.796 ± 0.002	53.763 ± 4.809
	EVMD-PMB-TCN	1440.112 ± 8.573	1178.206 ± 9.953	2.602 ± 0.023	0.798 ± 0.002	52.688 ± 4.433
	EVMD-PMB-CMHA-TCN	1429.203 ± 13.750	1171.709 ± 21.322	2.588 ± 0.050	0.801 ± 0.004	57.527 ± 4.335
	SVMD-TCN	**1427.848** ± 4.663	1187.000 ± 14.097	2.627 ± 0.033	**0.802** ± 0.001	60.753 ± 3.442
	SVMD-CMHA-TCN	1455.368 ± 7.015	1166.066 ± 11.483	2.574 ± 0.026	0.794 ± 0.002	57.527 ± 3.442
	SVMD-PMB-TCN	1429.925 ± 11.994	1175.717 ± 20.036	2.601 ± 0.045	0.801 ± 0.003	60.215 ± 3.041
	SVMD-PMB-CMHA-TCN	1437.130 ± 6.909	1179.676 ± 17.271	2.612 ± 0.041	0.799 ± 0.002	59.677 ± 4.059
September 2021	TCN [27]	4227.967 ± 2480.257	3757.517 ± 2573.502	8.051 ± 5.560	−1.520 ± 3.189	48.333 ± 2.546
	Diff-TCN [27]	1828.575 ± 0.333	**1355.131** ± 0.581	**2.994** ± 0.001	0.649 ± 0.000	**53.333** ± 0.000
	TCN	1817.750 ± 6.931	1363.192 ± 10.152	3.007 ± 0.020	0.653 ± 0.003	49.444 ± 7.556
	Diff-TCN	1853.894 ± 8.842	1390.480 ± 9.092	3.073 ± 0.020	0.639 ± 0.003	51.667 ± 5.000
	CMHA-TCN	**1809.330** ± 7.568	1358.390 ± 1.749	2.998 ± 0.002	**0.657** ± 0.003	51.111 ± 4.581
	Diff-CMHA-TCN	1860.126 ± 5.998	1397.622 ± 6.854	3.089 ± 0.015	0.637 ± 0.002	44.444 ± 4.969
	EVMD-TCN	1862.902 ± 3.663	1415.928 ± 7.704	3.124 ± 0.015	0.636 ± 0.001	38.889 ± 4.581
	EVMD-CMHA-TCN	1880.979 ± 5.186	1432.613 ± 4.193	3.163 ± 0.008	0.629 ± 0.002	38.889 ± 2.485
	EVMD-PMB-TCN	1867.572 ± 6.141	1411.543 ± 7.787	3.116 ± 0.015	0.634 ± 0.002	40.000 ± 4.714
	EVMD-PMB-CMHA-TCN	1882.523 ± 13.737	1439.204 ± 17.013	3.175 ± 0.035	0.628 ± 0.005	38.333 ± 3.191
	SVMD-TCN	1849.347 ± 5.755	1465.121 ± 4.389	3.223 ± 0.010	0.641 ± 0.002	38.333 ± 2.546
	SVMD-CMHA-TCN	1844.487 ± 6.644	1458.667 ± 6.526	3.211 ± 0.014	0.643 ± 0.003	40.556 ± 2.291
	SVMD-PMB-TCN	1843.399 ± 6.934	1459.830 ± 8.085	3.213 ± 0.017	0.644 ± 0.003	38.889 ± 3.143
	SVMD-PMB-CMHA-TCN	1842.013 ± 9.490	1450.192 ± 4.680	3.192 ± 0.010	0.644 ± 0.004	45.000 ± 3.191
October 2021	TCN [27]	8886.450 ± 1662.475	8557.621 ± 1633.287	14.677 ± 2.780	−2.307 ± 1.109	41.935 ± 0.000
	Diff-TCN [27]	**1989.893** ± 3.728	1584.011 ± 2.626	2.749 ± 0.005	**0.840** ± 0.001	58.065 ± 0.000
	TCN	2007.697 ± 9.019	1591.158 ± 7.059	2.760 ± 0.012	0.837 ± 0.002	53.763 ± 11.581
	Diff-TCN	2019.076 ± 8.012	**1557.258** ± 6.863	**2.696** ± 0.013	0.835 ± 0.001	**62.903** ± 4.466
	CMHA-TCN	2044.462 ± 42.503	1599.056 ± 30.382	2.769 ± 0.051	0.831 ± 0.007	51.613 ± 7.450
	Diff-CMHA-TCN	2021.156 ± 13.656	1574.925 ± 10.180	2.732 ± 0.019	0.835 ± 0.002	60.753 ± 4.335
	EVMD-TCN	2052.607 ± 17.553	1606.199 ± 12.241	2.779 ± 0.022	0.830 ± 0.003	53.226 ± 4.839
	EVMD-CMHA-TCN	2024.718 ± 22.981	1575.980 ± 15.130	2.730 ± 0.025	0.834 ± 0.004	56.989 ± 9.250
	EVMD-PMB-TCN	2047.226 ± 23.894	1604.887 ± 23.993	2.780 ± 0.040	0.830 ± 0.004	50.538 ± 4.809
	EVMD-PMB-CMHA-TCN	2064.402 ± 40.781	1615.894 ± 33.802	2.798 ± 0.057	0.828 ± 0.007	53.226 ± 7.622
	SVMD-TCN	2071.194 ± 29.032	1587.971 ± 28.631	2.756 ± 0.048	0.826 ± 0.005	58.602 ± 5.403
	SVMD-CMHA-TCN	2050.767 ± 22.127	1562.575 ± 24.209	2.712 ± 0.042	0.830 ± 0.004	56.989 ± 5.483
	SVMD-PMB-TCN	2064.178 ± 17.271	1571.404 ± 16.352	2.731 ± 0.028	0.828 ± 0.003	62.903 ± 3.607
	SVMD-PMB-CMHA-TCN	2059.831 ± 21.651	1562.294 ± 21.643	2.714 ± 0.036	0.828 ± 0.004	59.140 ± 5.790
November 2021	**TCN** [27]	5802.200 ± 4718.191	5303.472 ± 4837.427	8.703 ± 7.869	−3.334 ± 5.673	**60.556** ± 6.781
	Diff-TCN [27]	1974.333 ± 0.701	1521.326 ± 1.082	2.545 ± 0.002	0.698 ± 0.000	46.667 ± 0.000

Month	Model	RMSE	MAE	MAPE	R2	DA
	TCN	1963.753 ± 5.750	1502.442 ± 11.224	2.513 ± 0.020	0.701 ± 0.002	55.000 ± 3.191
	Diff-TCN	1993.603 ± 15.197	1535.962 ± 13.740	2.565 ± 0.021	0.692 ± 0.005	44.444 ± 3.143
	CMHA-TCN	1958.685 ± 8.969	1487.028 ± 15.346	2.487 ± 0.026	0.703 ± 0.003	57.222 ± 6.781
	Diff-CMHA-TCN	1978.768 ± 7.829	1524.412 ± 9.442	2.548 ± 0.015	0.697 ± 0.002	51.111 ± 4.969
	EVMD-TCN	1970.742 ± 6.468	1496.357 ± 13.930	2.500 ± 0.022	0.699 ± 0.002	56.667 ± 1.925
	EVMD-CMHA-TCN	1973.175 ± 3.818	1476.161 ± 8.254	2.466 ± 0.014	0.698 ± 0.001	53.889 ± 7.798
	EVMD-PMB-TCN	1976.372 ± 5.250	1496.612 ± 8.864	2.502 ± 0.015	0.697 ± 0.002	51.667 ± 5.693
	EVMD-PMB-CMHA-TCN	1988.024 ± 25.872	**1469.941** ± 19.265	2.457 ± 0.032	0.694 ± 0.008	55.000 ± 6.872
	SVMD-TCN	1986.977 ± 11.965	1538.947 ± 26.326	2.564 ± 0.042	0.694 ± 0.004	53.889 ± 1.242
	SVMD-CMHA-TCN	1977.024 ± 11.038	1499.965 ± 12.173	2.504 ± 0.020	0.697 ± 0.003	56.667 ± 3.333
	SVMD-PMB-TCN	1975.302 ± 11.057	1518.242 ± 11.997	2.531 ± 0.020	0.698 ± 0.003	54.444 ± 2.485
	SVMD-PMB-CMHA-TCN	**1947.589** ± 10.049	1471.361 ± 18.837	**2.453** ± 0.030	**0.706** ± 0.003	59.444 ± 4.479
December 2021	TCN [27]	4787.697 ± 2002.612	4255.849 ± 1989.920	8.780 ± 4.069	−2.790 ± 3.484	56.452 ± 5.509
	Diff-TCN [27]	1654.491 ± 2.666	1183.225 ± 1.248	2.425 ± 0.003	0.615 ± 0.001	44.624 ± 2.895
	TCN	1650.717 ± 13.277	1179.629 ± 3.233	2.418 ± 0.009	0.617 ± 0.006	48.925 ± 1.202
	Diff-TCN	1649.674 ± 18.940	1254.825 ± 30.847	2.569 ± 0.062	0.617 ± 0.009	49.462 ± 4.433
	CMHA-TCN	1655.364 ± 26.206	1174.099 ± 19.468	2.409 ± 0.040	0.614 ± 0.012	55.914 ± 6.083
	Diff-CMHA-TCN	1616.374 ± 23.497	1206.576 ± 35.737	2.474 ± 0.074	0.632 ± 0.011	56.452 ± 4.059
	EVMD-TCN	1609.607 ± 67.960	**1138.045** ± 32.937	**2.334** ± 0.071	0.635 ± 0.031	58.602 ± 8.818
	EVMD-CMHA-TCN	1624.997 ± 33.639	1178.300 ± 18.502	2.416 ± 0.039	0.628 ± 0.015	53.763 ± 4.433
	EVMD-PMB-TCN	1611.723 ± 24.383	1231.136 ± 35.684	2.515 ± 0.070	0.634 ± 0.011	55.376 ± 2.217
	EVMD-PMB-CMHA-TCN	1714.356 ± 90.975	1291.434 ± 72.467	2.644 ± 0.151	0.585 ± 0.045	51.613 ± 10.201
	SVMD-TCN	1644.270 ± 29.590	1222.634 ± 27.593	2.518 ± 0.057	0.619 ± 0.014	**63.441** ± 1.521
	SVMD-CMHA-TCN	1642.524 ± 38.597	1275.022 ± 57.068	2.620 ± 0.101	0.620 ± 0.018	60.215 ± 5.790
	SVMD-PMB-TCN	**1579.542** ± 48.219	1219.567 ± 19.329	2.507 ± 0.036	**0.649** ± 0.022	56.989 ± 4.023
	SVMD-PMB-CMHA-TCN	1602.519 ± 77.557	1203.340 ± 66.814	2.469 ± 0.137	0.638 ± 0.036	55.914 ± 7.372
January 2022	TCN [27]	4675.751 ± 1640.554	4040.488 ± 1664.237	10.310 ± 4.199	−1.105 ± 1.429	56.452 ± 4.059
	Diff-TCN [27]	1145.115 ± 0.956	793.481 ± 1.339	1.964 ± 0.004	0.888 ± 0.000	46.774 ± 3.607
	TCN	1174.692 ± 5.081	788.626 ± 5.462	1.949 ± 0.014	0.882 ± 0.001	52.151 ± 3.442
	Diff-TCN	**1126.166** ± 1.122	**779.339** ± 1.250	**1.924** ± 0.004	**0.891** ± 0.000	52.688 ± 3.041
	CMHA-TCN	1189.675 ± 8.045	801.455 ± 8.630	1.983 ± 0.021	0.879 ± 0.002	55.376 ± 2.217
	Diff-CMHA-TCN	1139.949 ± 14.575	790.033 ± 4.632	1.945 ± 0.011	0.889 ± 0.003	52.151 ± 2.895
	EVMD-TCN	1210.841 ± 16.676	820.927 ± 6.027	2.026 ± 0.015	0.874 ± 0.004	47.312 ± 3.566
	EVMD-CMHA-TCN	1231.519 ± 4.993	838.871 ± 3.392	2.075 ± 0.008	0.870 ± 0.001	45.161 ± 1.862
	EVMD-PMB-TCN	1233.754 ± 20.906	826.896 ± 21.297	2.045 ± 0.049	0.869 ± 0.004	56.452 ± 4.466
	EVMD-PMB-CMHA-TCN	1267.078 ± 23.511	853.059 ± 13.888	2.106 ± 0.033	0.862 ± 0.005	45.699 ± 2.895
	SVMD-TCN	1158.166 ± 10.285	796.604 ± 15.280	1.954 ± 0.037	0.885 ± 0.002	**56.989** ± 2.404
	SVMD-CMHA-TCN	1201.654 ± 23.405	832.474 ± 17.308	2.039 ± 0.041	0.876 ± 0.005	51.613 ± 3.226
	SVMD-PMB-TCN	1194.367 ± 10.433	826.960 ± 20.650	2.031 ± 0.048	0.878 ± 0.002	48.925 ± 3.914
	SVMD-PMB-CMHA-TCN	1220.762 ± 23.722	832.666 ± 28.046	2.046 ± 0.071	0.872 ± 0.005	51.613 ± 3.725
February 2022	TCN [27]	2280.962 ± 153.948	1852.761 ± 121.359	4.553 ± 0.294	0.163 ± 0.112	56.548 ± 3.811
	Diff-TCN [27]	1734.929 ± 0.144	1199.853 ± 0.115	2.943 ± 0.000	0.518 ± 0.000	50.595 ± 1.331
	TCN	1708.666 ± 6.764	1186.967 ± 7.597	2.915 ± 0.020	0.532 ± 0.004	51.786 ± 3.993
	Diff-TCN	1731.843 ± 2.721	1195.053 ± 4.340	2.931 ± 0.011	0.520 ± 0.002	50.000 ± 5.455
	CMHA-TCN	1710.697 ± 2.662	1191.329 ± 4.524	2.925 ± 0.012	0.531 ± 0.002	54.762 ± 2.662
	Diff-CMHA-TCN	1744.528 ± 14.476	1208.862 ± 18.132	2.970 ± 0.047	0.512 ± 0.008	48.809 ± 3.948
	EVMD-TCN	1699.033 ± 5.239	1185.935 ± 4.615	2.911 ± 0.011	0.538 ± 0.003	59.524 ± 1.684
	EVMD-CMHA-TCN	1715.193 ± 4.557	1196.636 ± 5.933	2.934 ± 0.015	0.529 ± 0.003	56.548 ± 1.331
	EVMD-PMB-TCN	**1695.129** ± 17.820	**1182.331** ± 21.605	**2.903** ± 0.052	**0.540** ± 0.010	**60.119** ± 4.799
	EVMD-PMB-CMHA-TCN	1732.880 ± 13.778	1244.275 ± 15.883	3.055 ± 0.041	0.519 ± 0.008	48.214 ± 2.728
	SVMD-TCN	1818.436 ± 10.241	1286.263 ± 6.549	3.151 ± 0.016	0.470 ± 0.006	51.191 ± 1.684
	SVMD-CMHA-TCN	1823.882 ± 11.477	1289.915 ± 7.420	3.160 ± 0.021	0.467 ± 0.007	51.191 ± 3.948
	SVMD-PMB-TCN	1832.815 ± 6.412	1295.107 ± 24.192	3.171 ± 0.063	0.462 ± 0.004	50.595 ± 5.615
	SVMD-PMB-CMHA-TCN	1801.185 ± 15.299	1305.566 ± 15.831	3.204 ± 0.043	0.480 ± 0.009	53.571 ± 4.611
March 2022	TCN [27]	1758.820 ± 134.272	1408.283 ± 99.856	3.438 ± 0.264	0.628 ± 0.057	54.301 ± 3.442
	Diff-TCN [27]	1339.693 ± 3.276	1020.901 ± 2.184	2.458 ± 0.006	0.786 ± 0.001	47.312 ± 3.566
	TCN	**1334.089** ± 11.230	**1016.965** ± 5.724	**2.452** ± 0.014	**0.787** ± 0.004	54.839 ± 0.000
	Diff-TCN	1348.205 ± 3.994	1026.822 ± 2.710	2.468 ± 0.007	0.783 ± 0.001	55.376 ± 7.313
	CMHA-TCN	1346.627 ± 1.468	1027.272 ± 4.454	2.474 ± 0.011	0.783 ± 0.001	47.312 ± 4.433
	Diff-CMHA-TCN	1370.085 ± 17.210	1036.330 ± 15.768	2.493 ± 0.040	0.776 ± 0.006	**57.527** ± 3.914
	EVMD-TCN	1409.354 ± 4.356	1073.621 ± 3.480	2.584 ± 0.011	0.763 ± 0.002	48.387 ± 3.226
	EVMD-CMHA-TCN	1434.778 ± 5.964	1094.871 ± 3.821	2.632 ± 0.009	0.754 ± 0.002	49.462 ± 1.521
	EVMD-PMB-TCN	1442.546 ± 12.616	1092.598 ± 7.371	2.634 ± 0.019	0.751 ± 0.004	44.086 ± 5.790
	EVMD-PMB-CMHA-TCN	1459.851 ± 24.830	1127.844 ± 16.038	2.714 ± 0.037	0.745 ± 0.009	47.849 ± 3.442
	SVMD-TCN	1355.884 ± 10.678	1003.955 ± 6.963	2.413 ± 0.018	0.780 ± 0.004	55.914 ± 3.041
	SVMD-CMHA-TCN	1406.137 ± 20.982	1040.843 ± 22.151	2.499 ± 0.051	0.764 ± 0.007	50.000 ± 4.059
	SVMD-PMB-TCN	1381.786 ± 9.180	1019.742 ± 16.436	2.449 ± 0.041	0.772 ± 0.003	53.226 ± 3.088
	SVMD-PMB-CMHA-TCN	1391.460 ± 33.998	1062.106 ± 46.380	2.548 ± 0.108	0.768 ± 0.011	51.075 ± 6.822
April 2022	TCN [27]	1565.154 ± 319.827	1259.713 ± 323.002	3.125 ± 0.808	0.592 ± 0.163	55.000 ± 4.615
	Diff-TCN [27]	1060.941 ± 1.217	860.866 ± 0.641	2.107 ± 0.002	0.820 ± 0.000	51.667 ± 2.546
	TCN	1062.638 ± 16.703	860.410 ± 9.262	2.107 ± 0.024	0.819 ± 0.006	48.889 ± 8.089
	Diff-TCN	1057.347 ± 5.461	856.182 ± 3.541	2.095 ± 0.009	0.821 ± 0.002	57.222 ± 2.992
	CMHA-TCN	1054.081 ± 9.912	851.500 ± 9.748	2.086 ± 0.024	0.822 ± 0.003	54.444 ± 6.285
	Diff-CMHA-TCN	1054.083 ± 11.246	844.881 ± 6.402	2.068 ± 0.016	0.822 ± 0.004	54.444 ± 2.485
	EVMD-TCN	1048.392 ± 10.710	844.331 ± 5.898	2.069 ± 0.016	0.824 ± 0.004	56.111 ± 2.992
	EVMD-CMHA-TCN	1042.435 ± 7.988	829.301 ± 5.481	2.032 ± 0.014	0.826 ± 0.003	53.889 ± 2.992
	EVMD-PMB-TCN	1044.992 ± 16.273	836.332 ± 9.298	2.049 ± 0.024	0.825 ± 0.005	55.556 ± 2.485
	EVMD-PMB-CMHA-TCN	1068.618 ± 13.523	845.484 ± 6.343	2.074 ± 0.017	0.817 ± 0.005	53.889 ± 2.992
	SVMD-TCN	**1004.523** ± 8.399	**790.795** ± 4.453	**1.940** ± 0.011	**0.839** ± 0.003	**68.889** ± 2.485
	SVMD-CMHA-TCN	1012.014 ± 4.249	796.949 ± 1.758	1.955 ± 0.004	0.836 ± 0.001	64.444 ± 1.571

Month	Model	RMSE	MAE	MAPE	R2	DA
	SVMD-PMB-TCN	1005.706 ± 4.074	794.648 ± 4.112	1.949 ± 0.009	0.838 ± 0.001	65.556 ± 4.157
	SVMD-PMB-CMHA-TCN	1028.572 ± 20.227	792.383 ± 10.538	1.949 ± 0.027	0.831 ± 0.007	64.444 ± 3.685
May 2022	TCN [27]	2043.495 ± 211.220	1628.884 ± 225.545	5.206 ± 0.776	0.629 ± 0.076	48.387 ± 1.862
	Diff-TCN [27]	1364.870 ± 0.390	1032.113 ± 0.098	3.256 ± 0.000	0.836 ± 0.000	48.387 ± 0.000
	TCN	1402.648 ± 16.090	1033.432 ± 8.782	3.263 ± 0.029	0.827 ± 0.004	50.000 ± 3.607
	Diff-TCN	1353.492 ± 9.243	1021.977 ± 5.193	3.223 ± 0.018	0.839 ± 0.002	**57.527** ± 2.217
	CMHA-TCN	1397.867 ± 11.624	1024.990 ± 3.101	3.237 ± 0.010	0.828 ± 0.003	52.688 ± 2.404
	Diff-CMHA-TCN	1342.746 ± 12.021	1016.568 ± 6.347	3.206 ± 0.021	0.841 ± 0.003	55.914 ± 3.041
	EVMD-TCN	1350.815 ± 6.575	1000.741 ± 3.386	3.154 ± 0.010	0.840 ± 0.002	53.763 ± 1.521
	EVMD-CMHA-TCN	**1329.947** ± 7.337	**988.366** ± 2.448	**3.111** ± 0.009	**0.844** ± 0.002	51.075 ± 4.718
	EVMD-PMB-TCN	1349.184 ± 16.996	1006.220 ± 3.890	3.169 ± 0.013	0.840 ± 0.004	51.075 ± 3.442
	EVMD-PMB-CMHA-TCN	1349.812 ± 23.903	999.895 ± 9.450	3.149 ± 0.033	0.840 ± 0.006	49.462 ± 4.809
	SVMD-TCN	1380.396 ± 10.937	1046.893 ± 9.812	3.307 ± 0.033	0.832 ± 0.003	52.151 ± 3.442
	SVMD-CMHA-TCN	1371.847 ± 2.395	1040.892 ± 5.391	3.286 ± 0.016	0.834 ± 0.001	52.688 ± 4.023
	SVMD-PMB-TCN	1367.988 ± 14.385	1041.296 ± 7.628	3.287 ± 0.027	0.835 ± 0.004	49.462 ± 5.483
	SVMD-PMB-CMHA-TCN	1368.614 ± 10.528	1027.219 ± 4.724	3.237 ± 0.015	0.835 ± 0.003	55.914 ± 1.521

Table 58: Average results of the *benchmark experiments* across 6 repetitions per split $M_1, \ldots, M_{12}$ corresponding to months June 2021 to May 2022 in relation to forecasting $\mathbf{S}_{\text{Close}}$ with respect to BTC/USD using the novel framework.

Month	Model	RMSE	MAE	MAPE	R2	DA
June 2022	**Diff-TCN** [27]	1186.328 ± 0.365	**803.783** ± 0.247	**3.383** ± 0.001	**0.930** ± 0.000	35.000 ± 3.727
	TCN	1279.727 ± 59.744	915.592 ± 70.247	3.891 ± 0.313	0.918 ± 0.008	42.222 ± 8.089
	Diff-TCN	1202.490 ± 3.151	820.651 ± 2.827	3.462 ± 0.013	0.928 ± 0.000	43.333 ± 2.722
	CMHA-TCN	1268.498 ± 31.814	889.927 ± 40.738	3.777 ± 0.181	0.920 ± 0.004	40.000 ± 5.092
	Diff-CMHA-TCN	**1185.668** ± 4.381	807.414 ± 6.562	3.404 ± 0.034	**0.930** ± 0.001	44.444 ± 8.749
	EVMD-TCN	1298.570 ± 33.604	932.828 ± 42.567	3.958 ± 0.192	0.916 ± 0.004	39.444 ± 2.992
	EVMD-CMHA-TCN	1272.578 ± 21.506	891.983 ± 26.158	3.773 ± 0.118	0.919 ± 0.003	42.222 ± 1.571
	EVMD-PMB-TCN	1269.594 ± 23.119	903.935 ± 38.239	3.842 ± 0.177	0.920 ± 0.003	40.556 ± 1.242
	EVMD-PMB-CMHA-TCN	1231.538 ± 53.731	844.843 ± 55.794	3.557 ± 0.242	0.924 ± 0.007	51.667 ± 11.345
	SVMD-TCN	1251.176 ± 23.212	882.381 ± 23.009	3.734 ± 0.104	0.922 ± 0.003	48.889 ± 5.984
	SVMD-CMHA-TCN	1227.368 ± 22.627	866.430 ± 20.289	3.665 ± 0.092	0.925 ± 0.003	51.111 ± 3.143
	SVMD-PMB-TCN	1224.979 ± 21.576	872.052 ± 21.251	3.680 ± 0.093	0.925 ± 0.003	**52.222** ± 3.685
	SVMD-PMB-CMHA-TCN	1268.550 ± 39.144	884.047 ± 42.302	3.745 ± 0.181	0.920 ± 0.005	51.111 ± 11.331
July 2022	**Diff-TCN** [27]	**695.401** ± 0.151	**511.683** ± 0.132	**2.378** ± 0.001	**0.767** ± 0.000	**58.065** ± 0.000
	TCN	705.765 ± 11.486	522.442 ± 9.924	2.432 ± 0.046	0.760 ± 0.008	50.538 ± 5.157
	Diff-TCN	706.000 ± 3.604	524.191 ± 2.797	2.435 ± 0.013	0.759 ± 0.003	43.548 ± 4.059
	CMHA-TCN	709.641 ± 42.390	551.318 ± 32.561	2.566 ± 0.145	0.756 ± 0.031	44.624 ± 6.011
	Diff-CMHA-TCN	701.580 ± 12.050	517.190 ± 8.540	2.404 ± 0.039	0.762 ± 0.008	47.849 ± 6.293
	EVMD-TCN	720.757 ± 7.504	555.774 ± 6.238	2.580 ± 0.029	0.749 ± 0.005	36.022 ± 4.335
	EVMD-CMHA-TCN	727.680 ± 3.342	574.174 ± 5.763	2.665 ± 0.027	0.745 ± 0.002	33.333 ± 1.521
	EVMD-PMB-TCN	759.119 ± 41.526	580.069 ± 32.303	2.692 ± 0.145	0.721 ± 0.032	41.398 ± 11.084
	EVMD-PMB-CMHA-TCN	789.144 ± 55.452	618.657 ± 39.216	2.870 ± 0.177	0.698 ± 0.044	40.860 ± 9.617
	SVMD-TCN	727.690 ± 40.587	561.896 ± 32.815	2.613 ± 0.149	0.744 ± 0.030	46.774 ± 6.650
	SVMD-CMHA-TCN	720.855 ± 10.046	544.823 ± 4.739	2.534 ± 0.021	0.749 ± 0.007	41.398 ± 2.217
	SVMD-PMB-TCN	731.889 ± 32.346	563.356 ± 17.541	2.618 ± 0.081	0.741 ± 0.023	39.785 ± 4.433
	SVMD-PMB-CMHA-TCN	727.243 ± 13.546	557.765 ± 14.680	2.594 ± 0.068	0.745 ± 0.010	43.011 ± 7.133
August 2022	Diff-TCN [27]	609.117 ± 0.161	411.614 ± 0.121	1.889 ± 0.001	0.840 ± 0.000	61.290 ± 0.000
	TCN	610.163 ± 2.815	413.991 ± 3.587	1.900 ± 0.017	0.840 ± 0.002	57.527 ± 8.415
	Diff-TCN	606.877 ± 1.680	**408.704** ± 2.375	1.875 ± 0.011	0.841 ± 0.001	55.376 ± 7.072
	CMHA-TCN	626.776 ± 22.615	426.913 ± 19.849	1.958 ± 0.090	0.831 ± 0.012	47.312 ± 10.144
	Diff-CMHA-TCN	609.391 ± 0.153	412.089 ± 0.232	1.891 ± 0.001	0.840 ± 0.000	**61.828** ± 1.202
	EVMD-TCN	611.290 ± 8.620	414.876 ± 6.647	1.903 ± 0.032	0.839 ± 0.004	51.613 ± 9.312
	EVMD-CMHA-TCN	**603.476** ± 3.424	408.742 ± 2.551	**1.873** ± 0.012	**0.843** ± 0.002	58.065 ± 10.535
	EVMD-PMB-TCN	610.547 ± 8.808	413.555 ± 7.354	1.896 ± 0.034	0.840 ± 0.005	54.301 ± 11.986
	EVMD-PMB-CMHA-TCN	613.853 ± 11.438	416.219 ± 10.155	1.908 ± 0.048	0.838 ± 0.006	52.688 ± 7.133
	SVMD-TCN	640.809 ± 13.148	446.879 ± 14.188	2.051 ± 0.063	0.823 ± 0.007	40.860 ± 5.790
	SVMD-CMHA-TCN	622.881 ± 7.173	426.416 ± 8.961	1.960 ± 0.040	0.833 ± 0.004	48.925 ± 4.335
	SVMD-PMB-TCN	620.465 ± 11.310	426.217 ± 13.647	1.960 ± 0.061	0.834 ± 0.006	46.774 ± 4.466
	SVMD-PMB-CMHA-TCN	623.311 ± 12.491	427.383 ± 8.103	1.962 ± 0.037	0.833 ± 0.007	48.925 ± 7.072
September 2022	Diff-TCN [27]	678.908 ± 0.099	443.799 ± 0.109	2.224 ± 0.000	0.448 ± 0.000	46.667 ± 0.000
	TCN	684.652 ± 3.978	445.139 ± 3.474	2.231 ± 0.017	0.438 ± 0.006	50.000 ± 6.086
	Diff-TCN	678.310 ± 0.603	**439.721** ± 1.023	**2.204** ± 0.004	0.449 ± 0.001	**57.222** ± 7.049
	CMHA-TCN	693.300 ± 11.330	468.607 ± 21.237	2.336 ± 0.099	0.424 ± 0.019	46.667 ± 1.925
	Diff-CMHA-TCN	680.722 ± 4.525	445.471 ± 5.369	2.231 ± 0.025	0.445 ± 0.007	45.000 ± 3.727
	EVMD-TCN	686.570 ± 2.247	450.647 ± 2.135	2.258 ± 0.009	0.435 ± 0.004	50.556 ± 3.557
	EVMD-CMHA-TCN	692.479 ± 3.220	463.224 ± 5.417	2.316 ± 0.022	0.425 ± 0.005	50.000 ± 1.925
	EVMD-PMB-TCN	687.763 ± 4.091	455.092 ± 4.792	2.277 ± 0.022	0.433 ± 0.007	52.778 ± 5.241
	EVMD-PMB-CMHA-TCN	702.465 ± 17.206	475.984 ± 15.936	2.376 ± 0.074	0.408 ± 0.029	50.556 ± 2.291
	SVMD-TCN	680.507 ± 6.376	459.425 ± 5.297	2.289 ± 0.025	0.445 ± 0.011	56.667 ± 2.722
	SVMD-CMHA-TCN	679.500 ± 3.788	458.649 ± 3.374	2.283 ± 0.014	0.447 ± 0.006	51.111 ± 1.571
	SVMD-PMB-TCN	687.461 ± 8.111	466.868 ± 4.610	2.324 ± 0.018	0.433 ± 0.013	51.111 ± 3.143
	SVMD-PMB-CMHA-TCN	**672.962** ± 11.368	462.771 ± 11.114	2.302 ± 0.051	**0.457** ± 0.018	55.556 ± 3.685
October 2022	Diff-TCN [27]	332.009 ± 1.005	257.026 ± 0.337	1.294 ± 0.002	0.662 ± 0.002	54.839 ± 0.000

Month	Model	RMSE	MAE	MAPE	R2	DA
	TCN	335.144 ± 15.048	260.746 ± 9.173	1.315 ± 0.049	0.655 ± 0.032	49.462 ± 4.433
	Diff-TCN	329.839 ± 2.713	259.538 ± 0.974	1.308 ± 0.005	0.666 ± 0.005	51.613 ± 7.213
	CMHA-TCN	333.371 ± 17.694	267.032 ± 9.650	1.348 ± 0.052	0.658 ± 0.038	48.925 ± 4.335
	Diff-CMHA-TCN	331.460 ± 1.544	258.026 ± 0.710	1.300 ± 0.004	0.663 ± 0.003	54.839 ± 0.000
	EVMD-TCN	333.217 ± 4.211	266.001 ± 4.626	1.342 ± 0.025	0.660 ± 0.009	47.312 ± 6.628
	EVMD-CMHA-TCN	352.690 ± 21.954	265.946 ± 3.211	1.340 ± 0.017	0.617 ± 0.049	51.075 ± 6.011
	EVMD-PMB-TCN	342.093 ± 12.002	263.133 ± 3.453	1.326 ± 0.019	0.641 ± 0.025	49.462 ± 6.628
	EVMD-PMB-CMHA-TCN	364.148 ± 21.173	266.137 ± 5.299	1.341 ± 0.028	0.592 ± 0.048	52.151 ± 6.011
	SVMD-TCN	355.494 ± 42.435	269.481 ± 23.667	1.359 ± 0.118	0.607 ± 0.097	52.151 ± 2.895
	SVMD-CMHA-TCN	**322.512** ± 4.915	**251.418** ± 2.708	**1.268** ± 0.015	**0.681** ± 0.010	53.763 ± 3.041
	SVMD-PMB-TCN	324.075 ± 8.329	252.886 ± 4.322	1.276 ± 0.023	0.678 ± 0.017	**54.839** ± 7.213
	SVMD-PMB-CMHA-TCN	335.861 ± 15.636	268.993 ± 14.402	1.360 ± 0.077	0.653 ± 0.033	50.000 ± 4.466
November 2022	Diff-TCN [27]	753.765 ± 0.959	459.732 ± 0.966	2.638 ± 0.004	0.821 ± 0.001	56.667 ± 0.000
	TCN	758.425 ± 2.443	455.434 ± 3.365	2.614 ± 0.020	0.818 ± 0.001	56.667 ± 1.925
	Diff-TCN	755.441 ± 4.095	454.939 ± 4.426	2.612 ± 0.026	0.820 ± 0.002	53.889 ± 4.875
	CMHA-TCN	762.393 ± 7.199	459.038 ± 8.910	2.639 ± 0.053	0.816 ± 0.004	54.444 ± 9.162
	Diff-CMHA-TCN	**749.677** ± 1.473	455.498 ± 2.053	2.614 ± 0.012	**0.823** ± 0.001	53.889 ± 1.242
	EVMD-TCN	766.958 ± 3.831	443.961 ± 2.410	2.546 ± 0.015	0.814 ± 0.002	**60.000** ± 3.849
	EVMD-CMHA-TCN	778.777 ± 5.579	445.175 ± 5.177	2.553 ± 0.032	0.808 ± 0.003	55.556 ± 3.685
	EVMD-PMB-TCN	770.796 ± 3.372	446.496 ± 7.868	2.558 ± 0.044	0.812 ± 0.002	58.333 ± 2.546
	EVMD-PMB-CMHA-TCN	796.221 ± 14.181	458.099 ± 16.517	2.630 ± 0.100	0.800 ± 0.007	57.778 ± 3.143
	SVMD-TCN	760.667 ± 6.094	444.235 ± 5.196	2.547 ± 0.030	0.817 ± 0.003	54.444 ± 4.969
	SVMD-CMHA-TCN	754.527 ± 5.608	**429.588** ± 6.022	**2.461** ± 0.035	0.820 ± 0.003	52.778 ± 6.503
	SVMD-PMB-TCN	766.219 ± 4.058	438.576 ± 3.304	2.513 ± 0.020	0.815 ± 0.002	51.667 ± 6.310
	SVMD-PMB-CMHA-TCN	783.615 ± 21.601	465.257 ± 19.327	2.672 ± 0.113	0.806 ± 0.011	51.667 ± 7.638
December 2022	Diff-TCN [27]	249.112 ± 0.197	178.672 ± 0.325	1.050 ± 0.002	0.361 ± 0.001	61.290 ± 0.000
	TCN	245.887 ± 0.513	175.020 ± 1.545	1.030 ± 0.010	0.378 ± 0.003	55.914 ± 7.828
	Diff-TCN	247.798 ± 1.306	174.794 ± 2.395	1.028 ± 0.015	0.368 ± 0.007	58.065 ± 7.213
	CMHA-TCN	250.820 ± 7.038	182.011 ± 9.260	1.070 ± 0.053	0.352 ± 0.037	55.376 ± 8.818
	Diff-CMHA-TCN	247.499 ± 0.597	175.291 ± 0.876	1.030 ± 0.005	0.370 ± 0.003	61.290 ± 0.000
	EVMD-TCN	251.162 ± 7.297	172.177 ± 10.880	1.013 ± 0.066	0.350 ± 0.038	55.376 ± 13.224
	EVMD-CMHA-TCN	249.494 ± 5.267	165.120 ± 10.951	0.970 ± 0.064	0.359 ± 0.028	65.054 ± 7.772
	EVMD-PMB-TCN	253.139 ± 5.210	173.440 ± 9.460	1.020 ± 0.057	0.340 ± 0.027	59.140 ± 11.123
	EVMD-PMB-CMHA-TCN	256.956 ± 20.510	178.697 ± 27.042	1.050 ± 0.158	0.316 ± 0.116	62.366 ± 5.790
	SVMD-TCN	240.824 ± 4.854	159.347 ± 7.073	0.939 ± 0.043	0.403 ± 0.024	65.591 ± 10.480
	SVMD-CMHA-TCN	**238.849** ± 1.684	**153.572** ± 2.125	**0.904** ± 0.013	**0.413** ± 0.008	**67.204** ± 4.718
	SVMD-PMB-TCN	244.879 ± 4.202	164.654 ± 9.667	0.968 ± 0.056	0.383 ± 0.021	65.054 ± 4.335
	SVMD-PMB-CMHA-TCN	275.625 ± 64.029	198.546 ± 75.137	1.171 ± 0.449	0.176 ± 0.436	60.215 ± 12.307
January 2023	Diff-TCN [27]	534.797 ± 0.326	359.894 ± 0.293	1.738 ± 0.002	0.958 ± 0.000	32.258 ± 0.000
	TCN	532.644 ± 4.652	354.503 ± 7.427	1.705 ± 0.042	0.958 ± 0.001	33.333 ± 2.404
	Diff-TCN	537.195 ± 5.899	357.178 ± 7.787	1.724 ± 0.042	0.958 ± 0.001	37.097 ± 5.509
	CMHA-TCN	529.826 ± 14.138	352.112 ± 13.607	1.686 ± 0.064	0.959 ± 0.002	47.312 ± 14.265
	Diff-CMHA-TCN	539.465 ± 2.214	361.945 ± 1.783	1.750 ± 0.010	0.957 ± 0.000	32.796 ± 1.202
	EVMD-TCN	543.892 ± 11.282	363.275 ± 15.599	1.741 ± 0.079	0.957 ± 0.002	41.935 ± 14.546
	EVMD-CMHA-TCN	564.005 ± 9.260	376.395 ± 12.111	1.811 ± 0.060	0.953 ± 0.002	44.086 ± 6.628
	EVMD-PMB-TCN	563.468 ± 20.594	386.270 ± 26.515	1.857 ± 0.134	0.953 ± 0.003	39.247 ± 11.840
	EVMD-PMB-CMHA-TCN	665.514 ± 74.519	489.483 ± 94.035	2.399 ± 0.476	0.934 ± 0.015	41.935 ± 9.312
	SVMD-TCN	**524.215** ± 12.457	**346.650** ± 12.507	**1.672** ± 0.067	**0.960** ± 0.002	**52.688** ± 7.603
	SVMD-CMHA-TCN	539.335 ± 14.734	360.092 ± 14.874	1.742 ± 0.079	0.957 ± 0.002	48.925 ± 2.895
	SVMD-PMB-TCN	534.839 ± 7.746	352.537 ± 8.903	1.701 ± 0.047	0.958 ± 0.001	48.387 ± 6.452
	SVMD-PMB-CMHA-TCN	639.388 ± 61.795	457.744 ± 73.326	2.215 ± 0.367	0.939 ± 0.012	46.774 ± 10.158
February 2023	Diff-TCN [27]	610.780 ± 0.007	418.686 ± 0.072	1.781 ± 0.000	0.569 ± 0.000	67.857 ± 0.000
	TCN	609.658 ± 0.683	413.031 ± 3.583	1.757 ± 0.016	0.571 ± 0.001	**69.048** ± 4.454
	Diff-TCN	606.949 ± 1.087	419.478 ± 5.628	1.786 ± 0.026	0.574 ± 0.002	54.762 ± 10.648
	CMHA-TCN	609.573 ± 0.558	414.953 ± 2.295	1.765 ± 0.010	0.571 ± 0.001	67.857 ± 0.000
	Diff-CMHA-TCN	607.760 ± 1.062	415.842 ± 2.185	1.770 ± 0.009	0.573 ± 0.002	67.262 ± 4.799
	EVMD-TCN	601.869 ± 0.706	413.402 ± 3.284	1.759 ± 0.015	0.581 ± 0.001	58.333 ± 3.948
	EVMD-CMHA-TCN	**601.447** ± 3.339	**411.071** ± 5.214	**1.750** ± 0.022	**0.582** ± 0.005	59.524 ± 4.909
	EVMD-PMB-TCN	603.493 ± 2.037	418.927 ± 5.018	1.783 ± 0.022	0.579 ± 0.003	57.143 ± 2.916
	EVMD-PMB-CMHA-TCN	608.621 ± 11.749	431.929 ± 18.573	1.843 ± 0.081	0.572 ± 0.017	47.619 ± 7.339
	SVMD-TCN	645.839 ± 6.064	451.971 ± 12.842	1.925 ± 0.055	0.518 ± 0.009	47.024 ± 8.605
	SVMD-CMHA-TCN	638.005 ± 1.969	438.248 ± 8.221	1.866 ± 0.036	0.530 ± 0.003	53.571 ± 10.101
	SVMD-PMB-TCN	636.125 ± 1.938	438.005 ± 5.402	1.865 ± 0.024	0.532 ± 0.003	51.191 ± 7.043
	SVMD-PMB-CMHA-TCN	646.530 ± 6.817	452.738 ± 16.829	1.932 ± 0.073	0.517 ± 0.010	41.071 ± 3.419
March 2023	Diff-TCN [27]	883.047 ± 0.087	661.106 ± 0.073	2.639 ± 0.000	0.899 ± 0.000	48.387 ± 0.000
	TCN	886.558 ± 2.684	663.560 ± 1.825	2.647 ± 0.006	0.899 ± 0.001	48.387 ± 0.000
	Diff-TCN	886.553 ± 3.228	659.294 ± 2.705	2.636 ± 0.008	0.899 ± 0.001	49.462 ± 5.483
	CMHA-TCN	885.597 ± 3.836	662.301 ± 2.606	2.643 ± 0.008	0.899 ± 0.001	48.925 ± 2.895
	Diff-CMHA-TCN	885.615 ± 1.685	660.314 ± 1.164	2.638 ± 0.003	0.899 ± 0.000	48.387 ± 3.226
	EVMD-TCN	889.497 ± 5.745	653.483 ± 2.281	2.620 ± 0.007	0.898 ± 0.001	55.914 ± 4.433
	EVMD-CMHA-TCN	901.421 ± 6.065	**645.056** ± 1.765	**2.602** ± 0.006	0.895 ± 0.001	60.753 ± 4.335
	EVMD-PMB-TCN	893.003 ± 4.592	651.221 ± 3.586	2.613 ± 0.012	0.897 ± 0.001	59.677 ± 3.088
	EVMD-PMB-CMHA-TCN	923.382 ± 35.853	665.692 ± 18.109	2.696 ± 0.072	0.890 ± 0.009	57.527 ± 6.293
	SVMD-TCN	**880.659** ± 4.600	658.190 ± 1.370	2.645 ± 0.004	**0.900** ± 0.001	61.828 ± 4.335
	SVMD-CMHA-TCN	881.136 ± 2.667	654.434 ± 1.236	2.630 ± 0.005	**0.900** ± 0.001	**66.667** ± 2.404
	SVMD-PMB-TCN	882.401 ± 2.748	655.803 ± 0.401	2.635 ± 0.002	0.900 ± 0.001	65.054 ± 2.895
	SVMD-PMB-CMHA-TCN	930.450 ± 41.530	668.183 ± 37.500	2.696 ± 0.141	0.888 ± 0.010	64.516 ± 8.329
April 2023	Diff-TCN [27]	594.257 ± 0.281	423.167 ± 0.270	1.462 ± 0.001	0.639 ± 0.000	50.000 ± 0.000
	TCN	601.038 ± 2.715	426.953 ± 2.257	1.474 ± 0.007	0.631 ± 0.003	50.000 ± 0.000

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-TCN	595.467 ± 1.062	423.484 ± 0.931	1.464 ± 0.003	0.638 ± 0.001	47.222 ± 3.557
	CMHA-TCN	599.629 ± 2.074	426.687 ± 1.011	1.473 ± 0.003	0.633 ± 0.003	50.000 ± 0.000
	Diff-CMHA-TCN	597.510 ± 0.519	421.038 ± 0.278	1.456 ± 0.001	0.635 ± 0.001	48.333 ± 2.546
	EVMD-TCN	591.106 ± 2.844	417.373 ± 1.973	1.440 ± 0.006	0.643 ± 0.003	51.111 ± 1.571
	EVMD-CMHA-TCN	**589.636** ± 2.120	419.354 ± 1.520	1.448 ± 0.005	**0.645** ± 0.003	53.889 ± 2.291
	EVMD-PMB-TCN	590.929 ± 2.679	**416.201** ± 1.499	**1.437** ± 0.004	0.643 ± 0.003	52.222 ± 2.485
	EVMD-PMB-CMHA-TCN	605.186 ± 11.136	431.266 ± 10.218	1.490 ± 0.035	0.626 ± 0.014	48.889 ± 3.685
	SVMD-TCN	618.378 ± 2.170	456.597 ± 2.350	1.582 ± 0.008	0.609 ± 0.003	53.333 ± 0.000
	SVMD-CMHA-TCN	614.992 ± 4.050	453.313 ± 2.000	1.571 ± 0.007	0.614 ± 0.005	53.889 ± 2.291
	SVMD-PMB-TCN	613.400 ± 2.554	451.967 ± 1.155	1.566 ± 0.004	0.616 ± 0.003	**56.111** ± 2.291
	SVMD-PMB-CMHA-TCN	636.690 ± 16.778	475.940 ± 12.388	1.648 ± 0.039	0.586 ± 0.022	48.333 ± 2.546
May 2023	Diff-TCN [27]	490.723 ± 0.102	377.575 ± 0.038	1.364 ± 0.000	0.637 ± 0.000	54.839 ± 0.000
	TCN	**485.287** ± 0.841	379.245 ± 2.169	1.371 ± 0.008	0.645 ± 0.001	54.839 ± 0.000
	Diff-TCN	488.899 ± 0.926	376.207 ± 1.735	1.359 ± 0.006	0.640 ± 0.001	55.914 ± 6.885
	CMHA-TCN	486.859 ± 0.431	380.178 ± 1.671	1.374 ± 0.006	0.643 ± 0.001	54.839 ± 0.000
	Diff-CMHA-TCN	489.048 ± 1.102	374.810 ± 1.610	1.355 ± 0.006	0.640 ± 0.002	52.151 ± 2.895
	EVMD-TCN	494.145 ± 2.547	376.374 ± 1.490	1.359 ± 0.005	0.632 ± 0.004	**56.989** ± 5.483
	EVMD-CMHA-TCN	490.974 ± 0.913	**372.321** ± 1.401	**1.344** ± 0.005	0.637 ± 0.001	49.462 ± 2.404
	EVMD-PMB-TCN	494.512 ± 2.012	374.795 ± 3.042	1.353 ± 0.011	0.632 ± 0.003	55.376 ± 2.217
	EVMD-PMB-CMHA-TCN	497.962 ± 12.804	380.142 ± 17.567	1.372 ± 0.063	0.626 ± 0.020	56.989 ± 4.023
	SVMD-TCN	509.789 ± 3.611	390.703 ± 3.698	1.411 ± 0.013	0.609 ± 0.005	48.925 ± 3.442
	SVMD-CMHA-TCN	505.429 ± 1.362	384.733 ± 1.644	1.390 ± 0.006	0.615 ± 0.002	50.000 ± 2.464
	SVMD-PMB-TCN	506.605 ± 1.840	385.150 ± 1.499	1.392 ± 0.006	0.614 ± 0.003	50.538 ± 3.041
	SVMD-PMB-CMHA-TCN	500.786 ± 8.327	380.853 ± 6.817	1.377 ± 0.025	0.622 ± 0.013	55.914 ± 2.404
June 2023	Diff-TCN [27]	685.839 ± 0.164	487.680 ± 0.128	1.766 ± 0.001	0.874 ± 0.000	46.667 ± 0.000
	TCN	695.556 ± 2.149	494.635 ± 1.931	1.790 ± 0.007	0.870 ± 0.001	46.667 ± 0.000
	Diff-TCN	682.763 ± 4.321	481.943 ± 4.995	1.746 ± 0.018	0.875 ± 0.002	53.333 ± 6.939
	CMHA-TCN	699.880 ± 3.457	498.218 ± 3.554	1.803 ± 0.012	0.869 ± 0.001	46.667 ± 0.000
	Diff-CMHA-TCN	686.095 ± 3.350	486.294 ± 2.429	1.761 ± 0.009	0.874 ± 0.001	47.222 ± 3.557
	EVMD-TCN	687.025 ± 3.946	487.071 ± 3.860	1.761 ± 0.014	0.873 ± 0.002	51.667 ± 3.191
	EVMD-CMHA-TCN	682.608 ± 5.747	**477.674** ± 4.199	**1.724** ± 0.014	0.875 ± 0.002	**57.778** ± 3.685
	EVMD-PMB-TCN	679.753 ± 1.444	480.640 ± 2.619	1.737 ± 0.009	0.876 ± 0.001	52.778 ± 2.291
	EVMD-PMB-CMHA-TCN	696.282 ± 15.149	487.495 ± 12.221	1.754 ± 0.040	0.870 ± 0.006	56.667 ± 1.925
	SVMD-TCN	680.554 ± 8.523	488.332 ± 11.022	1.765 ± 0.040	0.876 ± 0.003	51.667 ± 3.727
	SVMD-CMHA-TCN	**676.250** ± 3.688	483.263 ± 4.896	1.747 ± 0.018	**0.877** ± 0.001	56.111 ± 3.557
	SVMD-PMB-TCN	676.273 ± 2.468	484.430 ± 4.361	1.751 ± 0.016	0.877 ± 0.001	52.222 ± 3.685
	SVMD-PMB-CMHA-TCN	697.668 ± 22.703	489.378 ± 26.746	1.762 ± 0.094	0.869 ± 0.009	57.778 ± 5.984
July 2023	Diff-TCN [27]	393.046 ± 0.058	258.538 ± 0.146	0.854 ± 0.001	0.546 ± 0.000	54.839 ± 0.000
	TCN	395.037 ± 2.354	263.163 ± 4.902	0.869 ± 0.016	0.541 ± 0.005	54.839 ± 0.000
	Diff-TCN	388.546 ± 1.790	254.912 ± 1.066	0.842 ± 0.004	0.556 ± 0.004	54.839 ± 1.862
	CMHA-TCN	393.656 ± 1.254	260.199 ± 2.340	0.859 ± 0.008	0.544 ± 0.003	54.839 ± 0.000
	Diff-CMHA-TCN	388.485 ± 2.608	254.310 ± 1.994	0.840 ± 0.007	0.556 ± 0.006	55.376 ± 5.715
	EVMD-TCN	381.552 ± 1.669	252.862 ± 1.576	0.834 ± 0.005	0.572 ± 0.004	55.376 ± 1.202
	EVMD-CMHA-TCN	374.002 ± 1.392	252.347 ± 0.977	0.832 ± 0.003	0.589 ± 0.003	55.376 ± 1.202
	EVMD-PMB-TCN	380.450 ± 1.491	254.439 ± 1.870	0.839 ± 0.006	0.574 ± 0.003	55.376 ± 2.217
	EVMD-PMB-CMHA-TCN	375.462 ± 5.665	265.265 ± 7.714	0.877 ± 0.026	0.585 ± 0.013	53.226 ± 3.088
	SVMD-TCN	383.173 ± 3.821	258.054 ± 7.653	0.852 ± 0.025	0.568 ± 0.009	63.441 ± 3.041
	SVMD-CMHA-TCN	378.754 ± 1.571	**250.186** ± 2.558	**0.826** ± 0.008	0.578 ± 0.004	**63.978** ± 3.442
	SVMD-PMB-TCN	378.421 ± 2.756	253.946 ± 4.740	0.839 ± 0.016	0.579 ± 0.006	63.441 ± 3.566
	SVMD-PMB-CMHA-TCN	**372.512** ± 16.267	251.023 ± 18.040	0.830 ± 0.061	**0.591** ± 0.037	61.290 ± 4.165
August 2023	Diff-TCN [27]	586.169 ± 0.040	330.188 ± 0.033	1.204 ± 0.000	0.854 ± 0.000	58.065 ± 0.000
	TCN	**582.752** ± 2.179	**328.611** ± 0.748	**1.198** ± 0.003	**0.856** ± 0.001	**58.065** ± 0.000
	Diff-TCN	589.526 ± 2.010	331.088 ± 1.654	1.209 ± 0.006	0.853 ± 0.001	53.763 ± 2.404
	CMHA-TCN	583.875 ± 6.155	329.773 ± 5.569	1.202 ± 0.021	0.855 ± 0.003	56.989 ± 2.404
	Diff-CMHA-TCN	587.610 ± 0.739	330.779 ± 0.625	1.207 ± 0.003	0.854 ± 0.000	55.914 ± 1.521
	EVMD-TCN	589.544 ± 1.853	329.427 ± 1.306	1.204 ± 0.005	0.853 ± 0.001	52.151 ± 3.442
	EVMD-CMHA-TCN	603.316 ± 4.879	335.997 ± 3.117	1.230 ± 0.012	0.846 ± 0.003	47.849 ± 2.895
	EVMD-PMB-TCN	594.243 ± 2.033	333.252 ± 3.106	1.218 ± 0.011	0.850 ± 0.001	49.462 ± 3.041
	EVMD-PMB-CMHA-TCN	636.792 ± 26.827	366.019 ± 31.547	1.343 ± 0.117	0.828 ± 0.015	51.075 ± 4.335
	SVMD-TCN	589.820 ± 3.131	348.991 ± 9.713	1.275 ± 0.034	0.852 ± 0.002	57.527 ± 1.202
	SVMD-CMHA-TCN	595.920 ± 6.922	343.070 ± 3.477	1.255 ± 0.013	0.849 ± 0.004	56.452 ± 3.088
	SVMD-PMB-TCN	589.832 ± 1.524	342.160 ± 3.274	1.250 ± 0.012	0.852 ± 0.001	54.839 ± 2.634
	SVMD-PMB-CMHA-TCN	626.743 ± 16.282	364.817 ± 18.164	1.335 ± 0.065	0.833 ± 0.009	52.688 ± 6.628
September 2023	**Diff-TCN** [27]	**306.664** ± 0.316	**213.989** ± 0.135	**0.814** ± 0.001	**0.591** ± 0.001	53.333 ± 0.000
	TCN	312.226 ± 2.201	219.896 ± 2.512	0.836 ± 0.009	0.576 ± 0.006	53.333 ± 0.000
	Diff-TCN	307.136 ± 1.727	216.226 ± 2.561	0.823 ± 0.010	0.590 ± 0.005	53.889 ± 2.992
	CMHA-TCN	309.473 ± 4.467	217.683 ± 5.099	0.828 ± 0.019	0.583 ± 0.012	53.333 ± 0.000
	Diff-CMHA-TCN	308.057 ± 1.567	214.917 ± 1.846	0.818 ± 0.007	0.587 ± 0.004	51.667 ± 1.667
	EVMD-TCN	310.919 ± 2.157	217.675 ± 3.631	0.828 ± 0.013	0.579 ± 0.006	52.778 ± 2.992
	EVMD-CMHA-TCN	312.765 ± 2.469	222.185 ± 3.486	0.845 ± 0.013	0.574 ± 0.007	**58.889** ± 6.849
	EVMD-PMB-TCN	308.928 ± 1.507	215.947 ± 2.626	0.821 ± 0.010	0.585 ± 0.004	57.222 ± 2.291
	EVMD-PMB-CMHA-TCN	344.454 ± 23.640	266.961 ± 16.933	1.016 ± 0.064	0.481 ± 0.072	52.222 ± 5.666
	SVMD-TCN	328.509 ± 3.104	245.760 ± 3.956	0.936 ± 0.014	0.530 ± 0.009	52.778 ± 1.242
	SVMD-CMHA-TCN	326.277 ± 4.437	241.567 ± 5.630	0.919 ± 0.021	0.537 ± 0.013	52.778 ± 4.045
	SVMD-PMB-TCN	323.689 ± 6.583	236.657 ± 8.256	0.900 ± 0.031	0.544 ± 0.019	55.000 ± 5.358
	SVMD-PMB-CMHA-TCN	327.646 ± 11.599	254.614 ± 17.479	0.969 ± 0.067	0.532 ± 0.033	51.667 ± 5.000
October 2023	**Diff-TCN** [27]	732.553 ± 0.274	**442.354** ± 0.154	**1.459** ± 0.001	**0.937** ± 0.000	45.161 ± 0.000
	TCN	742.023 ± 5.409	448.312 ± 4.111	1.476 ± 0.012	0.936 ± 0.001	45.161 ± 0.000
	Diff-TCN	738.383 ± 4.582	446.701 ± 1.995	1.472 ± 0.007	0.936 ± 0.001	44.624 ± 1.202

Month	Model	RMSE	MAE	MAPE	R2	DA
	CMHA-TCN	743.267 ± 11.075	450.332 ± 7.514	1.482 ± 0.022	0.935 ± 0.002	46.774 ± 5.185
	Diff-CMHA-TCN	**732.353** ± 3.444	443.547 ± 2.576	1.462 ± 0.007	**0.937** ± 0.001	44.624 ± 3.442
	EVMD-TCN	751.925 ± 7.813	469.521 ± 6.448	1.542 ± 0.019	0.934 ± 0.001	41.398 ± 3.442
	EVMD-CMHA-TCN	794.434 ± 19.109	508.962 ± 14.970	1.665 ± 0.046	0.926 ± 0.004	35.484 ± 3.725
	EVMD-PMB-TCN	758.290 ± 17.321	478.844 ± 16.347	1.571 ± 0.050	0.933 ± 0.003	41.935 ± 2.634
	EVMD-PMB-CMHA-TCN	912.793 ± 52.124	590.387 ± 42.311	1.917 ± 0.128	0.902 ± 0.011	44.086 ± 4.023
	SVMD-TCN	741.515 ± 14.689	449.381 ± 11.958	1.485 ± 0.036	0.936 ± 0.003	**48.925** ± 3.442
	SVMD-CMHA-TCN	751.097 ± 9.472	460.198 ± 7.505	1.517 ± 0.022	0.934 ± 0.002	41.935 ± 3.226
	SVMD-PMB-TCN	751.293 ± 4.849	459.416 ± 7.037	1.515 ± 0.021	0.934 ± 0.001	47.312 ± 3.566
	SVMD-PMB-CMHA-TCN	830.995 ± 26.969	530.052 ± 19.212	1.737 ± 0.062	0.919 ± 0.005	43.548 ± 1.613
November 2023	Diff-TCN [27]	805.837 ± 0.130	553.108 ± 0.052	1.510 ± 0.000	0.401 ± 0.000	46.667 ± 0.000
	TCN	808.585 ± 2.122	555.812 ± 1.413	1.517 ± 0.004	0.397 ± 0.003	46.667 ± 0.000
	Diff-TCN	795.745 ± 0.819	**548.001** ± 0.754	**1.496** ± 0.002	0.416 ± 0.001	**56.111** ± 1.242
	CMHA-TCN	808.018 ± 5.415	554.848 ± 4.073	1.514 ± 0.011	0.398 ± 0.008	48.333 ± 2.546
	Diff-CMHA-TCN	797.777 ± 5.176	553.261 ± 2.940	1.510 ± 0.008	0.413 ± 0.008	51.111 ± 4.969
	EVMD-TCN	796.360 ± 7.216	560.794 ± 10.804	1.532 ± 0.029	0.415 ± 0.011	47.778 ± 4.581
	EVMD-CMHA-TCN	**765.881** ± 11.242	553.488 ± 10.165	1.512 ± 0.027	**0.459** ± 0.016	48.333 ± 5.000
	EVMD-PMB-TCN	783.267 ± 6.883	555.277 ± 12.138	1.517 ± 0.033	0.434 ± 0.010	49.444 ± 2.992
	EVMD-PMB-CMHA-TCN	789.880 ± 85.069	610.237 ± 99.372	1.661 ± 0.264	0.418 ± 0.132	54.444 ± 4.157
	SVMD-TCN	808.506 ± 8.834	577.560 ± 8.908	1.576 ± 0.024	0.397 ± 0.013	44.444 ± 2.485
	SVMD-CMHA-TCN	802.960 ± 4.896	572.339 ± 6.981	1.562 ± 0.019	0.405 ± 0.007	46.111 ± 3.557
	SVMD-PMB-TCN	801.754 ± 5.606	573.200 ± 5.582	1.564 ± 0.015	0.407 ± 0.008	42.222 ± 1.571
	SVMD-PMB-CMHA-TCN	778.197 ± 51.128	577.010 ± 60.072	1.572 ± 0.162	0.439 ± 0.077	55.000 ± 5.693
December 2023	**Diff-TCN** [27]	**980.845** ± 0.176	765.812 ± 0.225	1.808 ± 0.001	**0.460** ± 0.000	39.785 ± 1.521
	TCN	985.436 ± 6.293	767.203 ± 12.925	1.812 ± 0.030	0.455 ± 0.007	47.312 ± 9.796
	Diff-TCN	982.527 ± 0.514	761.723 ± 0.579	1.799 ± 0.001	0.458 ± 0.001	54.839 ± 1.862
	CMHA-TCN	980.965 ± 3.491	761.637 ± 9.924	1.799 ± 0.023	0.460 ± 0.004	49.462 ± 9.972
	Diff-CMHA-TCN	983.764 ± 2.457	766.052 ± 2.655	1.809 ± 0.006	0.457 ± 0.003	48.387 ± 1.862
	EVMD-TCN	983.973 ± 2.279	767.005 ± 2.177	1.812 ± 0.005	0.456 ± 0.003	53.226 ± 3.088
	EVMD-CMHA-TCN	990.235 ± 6.839	757.699 ± 5.080	1.790 ± 0.012	0.449 ± 0.008	**57.527** ± 2.895
	EVMD-PMB-TCN	985.881 ± 6.589	769.109 ± 7.585	1.817 ± 0.018	0.454 ± 0.007	48.387 ± 3.226
	EVMD-PMB-CMHA-TCN	1105.638 ± 43.339	845.346 ± 44.267	1.996 ± 0.101	0.312 ± 0.054	54.839 ± 5.889
	SVMD-TCN	1009.814 ± 6.882	**753.804** ± 10.076	**1.779** ± 0.024	0.427 ± 0.008	55.914 ± 7.133
	SVMD-CMHA-TCN	1020.936 ± 8.481	770.637 ± 11.215	1.818 ± 0.026	0.415 ± 0.010	50.538 ± 4.809
	SVMD-PMB-TCN	1021.331 ± 8.692	775.192 ± 14.201	1.829 ± 0.033	0.414 ± 0.010	49.462 ± 5.157
	SVMD-PMB-CMHA-TCN	1103.004 ± 79.536	866.724 ± 88.010	2.045 ± 0.205	0.313 ± 0.104	47.849 ± 6.011
January 2024	Diff-TCN [27]	1237.367 ± 0.202	849.537 ± 0.152	1.970 ± 0.000	0.576 ± 0.000	52.151 ± 1.202
	TCN	1239.881 ± 1.964	852.466 ± 2.706	1.976 ± 0.006	0.575 ± 0.001	50.538 ± 6.885
	Diff-TCN	1231.463 ± 0.602	840.188 ± 0.739	1.948 ± 0.002	0.580 ± 0.000	**64.516** ± 1.862
	CMHA-TCN	1235.022 ± 3.607	846.590 ± 7.903	1.963 ± 0.019	0.578 ± 0.003	55.376 ± 7.772
	Diff-CMHA-TCN	1232.075 ± 3.458	838.771 ± 6.991	1.944 ± 0.016	0.580 ± 0.002	63.441 ± 6.628
	EVMD-TCN	1244.632 ± 1.771	850.728 ± 2.159	1.974 ± 0.005	0.571 ± 0.001	49.462 ± 3.041
	EVMD-CMHA-TCN	1247.939 ± 3.447	851.154 ± 4.813	1.977 ± 0.013	0.569 ± 0.002	56.452 ± 4.059
	EVMD-PMB-TCN	1246.002 ± 5.097	852.093 ± 5.059	1.977 ± 0.012	0.570 ± 0.004	55.376 ± 5.072
	EVMD-PMB-CMHA-TCN	1331.581 ± 58.863	954.320 ± 65.942	2.219 ± 0.153	0.508 ± 0.044	61.290 ± 3.226
	SVMD-TCN	1206.190 ± 7.065	835.146 ± 5.317	1.944 ± 0.014	0.597 ± 0.005	59.140 ± 1.521
	SVMD-CMHA-TCN	1199.277 ± 1.285	837.161 ± 6.428	1.946 ± 0.014	0.602 ± 0.001	59.677 ± 2.464
	SVMD-PMB-TCN	**1199.011** ± 2.143	**832.817** ± 4.577	**1.936** ± 0.010	**0.602** ± 0.001	60.753 ± 2.217
	SVMD-PMB-CMHA-TCN	1230.569 ± 30.954	876.247 ± 65.464	2.035 ± 0.148	0.581 ± 0.021	59.677 ± 6.106
February 2024	Diff-TCN [27]	1458.531 ± 0.576	952.096 ± 0.429	1.810 ± 0.001	0.918 ± 0.000	32.759 ± 2.634
	TCN	1481.632 ± 13.689	966.990 ± 8.775	1.841 ± 0.018	0.916 ± 0.002	31.609 ± 1.285
	Diff-TCN	1481.691 ± 0.563	961.274 ± 0.666	1.830 ± 0.001	0.916 ± 0.000	39.081 ± 1.625
	CMHA-TCN	**1456.032** ± 16.610	946.241 ± 12.686	1.798 ± 0.026	**0.918** ± 0.002	**55.172**±17.583
	Diff-CMHA-TCN	1480.716 ± 5.355	960.494 ± 3.926	1.827 ± 0.008	0.916 ± 0.001	37.356 ± 4.633
	EVMD-TCN	1543.800 ± 13.761	960.253 ± 8.706	1.828 ± 0.018	0.908 ± 0.002	47.126 ± 7.880
	EVMD-CMHA-TCN	1605.583 ± 24.822	978.513 ± 18.566	1.860 ± 0.034	0.901 ± 0.003	45.402 ± 3.680
	EVMD-PMB-TCN	1588.905 ± 63.823	981.430 ± 50.161	1.872 ± 0.098	0.903 ± 0.008	44.253 ± 6.727
	EVMD-PMB-CMHA-TCN	1843.073 ± 185.186	1175.766 ± 155.943	2.227 ± 0.291	0.868 ± 0.028	38.506 ± 4.633
	SVMD-TCN	1495.976 ± 20.370	**943.703** ± 15.640	**1.797** ± 0.033	0.914 ± 0.002	50.000 ± 2.634
	SVMD-CMHA-TCN	1522.459 ± 17.943	952.890 ± 12.431	1.813 ± 0.025	0.911 ± 0.002	47.701 ± 1.285
	SVMD-PMB-TCN	1534.720 ± 11.215	966.338 ± 7.951	1.841 ± 0.016	0.909 ± 0.001	47.701 ± 1.285
	SVMD-PMB-CMHA-TCN	1831.727 ± 130.336	1207.382 ± 108.101	2.300 ± 0.209	0.870 ± 0.019	43.103 ± 2.634
March 2024	Diff-TCN [27]	2561.874 ± 1.115	1972.313 ± 1.556	2.943 ± 0.002	0.321 ± 0.001	58.065 ± 0.000
	TCN	2553.211 ± 1.625	1962.232 ± 2.377	2.929 ± 0.003	0.326 ± 0.001	58.065 ± 0.000
	Diff-TCN	2525.564 ± 7.330	1940.741 ± 8.474	2.894 ± 0.013	0.340 ± 0.004	54.839 ± 4.928
	CMHA-TCN	2547.740 ± 13.652	1959.453 ± 11.105	2.925 ± 0.016	0.328 ± 0.007	59.140 ± 1.521
	Diff-CMHA-TCN	2524.375 ± 12.336	1941.595 ± 10.761	2.896 ± 0.016	0.341 ± 0.006	59.677 ± 3.088
	EVMD-TCN	2478.417 ± 15.174	1881.631 ± 11.574	2.807 ± 0.018	0.364 ± 0.008	**60.215** ± 4.809
	EVMD-CMHA-TCN	**2416.415** ± 10.609	**1833.957** ± 19.037	**2.734** ± 0.025	**0.396** ± 0.005	57.527 ± 7.546
	EVMD-PMB-TCN	2484.700 ± 10.464	1873.501 ± 4.223	2.796 ± 0.006	0.361 ± 0.005	**60.215** ± 3.041
	EVMD-PMB-CMHA-TCN	2705.067 ± 109.229	2152.698 ± 141.103	3.197 ± 0.195	0.242 ± 0.061	51.075 ± 4.335
	SVMD-TCN	2660.351 ± 9.465	2077.682 ± 13.654	3.101 ± 0.020	0.268 ± 0.005	46.237 ± 5.483
	SVMD-CMHA-TCN	2643.618 ± 7.369	2061.864 ± 7.683	3.076 ± 0.011	0.277 ± 0.004	45.699 ± 3.442
	SVMD-PMB-TCN	2654.804 ± 10.047	2078.399 ± 15.695	3.102 ± 0.023	0.271 ± 0.005	45.699 ± 4.718
	SVMD-PMB-CMHA-TCN	2688.275 ± 122.847	2092.010 ± 147.393	3.126 ± 0.219	0.251 ± 0.070	43.011 ± 3.566
April 2024	Diff-TCN [27]	1840.140 ± 0.263	1481.578 ± 0.203	2.256 ± 0.000	0.564 ± 0.000	50.000 ± 0.000
	TCN	1875.588 ± 17.614	1490.483 ± 12.165	2.272 ± 0.018	0.547 ± 0.009	50.000 ± 0.000
	Diff-TCN	**1826.481** ± 1.258	**1446.265** ± 5.782	**2.204** ± 0.008	**0.570** ± 0.001	**61.111** ± 4.157
	CMHA-TCN	1872.659 ± 7.577	1485.145 ± 7.178	2.264 ± 0.010	0.548 ± 0.004	50.000 ± 0.000

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	1829.875 ± 5.552	1450.306 ± 7.343	2.210 ± 0.011	0.569 ± 0.003	57.222 ± 4.045
	EVMD-TCN	1893.131 ± 31.549	1480.661 ± 24.965	2.260 ± 0.039	0.538 ± 0.015	44.444 ± 5.329
	EVMD-CMHA-TCN	1973.229 ± 56.848	1531.520 ± 31.488	2.343 ± 0.051	0.498 ± 0.029	50.000 ± 1.925
	EVMD-PMB-TCN	1903.818 ± 16.355	1495.041 ± 16.627	2.282 ± 0.025	0.533 ± 0.008	47.778 ± 6.285
	EVMD-PMB-CMHA-TCN	2261.297 ± 407.978	1826.152 ± 354.402	2.792 ± 0.550	0.320 ± 0.237	47.222 ± 8.259
	SVMD-TCN	1957.165 ± 31.254	1524.576 ± 15.028	2.325 ± 0.024	0.506 ± 0.016	50.000 ± 1.925
	SVMD-CMHA-TCN	1959.226 ± 44.576	1525.883 ± 22.332	2.328 ± 0.036	0.505 ± 0.022	49.444 ± 1.242
	SVMD-PMB-TCN	1957.800 ± 28.998	1519.844 ± 15.159	2.319 ± 0.024	0.506 ± 0.015	50.000 ± 1.925
	SVMD-PMB-CMHA-TCN	1887.793 ± 97.485	1500.673 ± 67.820	2.287 ± 0.101	0.540 ± 0.048	53.333 ± 8.607
May 2024	Diff-TCN [27]	1788.054 ± 0.156	1340.693 ± 0.186	2.054 ± 0.000	0.739 ± 0.000	47.312 ± 2.404
	TCN	1784.686 ± 4.254	1356.133 ± 8.087	2.079 ± 0.013	0.740 ± 0.001	48.925 ± 1.202
	Diff-TCN	1785.877 ± 6.632	1338.806 ± 10.177	2.053 ± 0.015	0.740 ± 0.002	55.914 ± 3.041
	CMHA-TCN	1774.649 ± 8.859	1347.341 ± 13.888	2.066 ± 0.021	0.743 ± 0.003	49.462 ± 2.404
	Diff-CMHA-TCN	1791.258 ± 4.675	1346.950 ± 4.526	2.066 ± 0.007	0.738 ± 0.001	54.301 ± 2.217
	EVMD-TCN	**1742.740** ± 6.807	1289.299 ± 12.516	1.981 ± 0.020	**0.752** ± 0.002	61.828 ± 3.442
	EVMD-CMHA-TCN	1748.471 ± 7.386	1277.636 ± 8.160	1.969 ± 0.015	0.751 ± 0.002	**65.054** ± 2.217
	EVMD-PMB-TCN	1750.708 ± 21.391	**1273.817** ± 5.452	**1.958** ± 0.009	0.750 ± 0.006	60.753 ± 2.217
	EVMD-PMB-CMHA-TCN	2115.324 ± 164.001	1568.155 ± 127.164	2.403 ± 0.191	0.633 ± 0.054	62.903 ± 10.328
	SVMD-TCN	1771.913 ± 8.103	1331.450 ± 20.349	2.037 ± 0.030	0.744 ± 0.002	48.925 ± 5.072
	SVMD-CMHA-TCN	1767.040 ± 6.756	1325.307 ± 15.072	2.027 ± 0.023	0.745 ± 0.002	48.925 ± 7.313
	SVMD-PMB-TCN	1773.243 ± 9.784	1325.827 ± 18.920	2.029 ± 0.030	0.744 ± 0.003	51.075 ± 2.895
	SVMD-PMB-CMHA-TCN	1755.419 ± 16.814	1295.706 ± 41.864	1.990 ± 0.067	0.749 ± 0.005	56.452 ± 3.088
June 2024	Diff-TCN [27]	1107.067 ± 0.598	847.765 ± 0.663	1.307 ± 0.001	0.885 ± 0.000	43.333 ± 0.000
	TCN	1129.156 ± 15.915	864.525 ± 13.458	1.333 ± 0.021	0.880 ± 0.003	45.000 ± 5.358
	Diff-TCN	1102.874 ± 2.996	836.090 ± 2.667	1.288 ± 0.004	0.885 ± 0.001	50.000 ± 3.333
	CMHA-TCN	1136.888 ± 32.255	868.612 ± 26.471	1.339 ± 0.041	0.878 ± 0.007	45.556 ± 4.969
	Diff-CMHA-TCN	1105.868 ± 5.684	843.719 ± 4.269	1.300 ± 0.007	0.885 ± 0.001	48.889 ± 5.329
	EVMD-TCN	1114.534 ± 15.909	837.868 ± 13.802	1.287 ± 0.021	0.883 ± 0.003	55.556 ± 6.285
	EVMD-CMHA-TCN	1179.384 ± 43.237	880.370 ± 41.176	1.351 ± 0.063	0.869 ± 0.009	48.333 ± 7.391
	EVMD-PMB-TCN	1148.559 ± 21.482	855.202 ± 20.810	1.315 ± 0.032	0.876 ± 0.005	50.556 ± 8.032
	EVMD-PMB-CMHA-TCN	1283.179 ± 161.412	987.046 ± 159.391	1.510 ± 0.245	0.843 ± 0.041	53.889 ± 9.702
	SVMD-TCN	1084.442 ± 27.865	813.730 ± 25.001	1.254 ± 0.038	0.889 ± 0.006	53.333 ± 7.201
	SVMD-CMHA-TCN	1097.235 ± 13.958	820.302 ± 9.985	1.265 ± 0.015	0.887 ± 0.003	53.889 ± 3.557
	SVMD-PMB-TCN	**1078.403** ± 17.333	**808.301** ± 11.285	**1.246** ± 0.019	**0.890** ± 0.004	**60.000** ± 6.383
	SVMD-PMB-CMHA-TCN	1178.528 ± 21.322	872.078 ± 28.542	1.343 ± 0.045	0.869 ± 0.005	48.889 ± 4.969
July 2024	**Diff-TCN** [27]	**1479.815** ± 0.721	**1146.112** ± 0.242	**1.845** ± 0.000	**0.874** ± 0.000	48.387 ± 4.928
	TCN	1480.656 ± 2.140	1148.249 ± 2.833	1.849 ± 0.005	0.874 ± 0.000	48.387 ± 1.862
	Diff-TCN	1506.818 ± 5.976	1183.553 ± 8.027	1.902 ± 0.011	0.869 ± 0.001	36.022 ± 3.442
	CMHA-TCN	1499.578 ± 13.569	1163.080 ± 10.002	1.871 ± 0.014	0.871 ± 0.002	48.925 ± 4.718
	Diff-CMHA-TCN	1512.253 ± 6.632	1191.421 ± 5.446	1.913 ± 0.009	0.868 ± 0.001	31.720 ± 3.442
	EVMD-TCN	1539.890 ± 8.750	1221.968 ± 10.154	1.965 ± 0.016	0.863 ± 0.002	44.086 ± 6.083
	EVMD-CMHA-TCN	1593.181 ± 19.648	1262.743 ± 11.467	2.029 ± 0.018	0.854 ± 0.004	44.086 ± 3.041
	EVMD-PMB-TCN	1548.937 ± 23.571	1219.101 ± 17.508	1.963 ± 0.027	0.862 ± 0.004	45.699 ± 2.895
	EVMD-PMB-CMHA-TCN	1826.389 ± 148.616	1417.120 ± 124.095	2.275 ± 0.190	0.807 ± 0.032	45.161 ± 1.862
	SVMD-TCN	1558.252 ± 6.278	1221.520 ± 4.704	1.966 ± 0.007	0.860 ± 0.001	43.548 ± 2.464
	SVMD-CMHA-TCN	1549.591 ± 5.363	1218.468 ± 4.711	1.962 ± 0.008	0.862 ± 0.001	43.011 ± 1.521
	SVMD-PMB-TCN	1560.194 ± 5.571	1226.483 ± 3.372	1.974 ± 0.005	0.860 ± 0.001	41.398 ± 3.442
	SVMD-PMB-CMHA-TCN	1614.520 ± 60.163	1260.526 ± 50.544	2.025 ± 0.078	0.850 ± 0.011	**51.075** ± 6.293
August 2024	Diff-TCN [27]	2102.084 ± 0.325	1506.422 ± 0.390	2.528 ± 0.001	0.294 ± 0.000	45.699 ± 1.202
	TCN	2100.244 ± 12.376	1510.468 ± 9.319	2.535 ± 0.017	0.295 ± 0.008	52.151 ± 5.072
	Diff-TCN	**2098.196** ± 2.918	**1492.559** ± 2.450	**2.504** ± 0.004	**0.297** ± 0.002	55.914 ± 5.483
	CMHA-TCN	2105.272 ± 10.187	1517.404 ± 10.069	2.547 ± 0.018	0.292 ± 0.007	47.849 ± 3.442
	Diff-CMHA-TCN	2107.840 ± 11.534	1495.381 ± 10.925	2.508 ± 0.018	0.290 ± 0.008	53.226 ± 7.153
	EVMD-TCN	2132.258 ± 10.193	1494.333 ± 5.470	2.508 ± 0.009	0.274 ± 0.007	54.301 ± 3.442
	EVMD-CMHA-TCN	2172.865 ± 34.056	1534.403 ± 29.692	2.574 ± 0.052	0.246 ± 0.024	**56.989** ± 4.023
	EVMD-PMB-TCN	2146.055 ± 14.552	1510.450 ± 15.351	2.535 ± 0.028	0.264 ± 0.010	53.226 ± 3.088
	EVMD-PMB-CMHA-TCN	2391.809 ± 98.184	1776.718 ± 115.531	2.988 ± 0.194	0.085 ± 0.075	45.699 ± 5.403
	SVMD-TCN	2159.701 ± 14.660	1544.086 ± 13.039	2.586 ± 0.021	0.255 ± 0.010	40.323 ± 1.613
	SVMD-CMHA-TCN	2142.251 ± 6.416	1519.696 ± 6.352	2.546 ± 0.011	0.267 ± 0.004	45.161 ± 4.562
	SVMD-PMB-TCN	2144.148 ± 7.502	1526.205 ± 2.428	2.555 ± 0.005	0.266 ± 0.005	44.086 ± 4.433
	SVMD-PMB-CMHA-TCN	2256.599 ± 118.066	1647.076 ± 117.643	2.757 ± 0.199	0.184 ± 0.086	53.226 ± 6.906
September 2024	**Diff-TCN** [27]	1301.508 ± 0.385	1062.665 ± 0.428	1.783 ± 0.001	0.865 ± 0.000	**60.556** ± 1.242
	TCN	1304.175 ± 5.316	1064.298 ± 10.264	1.785 ± 0.016	0.865 ± 0.001	50.556 ± 9.510
	Diff-TCN	1315.086 ± 2.887	1071.388 ± 2.074	1.797 ± 0.003	0.863 ± 0.001	42.778 ± 2.291
	CMHA-TCN	1302.465 ± 4.095	1057.654 ± 6.809	1.774 ± 0.010	0.865 ± 0.001	55.000 ± 3.191
	Diff-CMHA-TCN	1317.493 ± 4.777	1070.894 ± 6.630	1.796 ± 0.011	0.862 ± 0.001	49.444 ± 5.241
	EVMD-TCN	1290.957 ± 4.377	1046.297 ± 5.709	1.755 ± 0.009	0.868 ± 0.001	48.889 ± 5.329
	EVMD-CMHA-TCN	1302.344 ± 6.671	1054.164 ± 9.849	1.769 ± 0.015	0.865 ± 0.001	47.222 ± 4.479
	EVMD-PMB-TCN	**1287.008** ± 25.238	**1043.757** ± 24.175	**1.750** ± 0.038	**0.868** ± 0.005	52.222 ± 6.285
	EVMD-PMB-CMHA-TCN	1445.458 ± 62.221	1222.707 ± 63.700	2.049 ± 0.103	0.834 ± 0.015	49.444 ± 3.557
	SVMD-TCN	1377.032 ± 3.751	1109.852 ± 7.689	1.862 ± 0.012	0.849 ± 0.001	52.778 ± 2.291
	SVMD-CMHA-TCN	1370.811 ± 0.838	1099.290 ± 3.656	1.846 ± 0.005	0.851 ± 0.000	53.889 ± 2.291
	SVMD-PMB-TCN	1369.760 ± 11.944	1103.570 ± 12.106	1.852 ± 0.019	0.851 ± 0.003	55.000 ± 3.727
	SVMD-PMB-CMHA-TCN	1404.314 ± 29.551	1177.091 ± 49.794	1.970 ± 0.074	0.843 ± 0.007	48.889 ± 3.685
October 2024	**Diff-TCN** [27]	**1326.391** ± 1.115	1007.950 ± 0.493	1.526 ± 0.001	**0.864** ± 0.000	51.613 ± 0.000
	TCN	1334.836 ± 19.302	1021.768 ± 14.719	1.548 ± 0.024	0.862 ± 0.004	48.387 ± 3.725
	Diff-TCN	1345.335 ± 1.808	1019.835 ± 2.723	1.545 ± 0.004	0.860 ± 0.000	50.000 ± 3.088
	CMHA-TCN	1336.409 ± 18.800	1016.421 ± 12.473	1.539 ± 0.018	0.862 ± 0.004	51.075 ± 1.202

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	1330.991 ± 5.085	1009.358 ± 2.454	1.528 ± 0.004	0.863 ± 0.001	52.688 ± 2.404
	EVMD-TCN	1377.825 ± 2.928	1042.286 ± 3.242	1.579 ± 0.004	0.853 ± 0.001	58.065 ± 0.000
	EVMD-CMHA-TCN	1437.307 ± 27.960	1104.205 ± 27.219	1.673 ± 0.040	0.840 ± 0.006	**60.215** ± 4.023
	EVMD-PMB-TCN	1397.443 ± 9.123	1062.817 ± 8.754	1.609 ± 0.013	0.849 ± 0.002	54.301 ± 3.914
	EVMD-PMB-CMHA-TCN	1605.034 ± 101.058	1293.804 ± 99.056	1.972 ± 0.154	0.800 ± 0.025	51.075 ± 2.895
	SVMD-TCN	1339.116 ± 13.598	1006.705 ± 15.143	1.525 ± 0.022	0.861 ± 0.003	54.301 ± 5.072
	SVMD-CMHA-TCN	1334.302 ± 6.929	**1004.091** ± 8.980	**1.522** ± 0.013	0.862 ± 0.001	54.839 ± 2.634
	SVMD-PMB-TCN	1336.705 ± 18.695	1012.173 ± 19.384	1.534 ± 0.030	0.862 ± 0.004	52.688 ± 3.566
	SVMD-PMB-CMHA-TCN	1491.176 ± 87.746	1154.286 ± 82.736	1.750 ± 0.121	0.827 ± 0.020	54.301 ± 4.335
November 2024	Diff-TCN [27]	2733.692 ± 0.925	1918.751 ± 0.435	2.204 ± 0.001	0.930 ± 0.000	56.667 ± 0.000
	TCN	2760.856 ± 53.234	1937.784 ± 33.110	2.225 ± 0.035	0.928 ± 0.003	48.333 ± 8.975
	Diff-TCN	2764.843 ± 3.578	1921.508 ± 1.846	2.210 ± 0.003	0.928 ± 0.000	50.000 ± 1.925
	CMHA-TCN	2755.354 ± 37.922	1937.241 ± 32.255	2.228 ± 0.040	0.929 ± 0.002	48.333 ± 9.766
	Diff-CMHA-TCN	2739.491 ± 3.295	1918.451 ± 0.990	2.204 ± 0.001	0.929 ± 0.000	55.000 ± 4.194
	EVMD-TCN	2783.848 ± 62.408	1978.964 ± 42.922	2.287 ± 0.042	0.927 ± 0.003	46.667 ± 3.333
	EVMD-CMHA-TCN	2866.621 ± 67.362	2082.482 ± 70.029	2.415 ± 0.080	0.923 ± 0.004	45.000 ± 1.667
	EVMD-PMB-TCN	2773.204 ± 34.136	1980.379 ± 26.087	2.294 ± 0.027	0.928 ± 0.002	47.222 ± 1.242
	EVMD-PMB-CMHA-TCN	3350.054 ± 394.867	2589.541 ± 393.319	2.983 ± 0.423	0.893 ± 0.025	39.444 ± 5.906
	SVMD-TCN	**2659.155** ± 11.267	**1899.770** ± 9.565	**2.191** ± 0.010	**0.934** ± 0.001	**62.222** ± 3.143
	SVMD-CMHA-TCN	2703.910 ± 35.077	1940.988 ± 33.106	2.235 ± 0.035	0.931 ± 0.002	55.000 ± 5.358
	SVMD-PMB-TCN	2743.800 ± 53.393	2004.594 ± 58.584	2.303 ± 0.064	0.929 ± 0.003	51.111 ± 8.315
	SVMD-PMB-CMHA-TCN	3410.735 ± 309.865	2701.979 ± 315.600	3.083 ± 0.347	0.890 ± 0.019	42.222 ± 8.749
December 2024	**Diff-TCN** [27]	2242.631 ± 0.511	**1705.982** ± 0.221	**1.732** ± 0.000	0.560 ± 0.000	51.613 ± 0.000
	TCN	2246.397 ± 8.120	1721.408 ± 22.769	1.746 ± 0.019	0.559 ± 0.003	51.075 ± 2.217
	Diff-TCN	2251.261 ± 5.798	1722.556 ± 4.535	1.748 ± 0.005	0.557 ± 0.002	**59.140** ± 3.041
	CMHA-TCN	**2230.425** ± 17.857	1716.409 ± 6.857	1.742 ± 0.006	**0.565** ± 0.007	50.000 ± 2.464
	Diff-CMHA-TCN	2245.876 ± 4.104	1715.466 ± 12.202	1.742 ± 0.013	0.559 ± 0.002	51.075 ± 3.914
	EVMD-TCN	2285.619 ± 7.984	1788.931 ± 7.969	1.817 ± 0.009	0.543 ± 0.003	53.763 ± 3.566
	EVMD-CMHA-TCN	2312.195 ± 27.505	1845.447 ± 18.719	1.873 ± 0.022	0.532 ± 0.011	53.763 ± 3.041
	EVMD-PMB-TCN	2290.465 ± 22.133	1812.847 ± 17.321	1.842 ± 0.019	0.541 ± 0.009	55.376 ± 2.895
	EVMD-PMB-CMHA-TCN	2760.984 ± 915.073	2300.333 ± 802.388	2.314 ± 0.802	0.260 ± 0.572	48.925 ± 4.718
	SVMD-TCN	2302.331 ± 15.645	1810.670 ± 9.562	1.838 ± 0.011	0.536 ± 0.006	54.839 ± 4.165
	SVMD-CMHA-TCN	2312.956 ± 20.505	1821.583 ± 18.962	1.852 ± 0.020	0.532 ± 0.008	52.151 ± 3.442
	SVMD-PMB-TCN	2303.999 ± 16.533	1812.857 ± 20.489	1.841 ± 0.023	0.536 ± 0.007	54.301 ± 4.718
	SVMD-PMB-CMHA-TCN	2957.032 ± 782.082	2464.725 ± 685.585	2.483 ± 0.680	0.182 ± 0.444	51.075 ± 2.217
January 2025	Diff-TCN [27]	2219.311 ± 0.602	1693.500 ± 0.302	1.689 ± 0.000	0.684 ± 0.000	54.839 ± 0.000
	TCN	2218.181 ± 5.104	1697.056 ± 3.453	1.693 ± 0.003	0.684 ± 0.002	50.538 ± 5.790
	Diff-TCN	**2214.648** ± 1.488	1692.204 ± 1.631	1.688 ± 0.002	**0.685** ± 0.000	51.075 ± 2.217
	CMHA-TCN	2216.330 ± 10.761	1698.540 ± 11.540	1.694 ± 0.011	0.684 ± 0.003	52.151 ± 5.403
	Diff-CMHA-TCN	2214.725 ± 4.090	**1690.996** ± 2.442	**1.687** ± 0.002	**0.685** ± 0.001	55.914 ± 2.404
	EVMD-TCN	2227.549 ± 5.145	1738.534 ± 5.966	1.734 ± 0.006	0.681 ± 0.002	43.548 ± 2.464
	EVMD-CMHA-TCN	2241.543 ± 8.585	1769.132 ± 11.426	1.765 ± 0.011	0.677 ± 0.003	46.774 ± 1.613
	EVMD-PMB-TCN	2266.715 ± 23.400	1788.052 ± 24.915	1.783 ± 0.024	0.670 ± 0.007	39.247 ± 2.217
	EVMD-PMB-CMHA-TCN	3042.681 ± 1101.166	2543.575 ± 1093.529	2.530 ± 1.082	0.328 ± 0.547	44.086 ± 2.404
	SVMD-TCN	2236.593 ± 5.402	1705.990 ± 5.892	1.702 ± 0.006	0.679 ± 0.002	53.763 ± 1.521
	SVMD-CMHA-TCN	2230.278 ± 9.804	1699.836 ± 10.655	1.695 ± 0.011	0.680 ± 0.003	**56.452** ± 2.464
	SVMD-PMB-TCN	2236.945 ± 16.242	1718.272 ± 22.217	1.714 ± 0.022	0.679 ± 0.005	56.452 ± 5.509
	SVMD-PMB-CMHA-TCN	2384.078 ± 167.890	1922.098 ± 173.184	1.915 ± 0.172	0.633 ± 0.054	48.925 ± 3.914
February 2025	**Diff-TCN** [27]	**2001.072** ± 1.159	1455.517 ± 1.778	1.542 ± 0.002	**0.790** ± 0.000	35.714 ± 0.000
	TCN	2006.126 ± 26.443	1461.656 ± 25.871	1.548 ± 0.028	0.789 ± 0.006	40.476 ± 10.648
	Diff-TCN	2003.706 ± 4.840	**1449.801** ± 5.528	**1.536** ± 0.006	**0.790** ± 0.001	52.381 ± 3.948
	CMHA-TCN	2025.414 ± 19.828	1481.097 ± 22.992	1.569 ± 0.024	0.785 ± 0.004	36.309 ± 1.331
	Diff-CMHA-TCN	2004.686 ± 5.011	1456.247 ± 5.020	1.543 ± 0.005	0.789 ± 0.001	42.262 ± 9.086
	EVMD-TCN	2067.660 ± 57.073	1511.943 ± 60.624	1.607 ± 0.066	0.776 ± 0.012	47.619 ± 2.662
	EVMD-CMHA-TCN	2212.117 ± 85.598	1657.953 ± 88.898	1.770 ± 0.096	0.743 ± 0.020	44.048 ± 3.367
	EVMD-PMB-TCN	2038.960 ± 44.353	1481.154 ± 43.722	1.575 ± 0.048	0.782 ± 0.010	46.429 ± 3.571
	EVMD-PMB-CMHA-TCN	2297.211 ± 293.973	1709.824 ± 202.028	1.836 ± 0.231	0.719 ± 0.072	51.191 ± 9.374
	SVMD-TCN	2051.490 ± 23.176	1509.831 ± 11.212	1.600 ± 0.013	0.779 ± 0.005	52.976 ± 3.811
	SVMD-CMHA-TCN	2046.353 ± 27.249	1503.700 ± 16.609	1.594 ± 0.018	0.780 ± 0.006	**53.571** ± 4.124
	SVMD-PMB-TCN	2072.329 ± 26.592	1521.812 ± 15.188	1.613 ± 0.017	0.775 ± 0.006	50.595 ± 4.333
	SVMD-PMB-CMHA-TCN	2304.628 ± 196.256	1686.586 ± 110.137	1.814 ± 0.129	0.720 ± 0.047	51.191 ± 4.909
March 2025	Diff-TCN [27]	2986.487 ± 0.205	2147.138 ± 0.399	2.507 ± 0.001	0.061 ± 0.000	45.161 ± 0.000
	TCN	2978.820 ± 7.439	2132.523 ± 9.102	2.489 ± 0.011	0.066 ± 0.005	55.376 ± 5.072
	Diff-TCN	2940.838 ± 5.973	**2127.146** ± 3.486	**2.486** ± 0.004	0.089 ± 0.004	54.301 ± 2.895
	CMHA-TCN	2970.131 ± 22.389	2137.721 ± 13.873	2.497 ± 0.015	0.071 ± 0.014	53.226 ± 8.277
	Diff-CMHA-TCN	2958.459 ± 24.567	2133.972 ± 12.466	2.493 ± 0.014	0.078 ± 0.015	48.925 ± 3.442
	EVMD-TCN	2988.347 ± 7.294	2178.620 ± 13.109	2.548 ± 0.016	0.060 ± 0.005	46.237 ± 4.023
	EVMD-CMHA-TCN	2937.069 ± 12.924	2169.887 ± 12.429	2.543 ± 0.016	0.092 ± 0.008	55.376 ± 4.718
	EVMD-PMB-TCN	2976.576 ± 15.842	2174.681 ± 14.475	2.543 ± 0.015	0.067 ± 0.010	51.613 ± 2.634
	EVMD-PMB-CMHA-TCN	3000.139 ± 122.520	2250.108 ± 94.840	2.634 ± 0.111	0.051 ± 0.077	**56.989** ± 7.603
	SVMD-TCN	2993.332 ± 5.695	2241.192 ± 5.686	2.621 ± 0.007	0.057 ± 0.004	40.860 ± 1.521
	SVMD-CMHA-TCN	2986.105 ± 3.595	2239.755 ± 3.686	2.622 ± 0.004	0.061 ± 0.002	39.785 ± 3.041
	SVMD-PMB-TCN	2985.995 ± 7.401	2234.434 ± 7.791	2.614 ± 0.010	0.061 ± 0.005	40.860 ± 1.521
	SVMD-PMB-CMHA-TCN	**2897.251** ± 40.914	2193.969 ± 57.967	2.570 ± 0.068	**0.116** ± 0.025	44.086 ± 9.617
April 2025	Diff-TCN [27]	2341.482 ± 0.703	1617.381 ± 0.477	1.919 ± 0.001	0.819 ± 0.000	60.000 ± 0.000
	TCN	2353.006 ± 6.712	1633.564 ± 11.435	1.936 ± 0.013	0.817 ± 0.001	55.000 ± 11.667
	Diff-TCN	2307.565 ± 6.594	1575.308 ± 2.376	1.865 ± 0.003	0.824 ± 0.001	63.333 ± 7.698
	CMHA-TCN	2351.702 ± 6.590	1632.592 ± 7.189	1.935 ± 0.008	0.818 ± 0.001	46.667 ± 9.428

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	2333.309 ± 6.973	1589.962 ± 14.179	1.885 ± 0.018	0.820 ± 0.001	**66.667** ± 5.092
	EVMD-TCN	2293.827 ± 28.823	1573.625 ± 33.603	1.853 ± 0.037	0.826 ± 0.004	61.667 ± 7.391
	EVMD-CMHA-TCN	**2249.976** ± 27.171	**1529.557** ± 23.202	**1.796** ± 0.025	**0.833** ± 0.004	63.333 ± 7.454
	EVMD-PMB-TCN	2295.658 ± 21.682	1575.634 ± 37.563	1.852 ± 0.044	0.826 ± 0.003	61.667 ± 5.693
	EVMD-PMB-CMHA-TCN	2567.940 ± 157.390	1911.893 ± 189.834	2.225 ± 0.211	0.782 ± 0.027	51.111 ± 2.485
	SVMD-TCN	2410.492 ± 7.077	1642.961 ± 8.201	1.940 ± 0.010	0.808 ± 0.001	50.000 ± 4.714
	SVMD-CMHA-TCN	2396.035 ± 8.388	1632.949 ± 10.165	1.928 ± 0.012	0.810 ± 0.001	47.778 ± 4.157
	SVMD-PMB-TCN	2415.951 ± 14.979	1651.069 ± 19.964	1.949 ± 0.022	0.807 ± 0.002	49.444 ± 5.583
	SVMD-PMB-CMHA-TCN	2401.738 ± 52.298	1710.681 ± 56.213	2.000 ± 0.060	0.809 ± 0.008	55.000 ± 5.693
May 2025	Diff-TCN [27]	1926.895 ± 0.534	1417.274 ± 0.489	1.363 ± 0.001	0.832 ± 0.000	54.839 ± 0.000
	TCN	1931.990 ± 9.778	1416.745 ± 10.115	1.362 ± 0.010	0.831 ± 0.002	52.151 ± 2.895
	Diff-TCN	1930.710 ± 1.290	1406.321 ± 4.547	1.352 ± 0.004	0.831 ± 0.000	55.376 ± 2.217
	CMHA-TCN	1941.054 ± 4.667	1421.746 ± 4.853	1.367 ± 0.005	0.829 ± 0.001	47.849 ± 2.895
	Diff-CMHA-TCN	1931.887 ± 3.287	1422.788 ± 5.495	1.368 ± 0.005	0.831 ± 0.001	46.774 ± 3.088
	EVMD-TCN	1966.877 ± 14.687	1432.837 ± 10.465	1.379 ± 0.010	0.825 ± 0.003	53.226 ± 4.059
	EVMD-CMHA-TCN	2026.114 ± 25.363	1475.822 ± 15.409	1.419 ± 0.015	0.814 ± 0.005	52.151 ± 2.217
	EVMD-PMB-TCN	1991.360 ± 16.935	1455.535 ± 12.380	1.400 ± 0.012	0.820 ± 0.003	50.538 ± 2.404
	EVMD-PMB-CMHA-TCN	2273.608 ± 179.004	1697.557 ± 144.896	1.628 ± 0.136	0.764 ± 0.037	50.538 ± 3.041
	SVMD-TCN	**1861.649** ± 11.291	**1319.835** ± 8.280	**1.270** ± 0.008	**0.843** ± 0.002	**65.591** ± 3.041
	SVMD-CMHA-TCN	1879.704 ± 18.091	1335.797 ± 18.191	1.285 ± 0.017	0.840 ± 0.003	59.140 ± 7.603
	SVMD-PMB-TCN	1886.816 ± 13.164	1344.700 ± 12.020	1.294 ± 0.011	0.839 ± 0.002	58.602 ± 3.442
	SVMD-PMB-CMHA-TCN	2491.082 ± 355.892	1925.190 ± 328.993	1.846 ± 0.312	0.713 ± 0.086	50.000 ± 5.185

Table 59: Average results of the *extended experiments* across 6 repetitions per split $M_1, \ldots, M_{36}$ corresponding to months June 2022 to May 2025 in relation to forecasting $\mathbf{S}_{\text{Close}}$ with respect to BTC/USD using the novel framework.

F.2.2 *ETH / USD*

Month	Model	RMSE	MAE	MAPE	R2	DA
June 2021	TCN [27]	145.923 ± 14.556	118.519 ± 10.393	5.245 ± 0.456	0.756 ± 0.050	53.333 ± 3.333
	Diff-TCN [27]	123.075 ± 0.316	100.685 ± 0.081	4.431 ± 0.004	0.828 ± 0.001	53.333 ± 0.000
	TCN	124.610 ± 1.493	101.231 ± 1.237	4.459 ± 0.053	0.824 ± 0.004	57.778 ± 6.573
	Diff-TCN	124.081 ± 1.882	103.047 ± 1.521	4.538 ± 0.064	0.825 ± 0.005	46.111 ± 8.480
	CMHA-TCN	125.321 ± 1.466	101.892 ± 0.834	4.485 ± 0.037	0.822 ± 0.004	53.889 ± 1.242
	Diff-CMHA-TCN	125.082 ± 2.635	103.360 ± 2.191	4.545 ± 0.085	0.823 ± 0.007	40.556 ± 2.291
	EVMD-TCN	**119.337** ± 1.177	97.967 ± 0.295	4.379 ± 0.017	**0.839** ± 0.003	50.000 ± 4.714
	EVMD-CMHA-TCN	121.525 ± 1.115	100.314 ± 0.411	4.489 ± 0.020	0.833 ± 0.003	53.333 ± 5.774
	EVMD-PMB-TCN	120.484 ± 0.751	**96.926** ± 1.104	**4.338** ± 0.042	0.835 ± 0.002	54.444 ± 1.571
	EVMD-PMB-CMHA-TCN	123.552 ± 2.872	101.534 ± 2.642	4.534 ± 0.116	0.827 ± 0.008	55.000 ± 5.000
	SVMD-TCN	122.820 ± 0.844	103.002 ± 1.053	4.576 ± 0.045	0.829 ± 0.002	50.000 ± 2.722
	SVMD-CMHA-TCN	122.400 ± 1.209	102.272 ± 1.677	4.551 ± 0.070	0.830 ± 0.003	50.556 ± 2.291
	SVMD-PMB-TCN	120.531 ± 1.083	99.564 ± 1.244	4.427 ± 0.053	0.835 ± 0.003	53.889 ± 2.291
	SVMD-PMB-CMHA-TCN	120.032 ± 0.546	98.758 ± 1.855	4.414 ± 0.079	0.837 ± 0.002	**60.556** ± 2.291
July 2021	TCN [27]	148.962 ± 99.134	129.441 ± 100.738	6.016 ± 4.634	0.065 ± 1.359	50.000 ± 8.484
	Diff-TCN [27]	87.689 ± 0.123	69.829 ± 0.145	3.299 ± 0.007	0.775 ± 0.001	61.290 ± 0.000
	TCN	87.566 ± 0.523	68.695 ± 0.853	3.267 ± 0.028	0.776 ± 0.003	59.677 ± 1.613
	Diff-TCN	87.432 ± 0.054	69.094 ± 0.394	3.270 ± 0.011	0.777 ± 0.000	61.290 ± 1.862
	CMHA-TCN	**87.079** ± 0.416	**68.210** ± 0.373	**3.241** ± 0.012	**0.778** ± 0.002	60.215 ± 2.404
	Diff-CMHA-TCN	87.251 ± 0.290	69.724 ± 0.815	3.288 ± 0.037	0.778 ± 0.002	60.215 ± 8.467
	EVMD-TCN	88.500 ± 0.180	70.844 ± 0.416	3.365 ± 0.014	0.771 ± 0.001	59.677 ± 2.464
	EVMD-CMHA-TCN	87.940 ± 0.272	70.669 ± 0.406	3.357 ± 0.019	0.774 ± 0.001	60.215 ± 1.521
	EVMD-PMB-TCN	89.027 ± 0.401	71.479 ± 0.459	3.390 ± 0.020	0.768 ± 0.002	60.753 ± 2.217
	EVMD-PMB-CMHA-TCN	88.568 ± 0.682	70.573 ± 0.635	3.364 ± 0.032	0.771 ± 0.004	59.677 ± 3.088
	SVMD-TCN	90.642 ± 0.205	71.897 ± 0.270	3.402 ± 0.011	0.760 ± 0.001	58.602 ± 1.202
	SVMD-CMHA-TCN	92.146 ± 0.458	72.020 ± 0.265	3.417 ± 0.008	0.752 ± 0.003	58.065 ± 4.165
	SVMD-PMB-TCN	90.397 ± 0.162	71.205 ± 0.657	3.367 ± 0.023	0.761 ± 0.001	**61.828** ± 3.442
	SVMD-PMB-CMHA-TCN	91.076 ± 0.634	72.751 ± 0.791	3.439 ± 0.029	0.758 ± 0.003	53.763 ± 6.885
August 2021	TCN [27]	256.975 ± 99.913	227.594 ± 103.840	7.278 ± 3.329	−0.434 ± 1.218	41.398 ± 4.718
	Diff-TCN [27]	125.388 ± 0.205	100.818 ± 0.116	3.255 ± 0.004	0.704 ± 0.001	61.290 ± 0.000
	TCN	126.638 ± 6.144	102.324 ± 5.936	3.299 ± 0.182	0.697 ± 0.031	58.065 ± 9.124
	Diff-TCN	123.588 ± 1.296	98.527 ± 1.451	3.182 ± 0.045	0.712 ± 0.006	63.978 ± 3.914
	CMHA-TCN	122.927 ± 0.918	98.903 ± 0.516	3.193 ± 0.016	0.715 ± 0.004	67.742 ± 3.725
	Diff-CMHA-TCN	123.095 ± 0.438	97.527 ± 0.676	3.152 ± 0.022	0.714 ± 0.002	70.968 ± 3.725
	EVMD-TCN	119.382 ± 0.464	97.070 ± 0.112	3.131 ± 0.004	0.731 ± 0.002	73.118 ± 2.404
	EVMD-CMHA-TCN	**118.612** ± 0.281	97.294 ± 0.406	3.141 ± 0.013	**0.735** ± 0.001	68.817 ± 3.041
	EVMD-PMB-TCN	120.139 ± 0.449	98.243 ± 0.256	3.169 ± 0.009	0.728 ± 0.002	73.118 ± 1.521
	EVMD-PMB-CMHA-TCN	119.067 ± 0.861	95.289 ± 1.503	**3.073** ± 0.050	0.733 ± 0.004	**75.269** ± 2.404
	SVMD-TCN	119.270 ± 0.883	**95.130** ± 0.822	3.080 ± 0.024	0.732 ± 0.004	67.742 ± 2.634
	SVMD-CMHA-TCN	121.330 ± 3.546	96.928 ± 3.499	3.137 ± 0.107	0.722 ± 0.017	63.441 ± 8.669
	SVMD-PMB-TCN	122.493 ± 1.857	98.305 ± 1.703	3.175 ± 0.052	0.717 ± 0.009	67.742 ± 9.496
	SVMD-PMB-CMHA-TCN	120.325 ± 1.868	96.633 ± 1.772	3.129 ± 0.053	0.727 ± 0.009	62.903 ± 6.650
September 2021	TCN [27]	281.726 ± 76.760	231.442 ± 74.286	6.790 ± 2.068	0.332 ± 0.368	56.111 ± 3.557
	Diff-TCN [27]	**186.016** ± 0.324	145.749 ± 0.116	4.469 ± 0.005	**0.729** ± 0.001	46.667 ± 0.000
	TCN	190.120 ± 2.883	145.687 ± 1.802	4.464 ± 0.056	0.717 ± 0.009	49.444 ± 4.479
	Diff-TCN	186.851 ± 0.756	145.091 ± 1.353	4.456 ± 0.040	0.726 ± 0.002	50.000 ± 4.714
	CMHA-TCN	186.153 ± 0.787	**143.626** ± 0.738	**4.407** ± 0.024	0.728 ± 0.002	47.778 ± 3.143
	Diff-CMHA-TCN	189.113 ± 3.038	147.654 ± 1.988	4.533 ± 0.065	0.720 ± 0.009	45.556 ± 8.089
	EVMD-TCN	194.678 ± 0.927	150.620 ± 0.855	4.624 ± 0.030	0.703 ± 0.003	51.667 ± 2.546
	EVMD-CMHA-TCN	195.174 ± 0.262	150.615 ± 0.227	4.627 ± 0.007	0.702 ± 0.001	51.111 ± 1.571
	EVMD-PMB-TCN	198.747 ± 1.295	155.786 ± 1.124	4.791 ± 0.038	0.691 ± 0.004	48.333 ± 3.727
	EVMD-PMB-CMHA-TCN	198.024 ± 4.772	155.682 ± 5.760	4.778 ± 0.195	0.693 ± 0.015	46.111 ± 5.583
	SVMD-TCN	198.123 ± 0.448	147.995 ± 0.405	4.546 ± 0.010	0.692 ± 0.001	51.111 ± 2.485
	SVMD-CMHA-TCN	199.165 ± 0.710	147.446 ± 0.462	4.533 ± 0.014	0.689 ± 0.002	56.111 ± 6.503
	SVMD-PMB-TCN	197.210 ± 0.656	148.335 ± 0.798	4.548 ± 0.021	0.695 ± 0.002	52.778 ± 3.557
	SVMD-PMB-CMHA-TCN	195.281 ± 0.978	144.773 ± 0.507	4.441 ± 0.014	0.701 ± 0.003	**57.222** ± 2.291
October 2021	TCN [27]	357.887 ± 169.963	319.856 ± 178.793	8.206 ± 4.658	−0.504 ± 1.326	50.538 ± 11.123
	Diff-TCN [27]	**138.948** ± 0.736	111.504 ± 0.442	2.892 ± 0.012	**0.815** ± 0.002	**58.065**± 0.000
	TCN	143.018 ± 5.338	111.747 ± 1.049	2.903 ± 0.029	0.804 ± 0.015	53.763 ± 5.790
	Diff-TCN	140.426 ± 1.000	112.155 ± 0.298	2.914 ± 0.009	0.811 ± 0.003	51.075 ± 2.217
	CMHA-TCN	144.426 ± 2.196	111.163 ± 0.857	2.893 ± 0.023	0.800 ± 0.006	49.462 ± 6.083
	Diff-CMHA-TCN	143.508 ± 1.090	115.409 ± 0.621	3.000 ± 0.017	0.803 ± 0.003	43.011 ± 3.566
	EVMD-TCN	147.196 ± 1.903	120.489 ± 0.486	3.141 ± 0.013	0.792 ± 0.005	47.849 ± 2.895
	EVMD-CMHA-TCN	147.475 ± 2.069	120.273 ± 0.417	3.139 ± 0.011	0.792 ± 0.006	47.312 ± 3.566
	EVMD-PMB-TCN	145.566 ± 2.007	119.960 ± 0.676	3.126 ± 0.021	0.797 ± 0.006	46.237 ± 3.566
	EVMD-PMB-CMHA-TCN	147.497 ± 1.684	120.466 ± 1.019	3.144 ± 0.026	0.791 ± 0.005	47.312 ± 2.404
	SVMD-TCN	142.250 ± 2.671	109.779 ± 0.452	2.853 ± 0.013	0.806 ± 0.007	54.301 ± 3.914
	SVMD-CMHA-TCN	142.647 ± 2.330	**108.511** ± 1.885	**2.815** ± 0.052	0.805 ± 0.006	**58.065**± 5.889
	SVMD-PMB-TCN	145.661 ± 1.991	111.195 ± 0.844	2.894 ± 0.022	0.797 ± 0.006	53.226 ± 2.464
	SVMD-PMB-CMHA-TCN	146.274 ± 1.907	110.725 ± 1.129	2.885 ± 0.031	0.795 ± 0.005	50.000 ± 1.613
November 2021	TCN [27]	361.265 ± 174.151	325.691 ± 171.830	7.260 ± 3.787	−2.397 ± 3.355	56.667 ± 7.201
	Diff-TCN [27]	182.804 ± 0.117	143.177 ± 0.078	3.296 ± 0.002	0.294 ± 0.001	53.333 ± 0.000
	TCN	181.399 ± 0.361	142.095 ± 0.962	3.268 ± 0.026	0.305 ± 0.003	**57.222** ± 4.875
	Diff-TCN	180.475 ± 0.608	141.392 ± 0.498	3.252 ± 0.012	0.312 ± 0.005	53.333 ± 0.000
	CMHA-TCN	183.047 ± 1.193	142.242 ± 1.089	3.263 ± 0.023	0.292 ± 0.009	48.333 ± 3.727

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	181.438 ± 1.506	143.411 ± 1.177	3.296 ± 0.030	0.305 ± 0.012	48.333 ± 3.191
	EVMD-TCN	190.160 ± 0.467	143.955 ± 0.405	3.312 ± 0.011	0.236 ± 0.004	52.778 ± 2.992
	EVMD-CMHA-TCN	188.558 ± 0.622	143.681 ± 0.879	3.308 ± 0.022	0.249 ± 0.005	55.000 ± 2.546
	EVMD-PMB-TCN	191.824 ± 0.506	145.767 ± 0.724	3.360 ± 0.019	0.223 ± 0.004	51.111 ± 1.571
	EVMD-PMB-CMHA-TCN	193.079 ± 1.715	147.241 ± 3.456	3.377 ± 0.072	0.213 ± 0.014	52.222 ± 1.571
	SVMD-TCN	178.961 ± 1.581	140.849 ± 1.133	3.233 ± 0.025	0.324 ± 0.012	52.778 ± 1.242
	SVMD-CMHA-TCN	183.433 ± 3.382	143.537 ± 1.820	3.290 ± 0.038	0.289 ± 0.026	51.111 ± 1.571
	SVMD-PMB-TCN	182.606 ± 2.973	142.943 ± 1.780	3.274 ± 0.038	0.296 ± 0.023	49.444 ± 3.557
	SVMD-PMB-CMHA-TCN	**178.248** ± 1.539	**140.147** ± 0.888	**3.213** ± 0.018	**0.329** ± 0.012	53.333 ± 1.925
December 2021	**TCN** [27]	1206.957 ± 209.400	1192.916 ± 212.052	29.338 ± 5.252	−28.412 ± 8.803	**58.065** ± 0.000
	Diff-TCN [27]	148.405 ± 0.923	115.157 ± 0.463	2.871 ± 0.012	0.568 ± 0.005	41.935 ± 0.000
	TCN	144.516 ± 1.309	113.462 ± 1.325	2.817 ± 0.033	0.591 ± 0.007	54.301 ± 3.442
	Diff-TCN	145.957 ± 0.180	115.767 ± 0.215	2.872 ± 0.006	0.583 ± 0.001	46.237 ± 2.404
	CMHA-TCN	**143.611** ± 2.122	**112.943** ± 2.468	**2.801** ± 0.060	**0.596** ± 0.012	56.452 ± 3.607
	Diff-CMHA-TCN	149.236 ± 5.741	117.356 ± 4.490	2.909 ± 0.120	0.563 ± 0.035	44.086 ± 5.483
	EVMD-TCN	154.650 ± 3.358	118.132 ± 2.117	2.940 ± 0.052	0.531 ± 0.020	48.387 ± 4.928
	EVMD-CMHA-TCN	159.564 ± 4.101	121.285 ± 2.861	3.020 ± 0.072	0.501 ± 0.026	50.000 ± 3.607
	EVMD-PMB-TCN	155.052 ± 3.344	120.887 ± 3.196	3.001 ± 0.078	0.529 ± 0.020	47.312 ± 3.566
	EVMD-PMB-CMHA-TCN	156.888 ± 3.776	119.724 ± 2.315	2.980 ± 0.055	0.517 ± 0.023	47.312 ± 3.566
	SVMD-TCN	154.534 ± 2.883	121.063 ± 1.350	3.009 ± 0.034	0.532 ± 0.017	43.548 ± 4.059
	SVMD-CMHA-TCN	162.543 ± 7.349	127.338 ± 6.223	3.167 ± 0.157	0.481 ± 0.047	40.323 ± 6.650
	SVMD-PMB-TCN	155.910 ± 2.194	119.539 ± 2.110	2.973 ± 0.045	0.523 ± 0.013	45.161 ± 5.268
	SVMD-PMB-CMHA-TCN	161.014 ± 14.673	122.382 ± 11.963	3.054 ± 0.306	0.488 ± 0.093	40.860 ± 8.467
January 2022	TCN [27]	359.144 ± 89.480	315.721 ± 94.905	10.805 ± 3.295	0.311 ± 0.383	51.613 ± 0.000
	Diff-TCN [27]	**133.139** ± 1.132	**100.438** ± 0.353	**3.385** ± 0.015	**0.911** ± 0.002	**51.613** ± 0.000
	TCN	140.859 ± 4.349	103.215 ± 1.938	3.472 ± 0.062	0.900 ± 0.006	47.849 ± 2.895
	Diff-TCN	134.078 ± 1.646	102.604 ± 1.112	3.461 ± 0.039	0.910 ± 0.002	49.462 ± 4.433
	CMHA-TCN	137.146 ± 4.627	102.914 ± 2.057	3.466 ± 0.079	0.905 ± 0.006	46.237 ± 5.483
	Diff-CMHA-TCN	134.417 ± 2.546	105.279 ± 1.502	3.558 ± 0.052	0.909 ± 0.004	38.710 ± 8.118
	EVMD-TCN	137.824 ± 1.682	102.203 ± 0.789	3.442 ± 0.027	0.904 ± 0.002	48.925 ± 5.715
	EVMD-CMHA-TCN	137.060 ± 1.806	102.035 ± 0.608	3.435 ± 0.023	0.906 ± 0.003	47.849 ± 7.072
	EVMD-PMB-TCN	140.883 ± 6.026	102.927 ± 3.696	3.460 ± 0.125	0.900 ± 0.009	50.000 ± 6.106
	EVMD-PMB-CMHA-TCN	137.714 ± 2.578	103.017 ± 1.211	3.486 ± 0.046	0.905 ± 0.004	48.387 ± 4.165
	SVMD-TCN	136.170 ± 1.702	106.084 ± 1.485	3.581 ± 0.046	0.907 ± 0.002	36.022 ± 3.914
	SVMD-CMHA-TCN	135.127 ± 2.135	105.242 ± 0.944	3.549 ± 0.033	0.908 ± 0.003	36.559 ± 5.157
	SVMD-PMB-TCN	135.183 ± 1.601	108.296 ± 1.047	3.666 ± 0.035	0.908 ± 0.002	34.409 ± 8.047
	SVMD-PMB-CMHA-TCN	137.575 ± 3.330	108.011 ± 1.772	3.647 ± 0.063	0.905 ± 0.005	44.624 ± 4.335
February 2022	TCN [27]	268.777 ± 63.770	226.064 ± 56.792	7.698 ± 1.859	−0.941 ± 0.921	57.143 ± 5.455
	Diff-TCN [27]	134.502 ± 0.159	104.135 ± 0.448	3.611 ± 0.018	0.540 ± 0.001	50.000 ± 0.000
	TCN	132.304 ± 0.834	104.582 ± 1.604	3.630 ± 0.061	0.555 ± 0.006	51.191 ± 4.909
	Diff-TCN	132.301 ± 1.071	103.180 ± 1.009	3.571 ± 0.037	0.555 ± 0.007	54.167 ± 3.811
	CMHA-TCN	132.960 ± 0.568	106.065 ± 0.726	3.682 ± 0.029	0.550 ± 0.004	50.000 ± 4.611
	Diff-CMHA-TCN	133.173 ± 1.374	104.788 ± 0.460	3.628 ± 0.016	0.549 ± 0.009	52.976 ± 6.967
	EVMD-TCN	136.906 ± 0.749	107.174 ± 0.374	3.707 ± 0.015	0.523 ± 0.005	50.595 ± 1.331
	EVMD-CMHA-TCN	137.743 ± 0.598	108.398 ± 1.025	3.758 ± 0.044	0.517 ± 0.004	52.976 ± 4.333
	EVMD-PMB-TCN	136.621 ± 1.255	105.373 ± 0.884	3.639 ± 0.034	0.525 ± 0.009	51.786 ± 4.494
	EVMD-PMB-CMHA-TCN	138.092 ± 0.767	108.962 ± 0.978	3.782 ± 0.040	0.515 ± 0.005	54.167 ± 4.799
	SVMD-TCN	132.393 ± 1.043	101.415 ± 0.721	3.528 ± 0.027	0.554 ± 0.007	55.952 ± 6.070
	SVMD-CMHA-TCN	134.086 ± 0.420	102.386 ± 0.515	3.560 ± 0.016	0.543 ± 0.003	58.929 ± 5.740
	SVMD-PMB-TCN	**130.913** ± 0.387	**100.540** ± 0.696	**3.499** ± 0.028	**0.564** ± 0.003	**64.881** ± 8.096
	SVMD-PMB-CMHA-TCN	135.223 ± 1.578	104.779 ± 1.446	3.646 ± 0.050	0.535 ± 0.011	61.309 ± 2.454
March 2022	TCN [27]	294.278 ± 73.294	244.444 ± 54.710	8.111 ± 1.707	−0.208 ± 0.582	44.086 ± 3.041
	Diff-TCN [27]	**88.223** ± 0.074	**71.327** ± 0.255	**2.535** ± 0.007	**0.898** ± 0.000	61.290 ± 0.000
	TCN	90.968 ± 1.223	73.475 ± 0.886	2.609 ± 0.030	0.891 ± 0.003	51.075 ± 5.072
	Diff-TCN	90.017 ± 0.164	73.500 ± 0.482	2.603 ± 0.015	0.894 ± 0.000	**63.441** ± 2.404
	CMHA-TCN	91.848 ± 0.636	72.698 ± 0.433	2.587 ± 0.017	0.889 ± 0.002	60.753 ± 3.442
	Diff-CMHA-TCN	91.569 ± 0.387	74.352 ± 0.587	2.634 ± 0.019	0.890 ± 0.001	59.140 ± 5.483
	EVMD-TCN	97.957 ± 1.477	80.241 ± 0.819	2.865 ± 0.035	0.874 ± 0.004	51.075 ± 2.895
	EVMD-CMHA-TCN	97.253 ± 0.246	79.981 ± 0.287	2.850 ± 0.011	0.876 ± 0.001	46.774 ± 4.839
	EVMD-PMB-TCN	99.251 ± 0.641	81.365 ± 0.734	2.900 ± 0.027	0.871 ± 0.002	42.473 ± 3.914
	EVMD-PMB-CMHA-TCN	97.777 ± 0.675	79.751 ± 0.537	2.849 ± 0.019	0.875 ± 0.002	55.376 ± 3.442
	SVMD-TCN	90.384 ± 0.479	71.979 ± 1.181	2.557 ± 0.035	0.893 ± 0.001	59.140 ± 4.023
	SVMD-CMHA-TCN	93.296 ± 0.916	74.414 ± 0.904	2.639 ± 0.030	0.886 ± 0.002	52.151 ± 7.772
	SVMD-PMB-TCN	91.296 ± 0.606	72.808 ± 1.112	2.586 ± 0.035	0.890 ± 0.002	60.215 ± 6.361
	SVMD-PMB-CMHA-TCN	91.980 ± 0.846	74.387 ± 1.327	2.637 ± 0.042	0.889 ± 0.002	55.914 ± 4.433
April 2022	TCN [27]	136.005 ± 22.166	112.059 ± 21.703	3.610 ± 0.723	0.555 ± 0.152	52.222 ± 3.143
	Diff-TCN [27]	102.314 ± 1.137	79.301 ± 0.525	2.593 ± 0.018	0.754 ± 0.005	43.333 ± 0.000
	TCN	**98.134** ± 0.879	75.996 ± 0.434	2.486 ± 0.014	**0.774** ± 0.004	54.444 ± 7.857
	Diff-TCN	99.769 ± 1.138	76.642 ± 1.153	2.501 ± 0.040	0.767 ± 0.005	51.667 ± 6.872
	CMHA-TCN	98.684 ± 1.414	75.016 ± 0.417	2.457 ± 0.015	0.772 ± 0.007	51.111 ± 1.571
	Diff-CMHA-TCN	100.403 ± 2.888	76.408 ± 2.512	2.497 ± 0.083	0.763 ± 0.014	55.000 ± 8.975
	EVMD-TCN	101.509 ± 0.791	74.679 ± 0.519	2.435 ± 0.019	0.758 ± 0.004	61.111 ± 1.571
	EVMD-CMHA-TCN	100.646 ± 0.680	74.044 ± 0.311	2.416 ± 0.012	0.762 ± 0.003	60.556 ± 1.242
	EVMD-PMB-TCN	99.313 ± 1.697	**73.232** ± 0.932	**2.386** ± 0.033	0.769 ± 0.008	**67.222** ± 3.557
	EVMD-PMB-CMHA-TCN	101.859 ± 3.042	74.978 ± 2.721	2.450 ± 0.094	0.756 ± 0.015	60.000 ± 5.092
	SVMD-TCN	100.520 ± 1.321	74.743 ± 1.024	2.447 ± 0.034	0.763 ± 0.006	56.111 ± 5.583
	SVMD-CMHA-TCN	100.006 ± 1.403	74.324 ± 1.026	2.432 ± 0.034	0.765 ± 0.007	56.111 ± 3.557
	SVMD-PMB-TCN	99.276 ± 0.932	73.777 ± 0.724	2.414 ± 0.024	0.769 ± 0.004	59.444 ± 5.241
	SVMD-PMB-CMHA-TCN	100.361 ± 1.772	74.108 ± 1.293	2.425 ± 0.045	0.764 ± 0.008	55.556 ± 5.666

Month	Model	RMSE	MAE	MAPE	R2	DA
May 2022	TCN [27]	847.872 ± 33.140	812.428 ± 34.576	39.513 ± 1.609	−4.638 ± 0.443	48.387 ± 0.000
	Diff-TCN [27]	120.823 ± 0.714	98.124 ± 0.235	4.532 ± 0.012	0.886 ± 0.001	48.387 ± 0.000
	TCN	127.195 ± 1.952	100.123 ± 1.238	4.653 ± 0.061	0.873 ± 0.004	50.000 ± 1.613
	Diff-TCN	117.804 ± 1.127	97.046 ± 0.863	4.485 ± 0.039	0.891 ± 0.002	51.075 ± 2.895
	CMHA-TCN	125.390 ± 3.189	97.969 ± 1.375	4.543 ± 0.075	0.877 ± 0.006	52.688 ± 3.041
	Diff-CMHA-TCN	**116.449** ± 1.390	96.238 ± 0.991	4.443 ± 0.049	**0.894** ± 0.003	56.452 ± 6.384
	EVMD-TCN	119.165 ± 1.865	95.290 ± 1.193	4.426 ± 0.062	0.889 ± 0.004	57.527 ± 3.442
	EVMD-CMHA-TCN	118.684 ± 2.337	93.580 ± 1.224	4.341 ± 0.062	0.890 ± 0.004	58.602 ± 2.217
	EVMD-PMB-TCN	119.887 ± 3.806	95.999 ± 2.158	4.460 ± 0.113	0.887 ± 0.007	55.914 ± 3.566
	EVMD-PMB-CMHA-TCN	122.990 ± 3.509	95.544 ± 2.090	4.448 ± 0.110	0.881 ± 0.007	60.753 ± 2.895
	SVMD-TCN	119.800 ± 3.040	96.359 ± 1.815	4.478 ± 0.093	0.887 ± 0.006	55.376 ± 3.442
	SVMD-CMHA-TCN	117.044 ± 0.417	94.404 ± 0.244	4.381 ± 0.011	0.893 ± 0.001	61.290 ± 3.226
	SVMD-PMB-TCN	122.877 ± 3.459	97.528 ± 1.608	4.542 ± 0.084	0.882 ± 0.007	53.763 ± 4.023
	SVMD-PMB-CMHA-TCN	117.845 ± 2.150	**92.792** ± 1.125	**4.300** ± 0.059	0.891 ± 0.004	**65.054** ± 5.072

Table 60: Average results of the *benchmark experiments* across 6 repetitions per split $M_1, \ldots, M_{12}$ corresponding to months June 2021 to May 2022 in relation to forecasting $\mathbf{S}_{\text{Close}}$ with respect to $ETH\,/\,USD$ using the novel framework.

Month	Model	RMSE	MAE	MAPE	R2	DA
June 2022	Diff-TCN [27]	86.894 ± 0.233	65.006 ± 0.194	5.035 ± 0.015	0.921 ± 0.000	33.333 ± 0.000
	TCN	100.566 ± 5.552	78.986 ± 6.693	6.151 ± 0.527	0.894 ± 0.011	33.889 ± 1.242
	Diff-TCN	84.701 ± 0.878	**63.325** ± 0.625	**4.903** ± 0.048	0.925 ± 0.002	35.556 ± 4.969
	CMHA-TCN	99.939 ± 4.118	78.134 ± 4.607	6.067 ± 0.357	0.896 ± 0.009	33.333 ± 0.000
	Diff-CMHA-TCN	**84.261** ± 1.969	63.718 ± 1.355	4.930 ± 0.105	**0.926** ± 0.004	**40.000** ± 8.165
	EVMD-TCN	101.572 ± 4.518	82.025 ± 4.166	6.324 ± 0.342	0.892 ± 0.010	32.222 ± 1.571
	EVMD-CMHA-TCN	100.549 ± 2.457	80.491 ± 2.302	6.213 ± 0.184	0.895 ± 0.005	30.000 ± 2.722
	EVMD-PMB-TCN	100.769 ± 3.233	81.245 ± 2.927	6.261 ± 0.248	0.894 ± 0.007	33.889 ± 1.242
	EVMD-PMB-CMHA-TCN	97.036 ± 4.061	77.210 ± 3.713	5.937 ± 0.283	0.902 ± 0.008	35.556 ± 5.666
	SVMD-TCN	98.389 ± 3.618	77.518 ± 3.697	5.994 ± 0.266	0.899 ± 0.007	33.333 ± 0.000
	SVMD-CMHA-TCN	92.463 ± 4.430	70.968 ± 4.384	5.506 ± 0.325	0.911 ± 0.009	40.000 ± 3.333
	SVMD-PMB-TCN	94.851 ± 3.547	73.548 ± 3.737	5.705 ± 0.283	0.906 ± 0.007	37.778 ± 3.685
	SVMD-PMB-CMHA-TCN	100.892 ± 3.109	79.326 ± 2.844	6.140 ± 0.211	0.894 ± 0.006	35.000 ± 1.667
July 2022	**Diff-TCN** [27]	77.421 ± 0.029	**54.948** ± 0.019	**4.006** ± 0.001	0.884 ± 0.000	54.839 ± 0.000
	TCN	81.353 ± 7.177	58.900 ± 5.779	4.336 ± 0.417	0.871 ± 0.024	58.065 ± 6.452
	Diff-TCN	**77.123** ± 0.362	55.319 ± 0.251	4.027 ± 0.016	**0.885** ± 0.001	53.226 ± 3.607
	CMHA-TCN	80.404 ± 2.385	55.365 ± 1.113	4.055 ± 0.070	0.875 ± 0.007	55.914 ± 8.467
	Diff-CMHA-TCN	78.046 ± 0.898	56.358 ± 0.494	4.095 ± 0.034	0.882 ± 0.003	49.462 ± 5.157
	EVMD-TCN	77.202 ± 0.877	55.393 ± 0.535	4.038 ± 0.043	0.885 ± 0.003	62.903 ± 4.059
	EVMD-CMHA-TCN	77.240 ± 0.598	55.750 ± 0.269	4.083 ± 0.027	0.884 ± 0.002	**65.054** ± 1.202
	EVMD-PMB-TCN	81.890 ± 2.623	57.709 ± 1.258	4.201 ± 0.082	0.870 ± 0.008	53.226 ± 9.265
	EVMD-PMB-CMHA-TCN	88.101 ± 7.976	63.761 ± 7.816	4.654 ± 0.584	0.848 ± 0.028	52.688 ± 8.669
	SVMD-TCN	79.150 ± 2.494	57.961 ± 0.840	4.264 ± 0.076	0.878 ± 0.008	51.075 ± 6.822
	SVMD-CMHA-TCN	77.534 ± 0.955	57.787 ± 0.433	4.259 ± 0.042	0.884 ± 0.003	62.903 ± 2.464
	SVMD-PMB-TCN	77.621 ± 1.497	58.995 ± 0.422	4.366 ± 0.043	0.883 ± 0.004	55.376 ± 3.442
	SVMD-PMB-CMHA-TCN	80.212 ± 1.868	57.146 ± 1.046	4.202 ± 0.079	0.875 ± 0.006	50.538 ± 7.133
August 2022	Diff-TCN [27]	78.153 ± 0.044	55.342 ± 0.064	3.315 ± 0.005	0.717 ± 0.000	48.387 ± 0.000
	TCN	79.035 ± 0.295	57.967 ± 0.575	3.476 ± 0.036	0.711 ± 0.002	45.161 ± 2.634
	Diff-TCN	78.030 ± 0.244	55.262 ± 0.035	3.308 ± 0.005	0.718 ± 0.002	49.462 ± 2.404
	CMHA-TCN	79.025 ± 0.744	57.467 ± 1.175	3.444 ± 0.074	0.711 ± 0.005	47.849 ± 2.895
	Diff-CMHA-TCN	78.489 ± 0.528	55.474 ± 0.568	3.325 ± 0.040	0.715 ± 0.004	50.000 ± 7.153
	EVMD-TCN	77.268 ± 0.515	**54.432** ± 0.697	**3.260** ± 0.043	0.723 ± 0.004	62.903 ± 4.839
	EVMD-CMHA-TCN	77.757 ± 0.360	55.695 ± 0.638	3.337 ± 0.040	0.720 ± 0.003	54.839 ± 1.862
	EVMD-PMB-TCN	**76.766** ± 0.204	54.973 ± 0.517	3.289 ± 0.035	**0.727** ± 0.002	64.516 ± 4.562
	EVMD-PMB-CMHA-TCN	77.481 ± 0.353	54.887 ± 0.498	3.281 ± 0.033	0.722 ± 0.003	**65.054** ± 7.313
	SVMD-TCN	79.240 ± 0.979	60.292 ± 1.041	3.611 ± 0.065	0.709 ± 0.007	53.763 ± 3.566
	SVMD-CMHA-TCN	79.068 ± 0.473	60.209 ± 0.375	3.606 ± 0.025	0.710 ± 0.004	55.914 ± 1.521
	SVMD-PMB-TCN	78.697 ± 0.314	59.604 ± 0.459	3.560 ± 0.029	0.713 ± 0.002	51.613 ± 5.587
	SVMD-PMB-CMHA-TCN	78.610 ± 0.334	59.841 ± 0.377	3.575 ± 0.021	0.714 ± 0.002	55.914 ± 6.083
September 2022	Diff-TCN [27]	62.199 ± 0.008	46.121 ± 0.004	3.115 ± 0.000	0.846 ± 0.000	53.333 ± 0.000
	TCN	63.052 ± 1.147	46.384 ± 0.997	3.148 ± 0.080	0.841 ± 0.006	48.889 ± 2.485
	Diff-TCN	61.868 ± 0.288	45.898 ± 0.224	3.099 ± 0.014	0.847 ± 0.001	52.778 ± 4.045
	CMHA-TCN	62.874 ± 0.621	45.443 ± 0.718	3.074 ± 0.046	0.842 ± 0.003	54.444 ± 4.157
	Diff-CMHA-TCN	62.177 ± 1.124	46.634 ± 0.433	3.148 ± 0.031	0.846 ± 0.005	47.222 ± 3.557
	EVMD-TCN	**59.535** ± 0.510	44.408 ± 0.179	2.999 ± 0.011	**0.859** ± 0.002	56.111 ± 6.503
	EVMD-CMHA-TCN	60.469 ± 0.369	44.600 ± 0.036	3.015 ± 0.005	0.854 ± 0.002	51.111 ± 3.685
	EVMD-PMB-TCN	60.080 ± 0.946	44.555 ± 0.295	3.015 ± 0.024	0.856 ± 0.005	57.778 ± 4.581
	EVMD-PMB-CMHA-TCN	60.435 ± 0.954	**44.300** ± 0.289	**2.993** ± 0.026	0.854 ± 0.005	**58.889** ± 4.157
	SVMD-TCN	61.856 ± 1.157	46.173 ± 0.958	3.116 ± 0.051	0.847 ± 0.006	51.667 ± 3.191
	SVMD-CMHA-TCN	60.377 ± 0.204	45.414 ± 0.356	3.065 ± 0.019	0.855 ± 0.001	55.000 ± 1.667
	SVMD-PMB-TCN	60.613 ± 0.594	46.089 ± 0.473	3.104 ± 0.027	0.853 ± 0.003	53.889 ± 5.241
	SVMD-PMB-CMHA-TCN	61.336 ± 1.153	46.154 ± 0.964	3.114 ± 0.053	0.850 ± 0.006	56.667 ± 6.383
October 2022	**Diff-TCN** [27]	40.162 ± 0.013	29.595 ± 0.002	2.096 ± 0.000	0.857 ± 0.000	**54.839** ± 0.000
	TCN	40.734 ± 1.859	29.766 ± 0.438	2.111 ± 0.030	0.852 ± 0.014	52.688 ± 3.041
	Diff-TCN	40.062 ± 0.561	29.445 ± 0.335	2.088 ± 0.024	0.857 ± 0.004	53.226 ± 5.509
	CMHA-TCN	42.453 ± 2.107	**29.346** ± 0.562	**2.078** ± 0.038	0.840 ± 0.016	53.763 ± 4.433

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	**40.043** ± 0.095	29.734 ± 0.044	2.106 ± 0.003	**0.858** ± 0.001	53.226 ± 2.464
	EVMD-TCN	41.816 ± 0.842	29.894 ± 0.457	2.124 ± 0.038	0.845 ± 0.006	51.613 ± 4.928
	EVMD-CMHA-TCN	42.527 ± 0.445	29.621 ± 0.106	2.102 ± 0.009	0.839 ± 0.003	51.075 ± 4.335
	EVMD-PMB-TCN	42.978 ± 1.106	30.153 ± 0.110	2.139 ± 0.012	0.836 ± 0.009	49.462 ± 3.041
	EVMD-PMB-CMHA-TCN	43.541 ± 1.541	29.825 ± 0.155	2.115 ± 0.014	0.831 ± 0.012	52.151 ± 4.335
	SVMD-TCN	40.722 ± 0.445	30.988 ± 1.167	2.206 ± 0.093	0.853 ± 0.003	49.462 ± 5.790
	SVMD-CMHA-TCN	40.695 ± 0.462	30.281 ± 0.525	2.152 ± 0.042	0.853 ± 0.003	50.538 ± 3.566
	SVMD-PMB-TCN	41.883 ± 0.790	30.903 ± 1.000	2.196 ± 0.077	0.844 ± 0.006	45.699 ± 2.895
	SVMD-PMB-CMHA-TCN	42.344 ± 1.281	29.923 ± 0.459	2.123 ± 0.037	0.841 ± 0.010	49.462 ± 3.566
November 2022	Diff-TCN [27]	79.683 ± 0.029	49.730 ± 0.010	3.904 ± 0.001	0.761 ± 0.000	53.333 ± 0.000
	TCN	80.089 ± 0.214	49.585 ± 0.256	3.900 ± 0.016	0.759 ± 0.001	51.667 ± 4.615
	Diff-TCN	**78.292** ± 0.546	49.783 ± 0.456	3.884 ± 0.030	**0.770** ± 0.003	46.667 ± 5.092
	CMHA-TCN	79.327 ± 0.788	**48.682** ± 1.034	**3.834** ± 0.077	0.763 ± 0.005	53.889 ± 3.557
	Diff-CMHA-TCN	79.164 ± 0.588	49.454 ± 1.072	3.873 ± 0.071	0.764 ± 0.004	53.333 ± 5.774
	EVMD-TCN	80.655 ± 0.641	51.659 ± 0.388	4.089 ± 0.029	0.755 ± 0.004	51.111 ± 2.485
	EVMD-CMHA-TCN	80.934 ± 0.398	51.012 ± 0.471	4.046 ± 0.033	0.754 ± 0.002	**55.000** ± 3.727
	EVMD-PMB-TCN	79.992 ± 0.418	51.894 ± 0.549	4.103 ± 0.043	0.759 ± 0.003	51.111 ± 4.157
	EVMD-PMB-CMHA-TCN	80.656 ± 0.713	51.568 ± 0.789	4.090 ± 0.064	0.755 ± 0.004	53.333 ± 2.722
	SVMD-TCN	83.371 ± 2.374	56.207 ± 1.983	4.418 ± 0.148	0.739 ± 0.015	47.222 ± 5.583
	SVMD-CMHA-TCN	83.030 ± 0.931	54.907 ± 1.119	4.320 ± 0.086	0.741 ± 0.006	43.333 ± 5.092
	SVMD-PMB-TCN	83.769 ± 1.230	57.095 ± 1.481	4.486 ± 0.111	0.736 ± 0.008	42.778 ± 4.875
	SVMD-PMB-CMHA-TCN	83.952 ± 2.384	56.286 ± 2.863	4.441 ± 0.226	0.735 ± 0.015	44.444 ± 5.329
December 2022	Diff-TCN [27]	29.974 ± 0.013	20.883 ± 0.015	1.687 ± 0.001	0.459 ± 0.001	54.839 ± 0.000
	TCN	30.244 ± 0.229	21.211 ± 0.109	1.717 ± 0.010	0.450 ± 0.008	46.774 ± 3.607
	Diff-TCN	30.828 ± 0.488	21.889 ± 0.839	1.768 ± 0.067	0.428 ± 0.018	51.075 ± 2.895
	CMHA-TCN	**29.681** ± 0.098	20.576 ± 0.089	1.664 ± 0.006	**0.470** ± 0.004	57.527 ± 1.202
	Diff-CMHA-TCN	30.972 ± 0.606	22.282 ± 0.989	1.799 ± 0.078	0.423 ± 0.023	46.237 ± 8.669
	EVMD-TCN	30.785 ± 0.379	21.454 ± 0.270	1.738 ± 0.020	0.430 ± 0.014	51.075 ± 6.822
	EVMD-CMHA-TCN	30.543 ± 0.422	20.898 ± 0.157	1.699 ± 0.014	0.439 ± 0.016	50.538 ± 5.157
	EVMD-PMB-TCN	29.766 ± 0.406	**18.994** ± 0.383	**1.544** ± 0.031	0.467 ± 0.015	**66.129** ± 4.466
	EVMD-PMB-CMHA-TCN	30.995 ± 0.746	21.283 ± 0.644	1.734 ± 0.050	0.422 ± 0.028	56.452 ± 4.466
	SVMD-TCN	31.386 ± 0.198	21.242 ± 0.536	1.723 ± 0.042	0.407 ± 0.007	56.452 ± 4.059
	SVMD-CMHA-TCN	31.518 ± 0.271	21.559 ± 0.722	1.750 ± 0.056	0.402 ± 0.010	55.376 ± 2.895
	SVMD-PMB-TCN	31.206 ± 0.186	21.912 ± 0.525	1.778 ± 0.041	0.414 ± 0.007	54.839 ± 3.226
	SVMD-PMB-CMHA-TCN	31.928 ± 1.084	21.949 ± 0.846	1.784 ± 0.070	0.386 ± 0.042	55.376 ± 7.546
January 2023	Diff-TCN [27]	43.767 ± 0.040	32.596 ± 0.047	2.172 ± 0.004	0.919 ± 0.000	35.484 ± 0.000
	TCN	43.928 ± 0.697	32.783 ± 0.821	2.183 ± 0.060	0.919 ± 0.003	37.634 ± 3.566
	Diff-TCN	43.493 ± 0.459	32.569 ± 0.397	2.170 ± 0.028	0.920 ± 0.002	34.946 ± 2.895
	CMHA-TCN	43.718 ± 0.607	32.492 ± 0.668	2.161 ± 0.049	0.920 ± 0.002	43.011 ± 9.617
	Diff-CMHA-TCN	43.971 ± 0.763	33.757 ± 0.906	2.250 ± 0.065	0.919 ± 0.003	32.796 ± 3.442
	EVMD-TCN	44.302 ± 0.563	33.051 ± 0.740	2.217 ± 0.056	0.917 ± 0.002	48.925 ± 2.895
	EVMD-CMHA-TCN	45.377 ± 1.346	34.125 ± 1.788	2.293 ± 0.130	0.913 ± 0.005	51.613 ± 4.165
	EVMD-PMB-TCN	44.915 ± 0.767	33.873 ± 1.095	2.279 ± 0.080	0.915 ± 0.003	51.075 ± 2.895
	EVMD-PMB-CMHA-TCN	47.583 ± 2.810	36.977 ± 3.356	2.487 ± 0.231	0.904 ± 0.011	45.699 ± 3.914
	SVMD-TCN	44.154 ± 0.732	32.846 ± 0.528	2.183 ± 0.034	0.918 ± 0.003	54.301 ± 3.442
	SVMD-CMHA-TCN	44.294 ± 0.662	32.782 ± 0.610	2.179 ± 0.042	0.917 ± 0.002	54.301 ± 8.619
	SVMD-PMB-TCN	**43.412** ± 0.826	**31.963** ± 0.660	**2.126** ± 0.044	**0.921** ± 0.003	**56.989** ± 8.467
	SVMD-PMB-CMHA-TCN	45.155 ± 2.215	34.292 ± 2.325	2.284 ± 0.163	0.914 ± 0.009	53.226 ± 9.076
February 2023	Diff-TCN [27]	42.909 ± 0.015	32.556 ± 0.051	2.009 ± 0.003	0.423 ± 0.000	52.976 ± 3.811
	TCN	42.797 ± 0.067	32.280 ± 0.111	1.991 ± 0.008	0.426 ± 0.002	60.119 ± 6.655
	Diff-TCN	42.700 ± 0.247	32.156 ± 0.332	1.984 ± 0.022	0.429 ± 0.007	59.524 ± 3.948
	CMHA-TCN	42.793 ± 0.067	32.316 ± 0.118	1.994 ± 0.008	0.426 ± 0.002	56.548 ± 2.454
	Diff-CMHA-TCN	**42.144** ± 0.316	**31.458** ± 0.445	**1.939** ± 0.029	**0.444** ± 0.008	**67.262** ± 8.605
	EVMD-TCN	45.354 ± 0.115	34.223 ± 0.125	2.115 ± 0.007	0.356 ± 0.003	58.929 ± 2.728
	EVMD-CMHA-TCN	46.118 ± 0.102	35.041 ± 0.072	2.168 ± 0.005	0.334 ± 0.003	57.143 ± 2.062
	EVMD-PMB-TCN	46.182 ± 0.116	34.819 ± 0.166	2.151 ± 0.010	0.332 ± 0.003	51.191 ± 2.662
	EVMD-PMB-CMHA-TCN	47.070 ± 0.587	36.104 ± 0.725	2.231 ± 0.042	0.306 ± 0.017	52.381 ± 3.948
	SVMD-TCN	45.434 ± 0.110	34.704 ± 0.174	2.144 ± 0.010	0.353 ± 0.003	37.500 ± 3.993
	SVMD-CMHA-TCN	45.480 ± 0.084	34.881 ± 0.137	2.155 ± 0.008	0.352 ± 0.002	38.095 ± 4.909
	SVMD-PMB-TCN	45.378 ± 0.211	35.066 ± 0.268	2.167 ± 0.017	0.355 ± 0.006	43.452 ± 3.205
	SVMD-PMB-CMHA-TCN	46.112 ± 0.555	35.635 ± 0.792	2.205 ± 0.049	0.334 ± 0.016	44.643 ± 4.494
March 2023	**Diff-TCN** [27]	54.547 ± 0.065	**43.444** ± 0.030	**2.597** ± 0.001	0.772 ± 0.001	49.462 ± 2.404
	TCN	**54.313** ± 0.223	43.567 ± 0.147	2.606 ± 0.013	**0.774** ± 0.002	49.462 ± 3.041
	Diff-TCN	54.874 ± 0.208	43.683 ± 0.143	2.613 ± 0.009	0.769 ± 0.002	46.237 ± 3.566
	CMHA-TCN	54.525 ± 0.134	43.551 ± 0.045	2.603 ± 0.004	0.772 ± 0.001	50.538 ± 2.404
	Diff-CMHA-TCN	55.176 ± 0.311	44.066 ± 0.246	2.634 ± 0.013	0.767 ± 0.003	46.774 ± 5.509
	EVMD-TCN	56.288 ± 0.193	44.024 ± 0.247	2.656 ± 0.012	0.757 ± 0.002	50.538 ± 1.521
	EVMD-CMHA-TCN	56.356 ± 0.123	44.479 ± 0.143	2.683 ± 0.008	0.756 ± 0.001	49.462 ± 1.521
	EVMD-PMB-TCN	56.683 ± 0.147	45.100 ± 0.068	2.717 ± 0.004	0.754 ± 0.001	47.849 ± 2.895
	EVMD-PMB-CMHA-TCN	56.747 ± 0.163	45.117 ± 0.556	2.724 ± 0.036	0.753 ± 0.001	51.613 ± 1.862
	SVMD-TCN	55.538 ± 0.158	43.602 ± 0.049	2.626 ± 0.004	0.763 ± 0.001	58.602 ± 3.914
	SVMD-CMHA-TCN	55.420 ± 0.107	43.539 ± 0.056	2.623 ± 0.004	0.764 ± 0.001	**60.215** ± 1.521
	SVMD-PMB-TCN	55.391 ± 0.086	43.688 ± 0.160	2.634 ± 0.011	0.765 ± 0.001	57.527 ± 2.895
	SVMD-PMB-CMHA-TCN	56.160 ± 0.603	43.950 ± 0.345	2.651 ± 0.019	0.758 ± 0.005	56.452 ± 4.839
April 2023	Diff-TCN [27]	50.136 ± 0.027	35.940 ± 0.031	1.859 ± 0.002	0.697 ± 0.000	50.000 ± 0.000
	TCN	50.204 ± 0.164	36.061 ± 0.177	1.864 ± 0.009	0.696 ± 0.002	49.444 ± 1.242
	Diff-TCN	50.578 ± 0.533	36.470 ± 0.535	1.887 ± 0.028	0.691 ± 0.007	42.222 ± 9.162
	CMHA-TCN	50.318 ± 0.174	35.951 ± 0.219	1.858 ± 0.011	0.694 ± 0.002	51.111 ± 2.485

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	51.427 ± 0.364	36.973 ± 0.610	1.913 ± 0.031	0.681 ± 0.004	40.556 ± 4.479
	EVMD-TCN	52.199 ± 0.142	37.203 ± 0.141	1.922 ± 0.007	0.671 ± 0.002	49.444 ± 1.242
	EVMD-CMHA-TCN	52.864 ± 0.254	37.917 ± 0.368	1.957 ± 0.017	0.663 ± 0.003	52.222 ± 2.485
	EVMD-PMB-TCN	52.338 ± 0.147	37.617 ± 0.275	1.942 ± 0.014	0.669 ± 0.002	53.333 ± 1.925
	EVMD-PMB-CMHA-TCN	53.423 ± 0.424	38.678 ± 0.522	1.996 ± 0.029	0.655 ± 0.005	52.222 ± 2.485
	SVMD-TCN	**49.852** ± 0.113	35.301 ± 0.157	1.829 ± 0.008	**0.700** ± 0.001	**58.889** ± 4.969
	SVMD-CMHA-TCN	49.893 ± 0.112	**35.184** ± 0.098	**1.823** ± 0.005	**0.700** ± 0.001	57.778 ± 4.157
	SVMD-PMB-TCN	50.058 ± 0.389	35.357 ± 0.434	1.832 ± 0.022	0.698 ± 0.005	61.111 ± 5.329
	SVMD-PMB-CMHA-TCN	51.160 ± 1.018	36.071 ± 1.224	1.864 ± 0.060	0.684 ± 0.013	57.222 ± 7.307
May 2023	Diff-TCN [27]	38.191 ± 0.011	26.882 ± 0.018	1.436 ± 0.001	0.266 ± 0.000	47.312 ± 2.404
	TCN	37.960 ± 0.273	26.671 ± 0.229	1.425 ± 0.012	0.275 ± 0.010	53.763 ± 7.828
	Diff-TCN	37.855 ± 0.318	26.774 ± 0.361	1.431 ± 0.019	0.279 ± 0.012	52.151 ± 6.011
	CMHA-TCN	38.112 ± 0.015	26.858 ± 0.040	1.435 ± 0.002	0.269 ± 0.001	48.387 ± 0.000
	Diff-CMHA-TCN	38.191 ± 0.335	27.323 ± 0.501	1.460 ± 0.027	0.266 ± 0.013	48.925 ± 6.822
	EVMD-TCN	35.731 ± 0.100	26.118 ± 0.098	1.398 ± 0.006	0.358 ± 0.004	59.140 ± 3.041
	EVMD-CMHA-TCN	35.508 ± 0.063	25.891 ± 0.033	1.386 ± 0.002	0.366 ± 0.002	60.215 ± 2.404
	EVMD-PMB-TCN	35.533 ± 0.083	25.624 ± 0.107	1.373 ± 0.006	0.365 ± 0.003	61.828 ± 3.914
	EVMD-PMB-CMHA-TCN	35.201 ± 0.235	25.681 ± 0.345	1.375 ± 0.020	0.377 ± 0.008	**65.054** ± 4.718
	SVMD-TCN	37.889 ± 0.139	27.278 ± 0.125	1.457 ± 0.007	0.278 ± 0.005	46.774 ± 4.059
	SVMD-CMHA-TCN	37.486 ± 0.125	27.018 ± 0.143	1.444 ± 0.008	0.293 ± 0.005	48.925 ± 2.895
	SVMD-PMB-TCN	37.266 ± 0.334	26.981 ± 0.255	1.442 ± 0.014	0.301 ± 0.013	49.462 ± 3.566
	SVMD-PMB-CMHA-TCN	**35.189** ± 0.579	**25.145** ± 0.446	**1.343** ± 0.024	**0.377** ± 0.021	53.226 ± 3.088
June 2023	Diff-TCN [27]	46.233 ± 0.028	35.289 ± 0.008	1.940 ± 0.001	0.638 ± 0.000	50.000 ± 0.000
	TCN	46.172 ± 0.287	35.079 ± 0.330	1.928 ± 0.018	0.639 ± 0.004	52.222 ± 4.969
	Diff-TCN	46.338 ± 0.257	35.007 ± 0.400	1.924 ± 0.022	0.636 ± 0.004	57.778 ± 7.115
	CMHA-TCN	46.195 ± 0.034	35.098 ± 0.075	1.929 ± 0.004	0.639 ± 0.001	50.000 ± 0.000
	Diff-CMHA-TCN	46.599 ± 0.540	35.690 ± 1.235	1.963 ± 0.067	0.632 ± 0.009	52.222 ± 7.617
	EVMD-TCN	46.709 ± 0.043	34.776 ± 0.030	1.917 ± 0.002	0.630 ± 0.001	59.444 ± 2.291
	EVMD-CMHA-TCN	46.917 ± 0.145	34.610 ± 0.098	1.909 ± 0.006	0.627 ± 0.002	57.222 ± 2.291
	EVMD-PMB-TCN	46.851 ± 0.382	33.703 ± 0.233	1.858 ± 0.013	0.628 ± 0.006	64.444 ± 4.581
	EVMD-PMB-CMHA-TCN	47.671 ± 0.764	35.576 ± 1.436	1.966 ± 0.084	0.615 ± 0.012	58.333 ± 3.191
	SVMD-TCN	45.782 ± 0.050	33.542 ± 0.157	1.846 ± 0.009	0.645 ± 0.001	65.000 ± 3.191
	SVMD-CMHA-TCN	45.672 ± 0.062	33.259 ± 0.123	1.830 ± 0.007	0.647 ± 0.001	**67.222** ± 5.241
	SVMD-PMB-TCN	45.892 ± 0.123	33.555 ± 0.214	1.847 ± 0.012	0.643 ± 0.002	62.222 ± 3.685
	SVMD-PMB-CMHA-TCN	**45.333** ± 0.117	**32.624** ± 0.292	**1.797** ± 0.017	**0.652** ± 0.002	66.111 ± 5.906
July 2023	Diff-TCN [27]	32.527 ± 0.028	19.871 ± 0.090	1.039 ± 0.005	0.169 ± 0.001	60.753 ± 1.202
	TCN	32.279 ± 0.373	18.938 ± 0.205	0.989 ± 0.011	0.182 ± 0.019	62.366 ± 1.521
	Diff-TCN	32.114 ± 0.191	19.352 ± 0.187	1.011 ± 0.010	0.190 ± 0.010	61.290 ± 0.000
	CMHA-TCN	32.369 ± 0.456	19.193 ± 0.464	1.003 ± 0.024	0.177 ± 0.023	61.828 ± 1.202
	Diff-CMHA-TCN	32.294 ± 0.459	19.608 ± 0.608	1.025 ± 0.032	0.181 ± 0.023	58.602 ± 7.313
	EVMD-TCN	**30.656** ± 0.250	17.125 ± 0.251	0.893 ± 0.013	**0.262** ± 0.012	**67.742** ± 3.725
	EVMD-CMHA-TCN	30.715 ± 0.200	**17.030** ± 0.121	**0.888** ± 0.006	0.259 ± 0.010	67.204 ± 2.217
	EVMD-PMB-TCN	30.847 ± 0.300	17.733 ± 0.145	0.925 ± 0.007	0.253 ± 0.015	65.591 ± 4.809
	EVMD-PMB-CMHA-TCN	31.082 ± 0.427	17.619 ± 0.592	0.919 ± 0.032	0.241 ± 0.021	63.978 ± 6.293
	SVMD-TCN	31.733 ± 0.235	18.809 ± 0.302	0.983 ± 0.015	0.209 ± 0.012	59.677 ± 1.613
	SVMD-CMHA-TCN	31.527 ± 0.132	18.538 ± 0.122	0.969 ± 0.006	0.220 ± 0.006	59.677 ± 2.464
	SVMD-PMB-TCN	31.418 ± 0.159	18.503 ± 0.252	0.968 ± 0.013	0.225 ± 0.008	58.065 ± 2.634
	SVMD-PMB-CMHA-TCN	30.752 ± 0.154	17.589 ± 0.273	0.920 ± 0.014	0.257 ± 0.007	63.978 ± 4.718
August 2023	Diff-TCN [27]	32.735 ± 0.019	20.061 ± 0.029	1.169 ± 0.002	0.863 ± 0.000	67.742 ± 0.000
	TCN	**32.339** ± 0.120	19.817 ± 0.119	1.154 ± 0.007	**0.866** ± 0.001	**68.817**± 2.404
	Diff-TCN	32.809 ± 0.144	20.156 ± 0.173	1.174 ± 0.010	0.862 ± 0.001	62.366 ± 4.433
	CMHA-TCN	32.395 ± 0.188	19.778 ± 0.149	1.151 ± 0.010	0.866 ± 0.002	66.667 ± 1.521
	Diff-CMHA-TCN	33.059 ± 0.284	20.620 ± 0.467	1.201 ± 0.027	0.860 ± 0.002	52.151 ± 10.766
	EVMD-TCN	34.224 ± 0.402	21.282 ± 0.435	1.240 ± 0.026	0.850 ± 0.004	47.849 ± 4.335
	EVMD-CMHA-TCN	34.124 ± 0.222	20.893 ± 0.174	1.216 ± 0.011	0.851 ± 0.002	54.301 ± 2.217
	EVMD-PMB-TCN	34.384 ± 0.376	21.501 ± 0.526	1.254 ± 0.031	0.849 ± 0.003	49.462 ± 1.521
	EVMD-PMB-CMHA-TCN	34.952 ± 0.791	21.505 ± 0.765	1.252 ± 0.046	0.843 ± 0.007	53.763 ± 3.566
	SVMD-TCN	33.067 ± 0.252	20.682 ± 0.209	1.204 ± 0.012	0.860 ± 0.002	58.065 ± 2.634
	SVMD-CMHA-TCN	33.168 ± 0.138	20.626 ± 0.138	1.202 ± 0.008	0.859 ± 0.001	58.065 ± 2.634
	SVMD-PMB-TCN	33.012 ± 0.121	20.457 ± 0.080	1.192 ± 0.005	0.860 ± 0.001	60.753 ± 1.202
	SVMD-PMB-CMHA-TCN	32.820 ± 0.359	**19.772** ± 0.358	**1.151** ± 0.021	0.862 ± 0.003	64.516 ± 1.862
September 2023	Diff-TCN [27]	21.567 ± 0.031	15.389 ± 0.066	0.955 ± 0.004	0.358 ± 0.002	43.333 ± 0.000
	TCN	21.616 ± 0.237	15.444 ± 0.448	0.958 ± 0.027	0.355 ± 0.014	44.444 ± 1.571
	Diff-TCN	21.807 ± 0.163	15.704 ± 0.307	0.974 ± 0.019	0.344 ± 0.010	43.889 ± 2.291
	CMHA-TCN	**21.487** ± 0.160	15.346 ± 0.374	0.952 ± 0.023	**0.363** ± 0.009	45.556 ± 3.685
	Diff-CMHA-TCN	21.634 ± 0.209	15.432 ± 0.328	0.957 ± 0.020	0.354 ± 0.013	43.333 ± 5.092
	EVMD-TCN	23.727 ± 0.109	16.666 ± 0.115	1.031 ± 0.007	0.223 ± 0.007	47.222 ± 1.242
	EVMD-CMHA-TCN	23.922 ± 0.124	16.847 ± 0.179	1.042 ± 0.010	0.210 ± 0.008	47.222 ± 2.291
	EVMD-PMB-TCN	23.985 ± 0.158	17.052 ± 0.345	1.055 ± 0.021	0.206 ± 0.010	44.444 ± 2.485
	EVMD-PMB-CMHA-TCN	25.057 ± 0.708	17.921 ± 0.608	1.109 ± 0.037	0.133 ± 0.048	49.444 ± 4.045
	SVMD-TCN	21.710 ± 0.158	**15.262** ± 0.355	**0.946** ± 0.021	0.350 ± 0.009	**53.889** ± 8.906
	SVMD-CMHA-TCN	21.634 ± 0.069	15.313 ± 0.175	0.950 ± 0.011	0.354 ± 0.004	46.667 ± 6.383
	SVMD-PMB-TCN	21.576 ± 0.069	15.359 ± 0.150	0.952 ± 0.009	0.358 ± 0.004	50.556 ± 4.875
	SVMD-PMB-CMHA-TCN	23.705 ± 1.194	16.482 ± 1.155	1.022 ± 0.072	0.223 ± 0.080	48.333 ± 5.693
October 2023	Diff-TCN [27]	33.193 ± 0.034	23.529 ± 0.041	1.412 ± 0.002	0.874 ± 0.000	45.161 ± 0.000
	TCN	33.155 ± 0.100	23.641 ± 0.145	1.417 ± 0.008	0.874 ± 0.001	49.462 ± 6.361
	Diff-TCN	33.239 ± 0.092	23.756 ± 0.155	1.425 ± 0.009	0.874 ± 0.001	40.860 ± 3.566
	CMHA-TCN	33.606 ± 0.666	24.132 ± 0.746	1.445 ± 0.043	0.871 ± 0.005	48.387 ± 6.715

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	32.734 ± 0.183	**23.152** ± 0.276	**1.391** ± 0.016	**0.878** ± 0.001	**58.065** ± 5.889
	EVMD-TCN	32.969 ± 0.358	23.633 ± 0.318	1.413 ± 0.017	0.876 ± 0.003	50.000 ± 4.839
	EVMD-CMHA-TCN	33.437 ± 0.271	23.948 ± 0.231	1.432 ± 0.013	0.872 ± 0.002	49.462 ± 2.404
	EVMD-PMB-TCN	**32.698** ± 0.414	23.390 ± 0.326	1.401 ± 0.019	**0.878** ± 0.003	52.688 ± 6.885
	EVMD-PMB-CMHA-TCN	34.384 ± 1.403	25.301 ± 1.368	1.511 ± 0.079	0.865 ± 0.011	44.624 ± 5.072
	SVMD-TCN	33.204 ± 0.174	24.128 ± 0.119	1.446 ± 0.007	0.874 ± 0.001	41.935 ± 4.928
	SVMD-CMHA-TCN	33.448 ± 0.214	24.380 ± 0.267	1.459 ± 0.015	0.872 ± 0.002	42.473 ± 4.335
	SVMD-PMB-TCN	33.443 ± 0.549	24.207 ± 0.455	1.449 ± 0.024	0.872 ± 0.004	46.237 ± 7.133
	SVMD-PMB-CMHA-TCN	35.070 ± 1.637	25.620 ± 1.106	1.529 ± 0.060	0.859 ± 0.014	43.548 ± 8.484
November 2023	Diff-TCN [27]	62.130 ± 0.109	39.794 ± 0.164	1.983 ± 0.008	0.493 ± 0.002	43.889 ± 1.242
	TCN	62.429 ± 0.222	40.400 ± 0.275	2.013 ± 0.013	0.489 ± 0.004	43.333 ± 0.000
	Diff-TCN	61.541 ± 0.252	**39.612** ± 0.218	**1.974** ± 0.011	0.503 ± 0.004	46.111 ± 3.557
	CMHA-TCN	62.354 ± 0.281	40.380 ± 0.308	2.012 ± 0.015	0.490 ± 0.005	43.333 ± 0.000
	Diff-CMHA-TCN	62.135 ± 0.715	40.369 ± 0.308	2.011 ± 0.015	0.493 ± 0.012	45.000 ± 6.872
	EVMD-TCN	62.031 ± 0.299	41.720 ± 0.207	2.079 ± 0.010	0.495 ± 0.005	53.333 ± 4.714
	EVMD-CMHA-TCN	**61.138** ± 0.241	41.355 ± 0.174	2.060 ± 0.008	**0.510** ± 0.004	**58.333** ± 1.667
	EVMD-PMB-TCN	61.468 ± 0.399	41.264 ± 0.373	2.057 ± 0.018	0.504 ± 0.006	56.667 ± 6.086
	EVMD-PMB-CMHA-TCN	62.339 ± 1.468	42.679 ± 1.199	2.125 ± 0.059	0.490 ± 0.024	55.000 ± 3.727
	SVMD-TCN	62.808 ± 0.303	41.151 ± 0.330	2.055 ± 0.016	0.482 ± 0.005	51.667 ± 2.546
	SVMD-CMHA-TCN	62.873 ± 0.117	41.209 ± 0.185	2.057 ± 0.009	0.481 ± 0.002	56.111 ± 2.291
	SVMD-PMB-TCN	62.745 ± 0.271	40.961 ± 0.433	2.045 ± 0.021	0.483 ± 0.004	54.444 ± 3.685
	SVMD-PMB-CMHA-TCN	61.689 ± 0.537	40.689 ± 0.584	2.030 ± 0.028	0.501 ± 0.009	58.333 ± 1.667
December 2023	Diff-TCN [27]	58.457 ± 0.049	45.781 ± 0.030	2.021 ± 0.001	0.228 ± 0.001	45.161 ± 1.862
	TCN	59.365 ± 0.423	46.043 ± 0.159	2.032 ± 0.007	0.203 ± 0.011	45.161 ± 0.000
	Diff-TCN	58.497 ± 0.176	45.702 ± 0.134	2.017 ± 0.006	0.227 ± 0.005	50.538 ± 5.483
	CMHA-TCN	59.016 ± 0.788	45.801 ± 0.544	2.022 ± 0.023	0.213 ± 0.021	46.774 ± 3.607
	Diff-CMHA-TCN	58.831 ± 0.240	**45.681** ± 0.237	**2.016** ± 0.010	0.218 ± 0.006	**51.613** ± 5.268
	EVMD-TCN	61.039 ± 0.517	47.847 ± 0.232	2.110 ± 0.010	0.158 ± 0.014	41.398 ± 2.895
	EVMD-CMHA-TCN	60.592 ± 0.076	47.595 ± 0.037	2.099 ± 0.002	0.170 ± 0.002	45.161 ± 0.000
	EVMD-PMB-TCN	60.882 ± 0.335	47.954 ± 0.212	2.115 ± 0.009	0.162 ± 0.009	40.860 ± 1.521
	EVMD-PMB-CMHA-TCN	61.831 ± 0.602	48.736 ± 0.431	2.149 ± 0.019	0.136 ± 0.017	47.849 ± 8.818
	SVMD-TCN	**56.992** ± 0.712	45.956 ± 0.345	2.034 ± 0.015	**0.266** ± 0.018	48.925 ± 2.217
	SVMD-CMHA-TCN	57.290 ± 0.566	46.032 ± 0.261	2.037 ± 0.011	0.258 ± 0.015	51.613 ± 2.634
	SVMD-PMB-TCN	57.103 ± 0.537	45.956 ± 0.218	2.034 ± 0.009	0.263 ± 0.014	49.462 ± 2.404
	SVMD-PMB-CMHA-TCN	57.646 ± 0.670	46.885 ± 0.336	2.075 ± 0.014	0.249 ± 0.018	48.925 ± 2.217
January 2024	**Diff-TCN** [27]	**75.407** ± 0.023	55.182 ± 0.020	2.300 ± 0.001	**0.656** ± 0.000	51.075 ± 3.914
	TCN	75.419 ± 0.170	55.165 ± 0.056	2.298 ± 0.002	0.656 ± 0.002	47.849 ± 1.202
	Diff-TCN	75.448 ± 0.152	55.146 ± 0.291	2.300 ± 0.012	0.656 ± 0.001	48.925 ± 4.718
	CMHA-TCN	75.420 ± 0.104	55.191 ± 0.026	2.298 ± 0.002	0.656 ± 0.001	48.387 ± 0.000
	Diff-CMHA-TCN	75.503 ± 0.642	**55.050** ± 1.179	**2.297** ± 0.049	0.655 ± 0.006	**52.688** ± 8.669
	EVMD-TCN	77.325 ± 0.106	57.789 ± 0.042	2.411 ± 0.002	0.639 ± 0.001	48.387 ± 2.634
	EVMD-CMHA-TCN	77.600 ± 0.132	58.105 ± 0.183	2.424 ± 0.007	0.636 ± 0.001	50.000 ± 2.464
	EVMD-PMB-TCN	77.339 ± 0.223	58.086 ± 0.223	2.423 ± 0.009	0.639 ± 0.002	49.462 ± 2.404
	EVMD-PMB-CMHA-TCN	79.849 ± 1.598	59.729 ± 1.214	2.490 ± 0.048	0.615 ± 0.015	47.849 ± 3.442
	SVMD-TCN	77.190 ± 0.132	57.935 ± 0.095	2.422 ± 0.004	0.640 ± 0.001	43.548 ± 1.613
	SVMD-CMHA-TCN	77.190 ± 0.179	57.921 ± 0.111	2.420 ± 0.004	0.640 ± 0.002	48.387 ± 4.928
	SVMD-PMB-TCN	77.020 ± 0.192	57.737 ± 0.103	2.413 ± 0.003	0.642 ± 0.002	48.387 ± 2.634
	SVMD-PMB-CMHA-TCN	77.529 ± 0.685	58.248 ± 0.352	2.435 ± 0.016	0.637 ± 0.006	44.086 ± 3.041
February 2024	Diff-TCN [27]	67.106 ± 0.206	51.696 ± 0.140	1.816 ± 0.005	0.959 ± 0.000	46.552 ± 13.318
	TCN	73.894 ± 1.711	55.590 ± 1.274	1.952 ± 0.047	0.951 ± 0.002	31.609 ± 1.285
	Diff-TCN	66.836 ± 0.766	51.389 ± 0.421	1.802 ± 0.015	0.960 ± 0.001	57.471 ± 8.829
	CMHA-TCN	72.980 ± 2.144	54.943 ± 1.129	1.928 ± 0.041	0.952 ± 0.003	32.184 ± 2.570
	Diff-CMHA-TCN	**66.101** ± 0.986	**51.053** ± 0.610	**1.792** ± 0.024	**0.960** ± 0.001	**59.195** ± 5.776
	EVMD-TCN	77.024 ± 2.530	59.083 ± 2.168	2.083 ± 0.074	0.946 ± 0.004	39.081 ± 3.251
	EVMD-CMHA-TCN	78.770 ± 2.308	60.695 ± 2.180	2.139 ± 0.077	0.944 ± 0.003	36.207 ± 2.634
	EVMD-PMB-TCN	76.493 ± 1.247	58.130 ± 1.119	2.048 ± 0.039	0.947 ± 0.002	36.207 ± 2.634
	EVMD-PMB-CMHA-TCN	81.595 ± 7.456	63.942 ± 6.915	2.254 ± 0.245	0.939 ± 0.011	38.506 ± 5.776
	SVMD-TCN	75.807 ± 1.978	58.052 ± 1.783	2.045 ± 0.063	0.948 ± 0.003	30.460 ± 2.370
	SVMD-CMHA-TCN	76.341 ± 1.470	58.588 ± 1.288	2.064 ± 0.045	0.947 ± 0.002	31.035 ± 1.991
	SVMD-PMB-TCN	74.012 ± 2.655	56.797 ± 2.175	2.003 ± 0.077	0.950 ± 0.004	32.759 ± 3.301
	SVMD-PMB-CMHA-TCN	83.720 ± 7.390	66.279 ± 6.663	2.337 ± 0.233	0.936 ± 0.012	33.333 ± 1.625
March 2024	Diff-TCN [27]	141.227 ± 0.024	106.469 ± 0.027	2.981 ± 0.001	0.579 ± 0.000	48.387 ± 0.000
	TCN	141.352 ± 0.053	106.713 ± 0.111	2.989 ± 0.004	0.579 ± 0.000	48.387 ± 0.000
	Diff-TCN	139.543 ± 0.651	**105.349** ± 0.625	**2.948** ± 0.017	0.589 ± 0.004	56.989 ± 3.566
	CMHA-TCN	141.410 ± 0.292	107.048 ± 0.511	2.998 ± 0.017	0.578 ± 0.002	48.925 ± 1.202
	Diff-CMHA-TCN	**139.396** ± 1.413	105.484 ± 0.992	2.953 ± 0.027	**0.590** ± 0.008	53.763 ± 8.467
	EVMD-TCN	144.361 ± 0.194	112.104 ± 0.277	3.152 ± 0.007	0.560 ± 0.001	52.151 ± 2.217
	EVMD-CMHA-TCN	144.818 ± 0.234	112.426 ± 0.433	3.161 ± 0.011	0.558 ± 0.001	52.688 ± 2.404
	EVMD-PMB-TCN	144.059 ± 0.730	112.392 ± 0.448	3.158 ± 0.013	0.562 ± 0.004	50.538 ± 1.521
	EVMD-PMB-CMHA-TCN	148.018 ± 2.422	116.427 ± 3.177	3.267 ± 0.078	0.538 ± 0.015	52.688 ± 4.433
	SVMD-TCN	144.499 ± 0.701	106.619 ± 0.561	2.989 ± 0.013	0.560 ± 0.004	**56.989** ± 4.023
	SVMD-CMHA-TCN	144.702 ± 0.337	107.154 ± 0.754	3.003 ± 0.019	0.558 ± 0.002	52.151 ± 5.403
	SVMD-PMB-TCN	144.766 ± 0.357	106.901 ± 0.504	2.996 ± 0.012	0.558 ± 0.002	56.989 ± 3.041
	SVMD-PMB-CMHA-TCN	153.945 ± 1.474	114.443 ± 3.969	3.212 ± 0.099	0.500 ± 0.010	55.376 ± 3.914
April 2024	Diff-TCN [27]	118.770 ± 0.308	88.308 ± 0.123	2.713 ± 0.005	0.540 ± 0.002	52.222 ± 4.969
	TCN	118.943 ± 0.629	88.232 ± 0.209	2.712 ± 0.007	0.539 ± 0.005	49.444 ± 2.992
	Diff-TCN	**118.751** ± 0.232	**86.731** ± 0.369	**2.667** ± 0.011	**0.540** ± 0.002	**58.889** ± 5.329
	CMHA-TCN	119.298 ± 1.040	88.512 ± 0.466	2.720 ± 0.016	0.536 ± 0.008	50.556 ± 4.045

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	119.153 ± 0.589	87.510 ± 0.472	2.689 ± 0.014	0.537 ± 0.005	56.111 ± 4.875
	EVMD-TCN	126.425 ± 0.941	90.099 ± 0.959	2.790 ± 0.030	0.479 ± 0.008	55.000 ± 2.546
	EVMD-CMHA-TCN	126.529 ± 1.559	89.761 ± 1.245	2.778 ± 0.039	0.478 ± 0.013	57.778 ± 3.685
	EVMD-PMB-TCN	125.273 ± 1.289	89.296 ± 1.009	2.762 ± 0.032	0.488 ± 0.011	56.111 ± 4.479
	EVMD-PMB-CMHA-TCN	127.214 ± 1.787	90.903 ± 2.122	2.817 ± 0.065	0.472 ± 0.015	56.111 ± 2.992
	SVMD-TCN	124.791 ± 0.535	92.031 ± 0.372	2.840 ± 0.012	0.492 ± 0.004	51.667 ± 2.546
	SVMD-CMHA-TCN	124.489 ± 0.422	91.924 ± 0.197	2.836 ± 0.005	0.495 ± 0.003	50.556 ± 1.242
	SVMD-PMB-TCN	125.212 ± 0.513	92.339 ± 0.358	2.849 ± 0.011	0.489 ± 0.004	51.667 ± 1.667
	SVMD-PMB-CMHA-TCN	127.442 ± 3.154	91.635 ± 1.450	2.831 ± 0.046	0.470 ± 0.027	57.222 ± 3.557
May 2024	**Diff-TCN** [27]	126.794 ± 0.047	**75.145** ± 0.028	**2.248** ± 0.001	**0.887** ± 0.000	**55.376**± 3.914
	TCN	127.484 ± 0.894	75.439 ± 0.464	2.255 ± 0.013	0.886 ± 0.002	45.161 ± 5.889
	Diff-TCN	127.117 ± 0.489	76.183 ± 0.704	2.277 ± 0.019	0.887 ± 0.001	44.624 ± 2.895
	CMHA-TCN	127.451 ± 0.551	75.502 ± 0.237	2.257 ± 0.006	0.886 ± 0.001	44.086 ± 4.809
	Diff-CMHA-TCN	**126.375** ± 0.530	75.521 ± 0.324	2.261 ± 0.008	0.888 ± 0.001	46.237 ± 4.433
	EVMD-TCN	129.434 ± 0.323	81.681 ± 0.413	2.432 ± 0.013	0.883 ± 0.001	43.548 ± 1.613
	EVMD-CMHA-TCN	132.037 ± 0.596	81.108 ± 0.303	2.416 ± 0.011	0.878 ± 0.001	48.925 ± 6.563
	EVMD-PMB-TCN	129.449 ± 0.422	81.502 ± 0.395	2.426 ± 0.011	0.883 ± 0.001	44.624 ± 3.442
	EVMD-PMB-CMHA-TCN	140.793 ± 4.129	88.003 ± 3.087	2.603 ± 0.085	0.861 ± 0.008	53.226 ± 3.607
	SVMD-TCN	128.516 ± 0.608	78.702 ± 0.201	2.334 ± 0.005	0.884 ± 0.001	51.613 ± 5.268
	SVMD-CMHA-TCN	128.478 ± 0.493	78.855 ± 0.435	2.339 ± 0.013	0.884 ± 0.001	54.839 ± 3.725
	SVMD-PMB-TCN	129.269 ± 0.482	79.378 ± 0.504	2.353 ± 0.014	0.883 ± 0.001	53.763 ± 1.521
	SVMD-PMB-CMHA-TCN	135.119 ± 2.216	84.450 ± 3.276	2.490 ± 0.089	0.872 ± 0.004	47.849 ± 10.101
June 2024	Diff-TCN [27]	67.016 ± 0.198	54.841 ± 0.074	1.544 ± 0.002	0.806 ± 0.001	48.333 ± 2.546
	TCN	67.143 ± 0.960	54.856 ± 0.627	1.544 ± 0.018	0.805 ± 0.006	50.000 ± 3.333
	Diff-TCN	**66.721** ± 0.166	54.722 ± 0.145	1.540 ± 0.004	**0.807** ± 0.001	56.111 ± 4.479
	CMHA-TCN	68.049 ± 0.433	55.524 ± 0.267	1.564 ± 0.008	0.800 ± 0.003	46.667 ± 0.000
	Diff-CMHA-TCN	67.002 ± 0.318	55.073 ± 0.353	1.549 ± 0.010	0.806 ± 0.002	51.111 ± 3.685
	EVMD-TCN	69.059 ± 1.065	54.896 ± 0.928	1.544 ± 0.027	0.793 ± 0.006	**62.778** ± 3.557
	EVMD-CMHA-TCN	67.858 ± 0.240	**53.679** ± 0.314	**1.509** ± 0.009	0.801 ± 0.001	60.556 ± 1.242
	EVMD-PMB-TCN	68.305 ± 0.568	54.228 ± 0.606	1.524 ± 0.017	0.798 ± 0.003	56.667 ± 2.722
	EVMD-PMB-CMHA-TCN	70.065 ± 3.712	55.461 ± 3.878	1.560 ± 0.114	0.787 ± 0.024	55.556 ± 3.685
	SVMD-TCN	71.244 ± 1.577	58.190 ± 1.414	1.638 ± 0.041	0.780 ± 0.010	47.222 ± 4.875
	SVMD-CMHA-TCN	71.326 ± 0.997	58.557 ± 1.054	1.649 ± 0.031	0.780 ± 0.006	46.667 ± 2.722
	SVMD-PMB-TCN	70.679 ± 0.823	57.819 ± 0.713	1.627 ± 0.021	0.784 ± 0.005	47.222 ± 1.242
	SVMD-PMB-CMHA-TCN	70.089 ± 2.467	56.759 ± 2.687	1.596 ± 0.076	0.787 ± 0.015	60.556 ± 2.992
July 2024	Diff-TCN [27]	92.836 ± 0.028	71.300 ± 0.041	2.205 ± 0.001	0.709 ± 0.000	50.538 ± 5.483
	TCN	93.383 ± 0.212	71.361 ± 0.208	2.208 ± 0.006	0.706 ± 0.001	53.763 ± 2.404
	Diff-TCN	92.816 ± 0.210	71.011 ± 0.171	2.196 ± 0.005	0.709 ± 0.001	47.312 ± 4.433
	CMHA-TCN	92.969 ± 0.164	71.246 ± 0.168	2.204 ± 0.005	0.708 ± 0.001	48.925 ± 5.072
	Diff-CMHA-TCN	**92.583** ± 0.429	**70.725** ± 0.239	**2.187** ± 0.007	**0.711** ± 0.003	51.613 ± 3.725
	EVMD-TCN	99.158 ± 0.371	72.665 ± 0.447	2.248 ± 0.014	0.668 ± 0.003	46.774 ± 1.613
	EVMD-CMHA-TCN	100.037 ± 0.683	72.911 ± 0.253	2.255 ± 0.007	0.662 ± 0.005	51.075 ± 1.202
	EVMD-PMB-TCN	98.489 ± 0.335	72.052 ± 0.567	2.231 ± 0.016	0.673 ± 0.002	49.462 ± 2.404
	EVMD-PMB-CMHA-TCN	102.794 ± 1.387	72.479 ± 1.434	2.243 ± 0.045	0.643 ± 0.009	50.000 ± 3.088
	SVMD-TCN	97.199 ± 1.913	73.871 ± 0.602	2.290 ± 0.019	0.681 ± 0.013	45.161 ± 1.862
	SVMD-CMHA-TCN	95.522 ± 0.580	72.483 ± 0.706	2.247 ± 0.022	0.692 ± 0.004	48.387 ± 4.165
	SVMD-PMB-TCN	95.394 ± 0.649	72.774 ± 0.362	2.256 ± 0.011	0.693 ± 0.004	48.387 ± 3.725
	SVMD-PMB-CMHA-TCN	98.401 ± 1.425	71.204 ± 1.774	2.211 ± 0.051	0.673 ± 0.009	**54.839** ± 6.452
August 2024	**Diff-TCN** [27]	**119.512** ± 0.174	81.796 ± 0.265	3.111 ± 0.010	**0.478** ± 0.002	37.634 ± 3.566
	TCN	120.422 ± 0.339	82.807 ± 0.525	3.149 ± 0.019	0.470 ± 0.003	36.559 ± 2.404
	Diff-TCN	120.202 ± 0.194	**80.997** ± 0.550	**3.076** ± 0.022	0.472 ± 0.002	50.000 ± 1.613
	CMHA-TCN	120.249 ± 1.540	82.454 ± 1.398	3.136 ± 0.052	0.471 ± 0.014	45.699 ± 12.412
	Diff-CMHA-TCN	121.825 ± 0.860	83.738 ± 1.050	3.182 ± 0.040	0.458 ± 0.008	41.398 ± 6.011
	EVMD-TCN	123.008 ± 0.324	83.835 ± 0.191	3.184 ± 0.007	0.447 ± 0.003	50.000 ± 1.613
	EVMD-CMHA-TCN	125.524 ± 1.102	85.473 ± 0.858	3.250 ± 0.033	0.424 ± 0.010	48.387 ± 2.634
	EVMD-PMB-TCN	122.856 ± 0.568	83.318 ± 0.316	3.165 ± 0.012	0.448 ± 0.005	**51.613**± 3.725
	EVMD-PMB-CMHA-TCN	135.155 ± 13.157	94.458 ± 12.045	3.603 ± 0.468	0.326 ± 0.137	48.387 ± 9.312
	SVMD-TCN	122.337 ± 0.669	82.928 ± 0.535	3.154 ± 0.020	0.453 ± 0.006	43.548 ± 4.059
	SVMD-CMHA-TCN	122.039 ± 0.999	83.016 ± 1.055	3.159 ± 0.042	0.456 ± 0.009	47.312 ± 4.809
	SVMD-PMB-TCN	122.208 ± 1.085	82.993 ± 1.166	3.158 ± 0.047	0.454 ± 0.010	47.849 ± 2.217
	SVMD-PMB-CMHA-TCN	142.699 ± 10.336	97.907 ± 9.354	3.751 ± 0.369	0.252 ± 0.109	50.538 ± 7.828
September 2024	Diff-TCN [27]	66.508 ± 0.030	57.115 ± 0.100	2.337 ± 0.004	0.766 ± 0.000	53.889 ± 2.992
	TCN	66.566 ± 0.183	56.859 ± 0.644	2.325 ± 0.026	0.766 ± 0.001	50.000 ± 4.714
	Diff-TCN	66.584 ± 0.079	57.016 ± 0.178	2.333 ± 0.007	0.765 ± 0.001	42.778 ± 2.291
	CMHA-TCN	66.407 ± 0.051	56.815 ± 0.303	2.324 ± 0.012	0.767 ± 0.000	55.000 ± 3.727
	Diff-CMHA-TCN	66.887 ± 0.068	57.523 ± 0.263	2.357 ± 0.011	0.763 ± 0.001	**54.444** ± 3.143
	EVMD-TCN	66.408 ± 0.052	56.527 ± 0.314	2.309 ± 0.013	0.767 ± 0.000	53.889 ± 1.242
	EVMD-CMHA-TCN	66.912 ± 0.230	56.718 ± 0.592	2.315 ± 0.024	0.763 ± 0.002	49.444 ± 1.242
	EVMD-PMB-TCN	66.530 ± 0.140	56.449 ± 0.353	2.306 ± 0.014	0.766 ± 0.001	53.333 ± 0.000
	EVMD-PMB-CMHA-TCN	70.756 ± 2.421	58.333 ± 1.428	2.384 ± 0.059	0.735 ± 0.018	53.333 ± 8.165
	SVMD-TCN	66.578 ± 0.477	56.494 ± 0.175	2.306 ± 0.007	0.765 ± 0.003	48.889 ± 3.143
	SVMD-CMHA-TCN	**66.191** ± 0.079	56.206 ± 0.211	2.295 ± 0.009	**0.768** ± 0.001	48.333 ± 4.194
	SVMD-PMB-TCN	66.540 ± 0.462	56.331 ± 0.246	2.301 ± 0.010	0.766 ± 0.003	48.889 ± 4.969
	SVMD-PMB-CMHA-TCN	67.575 ± 1.373	**54.953** ± 0.516	**2.244** ± 0.021	0.758 ± 0.010	52.778 ± 4.045
October 2024	**Diff-TCN** [27]	67.759 ± 0.173	**50.926** ± 0.126	**2.019** ± 0.004	0.591 ± 0.002	**58.065** ± 0.000
	TCN	67.578 ± 0.080	51.154 ± 0.250	2.027 ± 0.009	0.593 ± 0.001	49.462 ± 6.885
	Diff-TCN	68.172 ± 0.158	51.432 ± 0.183	2.040 ± 0.007	0.586 ± 0.002	47.312 ± 2.404
	CMHA-TCN	**67.507** ± 0.378	51.025 ± 0.374	2.022 ± 0.014	**0.594** ± 0.004	50.000 ± 6.906

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	68.641 ± 0.498	52.438 ± 0.398	2.080 ± 0.015	0.581 ± 0.006	39.785 ± 4.809
	EVMD-TCN	71.505 ± 0.276	54.397 ± 0.233	2.158 ± 0.009	0.545 ± 0.004	44.086 ± 3.041
	EVMD-CMHA-TCN	71.399 ± 0.393	54.151 ± 0.371	2.148 ± 0.014	0.546 ± 0.005	45.699 ± 1.202
	EVMD-PMB-TCN	70.075 ± 0.267	53.587 ± 0.397	2.125 ± 0.016	0.563 ± 0.003	39.785 ± 3.041
	EVMD-PMB-CMHA-TCN	74.133 ± 3.069	58.002 ± 3.459	2.296 ± 0.135	0.510 ± 0.041	47.312 ± 5.157
	SVMD-TCN	67.904 ± 0.539	51.319 ± 0.267	2.037 ± 0.011	0.589 ± 0.006	51.613 ± 4.165
	SVMD-CMHA-TCN	69.031 ± 0.703	52.169 ± 0.643	2.071 ± 0.026	0.576 ± 0.009	51.075 ± 2.217
	SVMD-PMB-TCN	69.607 ± 1.185	52.326 ± 0.749	2.079 ± 0.030	0.569 ± 0.015	53.763 ± 3.566
	SVMD-PMB-CMHA-TCN	73.401 ± 1.451	56.102 ± 1.139	2.229 ± 0.046	0.520 ± 0.019	50.538 ± 6.628
November 2024	Diff-TCN [27]	127.380 ± 0.172	96.189 ± 0.050	3.047 ± 0.001	0.877 ± 0.000	53.333 ± 0.000
	TCN	127.875 ± 0.269	96.272 ± 0.178	3.048 ± 0.007	0.876 ± 0.001	49.444 ± 4.875
	Diff-TCN	127.195 ± 0.222	**95.675** ± 0.074	**3.039** ± 0.002	**0.878** ± 0.000	56.667 ± 1.925
	CMHA-TCN	128.814 ± 0.629	96.612 ± 0.225	3.057 ± 0.006	0.874 ± 0.001	48.333 ± 4.615
	Diff-CMHA-TCN	**127.061** ± 0.486	95.844 ± 0.451	**3.039** ± 0.012	**0.878** ± 0.001	52.222 ± 4.157
	EVMD-TCN	128.247 ± 0.472	95.834 ± 0.204	3.054 ± 0.007	0.875 ± 0.001	**61.111** ± 1.571
	EVMD-CMHA-TCN	131.903 ± 1.996	97.613 ± 0.912	3.114 ± 0.029	0.868 ± 0.004	58.333 ± 1.667
	EVMD-PMB-TCN	130.835 ± 0.793	97.372 ± 0.281	3.102 ± 0.009	0.871 ± 0.002	57.778 ± 1.571
	EVMD-PMB-CMHA-TCN	142.584 ± 11.662	108.359 ± 11.043	3.465 ± 0.354	0.845 ± 0.026	51.111 ± 5.666
	SVMD-TCN	130.120 ± 0.430	96.236 ± 0.244	3.063 ± 0.008	0.872 ± 0.001	55.000 ± 3.727
	SVMD-CMHA-TCN	130.128 ± 0.722	96.369 ± 0.815	3.072 ± 0.027	0.872 ± 0.001	56.111 ± 4.875
	SVMD-PMB-TCN	129.371 ± 0.743	96.864 ± 0.519	3.089 ± 0.020	0.873 ± 0.002	51.111 ± 2.485
	SVMD-PMB-CMHA-TCN	138.353 ± 4.067	105.654 ± 4.646	3.396 ± 0.163	0.855 ± 0.009	52.222 ± 4.581
December 2024	Diff-TCN [27]	121.723 ± 0.273	88.775 ± 0.277	2.443 ± 0.009	0.751 ± 0.001	48.387 ± 0.000
	TCN	**121.207** ± 0.344	88.757 ± 0.496	2.439 ± 0.011	**0.753** ± 0.001	**50.538** ± 2.404
	Diff-TCN	122.777 ± 0.254	90.296 ± 0.295	2.485 ± 0.008	0.746 ± 0.001	45.161 ± 1.862
	CMHA-TCN	121.312 ± 0.328	**88.638** ± 0.112	**2.438** ± 0.005	0.752 ± 0.001	**50.538** ± 1.521
	Diff-CMHA-TCN	123.446 ± 0.500	91.234 ± 0.661	2.507 ± 0.018	0.744 ± 0.002	36.022 ± 2.217
	EVMD-TCN	126.570 ± 0.509	93.248 ± 0.070	2.567 ± 0.002	0.730 ± 0.002	46.774 ± 1.613
	EVMD-CMHA-TCN	127.298 ± 0.966	94.969 ± 0.836	2.616 ± 0.027	0.727 ± 0.004	50.000 ± 2.464
	EVMD-PMB-TCN	126.603 ± 0.205	94.849 ± 0.337	2.608 ± 0.009	0.730 ± 0.001	43.011 ± 1.521
	EVMD-PMB-CMHA-TCN	130.705 ± 4.102	102.245 ± 3.857	2.803 ± 0.106	0.712 ± 0.018	47.849 ± 2.217
	SVMD-TCN	122.083 ± 0.544	89.057 ± 0.435	2.452 ± 0.014	0.749 ± 0.002	47.849 ± 3.442
	SVMD-CMHA-TCN	124.391 ± 2.791	91.525 ± 2.974	2.515 ± 0.077	0.739 ± 0.012	47.312 ± 4.433
	SVMD-PMB-TCN	122.923 ± 0.484	89.590 ± 0.401	2.467 ± 0.013	0.746 ± 0.002	50.538 ± 2.404
	SVMD-PMB-CMHA-TCN	129.704 ± 3.417	99.405 ± 5.081	2.736 ± 0.139	0.717 ± 0.015	48.387 ± 3.725
January 2025	Diff-TCN [27]	110.118 ± 0.046	88.299 ± 0.065	2.651 ± 0.002	0.467 ± 0.000	54.301 ± 1.202
	TCN	109.818 ± 0.718	88.360 ± 0.414	2.651 ± 0.014	0.470 ± 0.007	51.075 ± 3.442
	Diff-TCN	109.818 ± 0.074	88.322 ± 0.123	2.651 ± 0.004	0.470 ± 0.001	48.925 ± 3.442
	CMHA-TCN	109.796 ± 0.164	88.176 ± 0.200	2.647 ± 0.005	0.470 ± 0.002	54.301 ± 7.772
	Diff-CMHA-TCN	110.105 ± 0.681	88.778 ± 0.505	2.665 ± 0.016	0.467 ± 0.007	46.237 ± 4.023
	EVMD-TCN	112.575 ± 0.403	89.889 ± 0.444	2.698 ± 0.012	0.443 ± 0.004	46.774 ± 1.613
	EVMD-CMHA-TCN	111.738 ± 1.043	88.629 ± 0.471	2.659 ± 0.015	0.451 ± 0.010	51.613 ± 3.725
	EVMD-PMB-TCN	111.403 ± 0.437	88.804 ± 0.179	2.664 ± 0.006	0.454 ± 0.004	47.849 ± 3.442
	EVMD-PMB-CMHA-TCN	115.396 ± 3.369	91.726 ± 3.206	2.761 ± 0.107	0.414 ± 0.035	52.688 ± 4.433
	SVMD-TCN	108.056 ± 0.321	87.131 ± 0.266	2.611 ± 0.008	0.487 ± 0.003	49.462 ± 1.521
	SVMD-CMHA-TCN	**107.975** ± 0.174	**86.666** ± 0.282	**2.598** ± 0.008	**0.487** ± 0.002	47.849 ± 4.335
	SVMD-PMB-TCN	108.049 ± 0.107	86.916 ± 0.414	2.604 ± 0.010	0.487 ± 0.001	50.538 ± 3.566
	SVMD-PMB-CMHA-TCN	114.116 ± 5.918	90.833 ± 6.423	2.732 ± 0.205	0.426 ± 0.060	**56.452** ± 3.088
February 2025	Diff-TCN [27]	108.939 ± 0.470	81.730 ± 0.254	3.063 ± 0.011	0.608 ± 0.003	39.286 ± 0.000
	TCN	**108.673** ± 0.290	**81.513** ± 0.263	**3.056** ± 0.013	**0.610** ± 0.002	42.262 ± 6.655
	Diff-TCN	108.876 ± 0.254	81.521 ± 0.217	3.057 ± 0.009	0.609 ± 0.002	47.024 ± 3.811
	CMHA-TCN	109.223 ± 1.645	82.100 ± 1.239	3.079 ± 0.050	0.606 ± 0.012	42.857 ± 7.986
	Diff-CMHA-TCN	109.002 ± 0.448	81.843 ± 0.451	3.063 ± 0.019	0.608 ± 0.003	45.238 ± 3.367
	EVMD-TCN	112.667 ± 0.676	85.260 ± 0.544	3.205 ± 0.021	0.581 ± 0.005	64.881 ± 4.333
	EVMD-CMHA-TCN	112.747 ± 1.284	85.647 ± 1.084	3.224 ± 0.043	0.581 ± 0.009	**67.262** ± 4.799
	EVMD-PMB-TCN	112.225 ± 0.635	85.250 ± 0.592	3.205 ± 0.025	0.584 ± 0.005	65.476 ± 6.070
	EVMD-PMB-CMHA-TCN	128.518 ± 6.824	101.055 ± 7.138	3.849 ± 0.277	0.453 ± 0.057	53.571 ± 4.611
	SVMD-TCN	110.678 ± 1.242	84.526 ± 1.003	3.180 ± 0.042	0.596 ± 0.009	54.167 ± 3.811
	SVMD-CMHA-TCN	110.208 ± 0.548	84.263 ± 0.363	3.169 ± 0.014	0.599 ± 0.004	55.952 ± 1.684
	SVMD-PMB-TCN	110.061 ± 1.055	83.889 ± 0.814	3.154 ± 0.033	0.600 ± 0.008	55.357 ± 1.786
	SVMD-PMB-CMHA-TCN	122.730 ± 11.422	96.021 ± 11.041	3.645 ± 0.435	0.499 ± 0.095	52.976 ± 5.615
March 2025	Diff-TCN [27]	108.273 ± 0.428	70.933 ± 0.320	3.422 ± 0.018	0.502 ± 0.004	45.161 ± 0.000
	TCN	107.799 ± 0.279	70.517 ± 0.241	3.401 ± 0.012	0.506 ± 0.003	46.774 ± 1.613
	Diff-TCN	106.369 ± 0.395	**69.367** ± 0.341	**3.348** ± 0.017	0.519 ± 0.004	**61.290** ± 3.725
	CMHA-TCN	108.181 ± 0.131	70.857 ± 0.146	3.419 ± 0.006	0.503 ± 0.001	45.161 ± 0.000
	Diff-CMHA-TCN	107.634 ± 1.482	69.590 ± 1.649	3.354 ± 0.078	0.508 ± 0.014	55.914 ± 5.157
	EVMD-TCN	104.090 ± 0.150	70.364 ± 0.337	3.409 ± 0.017	0.540 ± 0.001	55.376 ± 2.217
	EVMD-CMHA-TCN	**103.155** ± 0.302	70.421 ± 0.458	3.416 ± 0.025	**0.548** ± 0.003	55.376 ± 2.217
	EVMD-PMB-TCN	104.878 ± 0.394	70.294 ± 0.172	3.407 ± 0.010	0.533 ± 0.004	54.839 ± 2.634
	EVMD-PMB-CMHA-TCN	111.567 ± 5.145	80.288 ± 4.938	3.938 ± 0.258	0.470 ± 0.049	52.688 ± 1.521
	SVMD-TCN	111.527 ± 0.462	77.181 ± 0.565	3.734 ± 0.030	0.472 ± 0.004	46.774 ± 4.059
	SVMD-CMHA-TCN	111.286 ± 0.204	77.240 ± 0.306	3.738 ± 0.016	0.474 ± 0.002	47.312 ± 2.404
	SVMD-PMB-TCN	111.627 ± 0.555	77.151 ± 0.582	3.733 ± 0.031	0.471 ± 0.005	48.925 ± 1.202
	SVMD-PMB-CMHA-TCN	110.692 ± 0.857	79.394 ± 1.121	3.864 ± 0.065	0.479 ± 0.008	50.000 ± 5.815
April 2025	Diff-TCN [27]	79.010 ± 0.030	51.821 ± 0.028	3.130 ± 0.002	0.537 ± 0.000	46.667 ± 0.000
	TCN	79.029 ± 0.127	52.056 ± 0.257	3.147 ± 0.018	0.537 ± 0.002	46.667 ± 0.000
	Diff-TCN	78.219 ± 0.186	51.120 ± 0.135	3.089 ± 0.008	0.546 ± 0.002	54.444 ± 3.143
	CMHA-TCN	79.008 ± 0.089	52.065 ± 0.202	3.149 ± 0.014	0.537 ± 0.001	46.667 ± 0.000

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	79.432 ± 0.452	51.172 ± 0.131	3.092 ± 0.008	0.532 ± 0.005	54.444 ± 4.581
	EVMD-TCN	76.596 ± 0.230	**49.531** ± 0.737	**2.996** ± 0.045	0.565 ± 0.003	62.778 ± 1.242
	EVMD-CMHA-TCN	**76.022** ± 0.526	49.934 ± 1.558	3.020 ± 0.099	**0.572** ± 0.006	**65.000** ± 3.727
	EVMD-PMB-TCN	76.102 ± 0.236	50.118 ± 0.697	3.030 ± 0.043	0.571 ± 0.003	65.000 ± 3.727
	EVMD-PMB-CMHA-TCN	78.502 ± 0.820	52.467 ± 1.319	3.174 ± 0.080	0.543 ± 0.009	61.111 ± 3.685
	SVMD-TCN	80.252 ± 0.750	54.693 ± 0.984	3.298 ± 0.063	0.523 ± 0.009	45.000 ± 1.667
	SVMD-CMHA-TCN	79.755 ± 0.232	54.200 ± 0.336	3.268 ± 0.023	0.528 ± 0.003	44.444 ± 3.685
	SVMD-PMB-TCN	79.846 ± 0.284	54.265 ± 0.210	3.271 ± 0.013	0.527 ± 0.003	42.222 ± 3.143
	SVMD-PMB-CMHA-TCN	82.565 ± 2.832	57.459 ± 3.519	3.485 ± 0.223	0.494 ± 0.035	54.444 ± 4.581
May 2025	Diff-TCN [27]	104.509 ± 0.555	64.425 ± 0.382	2.651 ± 0.021	0.888 ± 0.001	51.613 ± 0.000
	TCN	104.671 ± 0.681	**64.053** ± 0.274	**2.636** ± 0.009	0.888 ± 0.002	54.301 ± 3.914
	Diff-TCN	105.810 ± 0.156	65.308 ± 0.174	2.685 ± 0.007	0.885 ± 0.000	50.538 ± 2.404
	CMHA-TCN	104.523 ± 0.633	64.180 ± 0.322	2.641 ± 0.015	0.888 ± 0.001	53.226 ± 5.185
	Diff-CMHA-TCN	105.516 ± 0.754	65.490 ± 0.861	2.692 ± 0.036	0.886 ± 0.002	54.301 ± 3.914
	EVMD-TCN	110.044 ± 0.442	67.031 ± 0.451	2.755 ± 0.018	0.876 ± 0.001	46.774 ± 2.464
	EVMD-CMHA-TCN	112.630 ± 0.561	67.296 ± 0.233	2.764 ± 0.011	0.870 ± 0.001	43.548 ± 2.464
	EVMD-PMB-TCN	111.706 ± 0.818	67.653 ± 0.555	2.777 ± 0.022	0.872 ± 0.002	45.699 ± 2.217
	EVMD-PMB-CMHA-TCN	126.310 ± 11.822	78.712 ± 7.765	3.245 ± 0.312	0.835 ± 0.031	49.462 ± 4.809
	SVMD-TCN	**103.160** ± 0.347	65.719 ± 0.196	2.712 ± 0.009	**0.891** ± 0.001	**56.989** ± 2.404
	SVMD-CMHA-TCN	103.746 ± 0.372	65.008 ± 0.285	2.683 ± 0.011	0.890 ± 0.001	54.839 ± 2.634
	SVMD-PMB-TCN	103.998 ± 0.883	65.955 ± 0.587	2.720 ± 0.022	0.889 ± 0.002	54.301 ± 3.442
	SVMD-PMB-CMHA-TCN	117.727 ± 6.940	72.825 ± 5.492	2.995 ± 0.215	0.857 ± 0.017	56.989 ± 6.361

Table 61: Average results of the *extended experiments* across 6 repetitions per split $M_1, \ldots, M_{36}$ corresponding to months June 2022 to May 2025 in relation to forecasting $\mathbf{S}_{\text{Close}}$ with respect to ETH/USD using the novel framework.

F.2.3 *LTC / USD*

Month	Model	RMSE	MAE	MAPE	R2	DA
June 2021	TCN [27]	11.221 ± 0.499	8.751 ± 0.544	5.725 ± 0.321	0.702 ± 0.026	52.222 ± 5.984
	Diff-TCN [27]	9.025 ± 0.004	6.880 ± 0.003	4.544 ± 0.002	0.807 ± 0.000	50.000 ± 0.000
	TCN	9.122 ± 0.083	6.935 ± 0.053	4.586 ± 0.032	0.803 ± 0.004	48.333 ± 2.546
	Diff-TCN	9.081 ± 0.025	6.978 ± 0.040	4.619 ± 0.028	0.805 ± 0.001	51.667 ± 2.546
	CMHA-TCN	9.173 ± 0.069	6.985 ± 0.070	4.626 ± 0.052	0.801 ± 0.003	47.778 ± 4.157
	Diff-CMHA-TCN	9.044 ± 0.037	6.950 ± 0.042	4.597 ± 0.029	0.807 ± 0.002	49.444 ± 2.291
	EVMD-TCN	8.955 ± 0.042	6.662 ± 0.039	4.391 ± 0.024	0.810 ± 0.002	57.778 ± 2.485
	EVMD-CMHA-TCN	**8.839** ± 0.075	**6.516** ± 0.068	**4.296** ± 0.044	**0.815** ± 0.003	**62.222** ± 3.143
	EVMD-PMB-TCN	8.973 ± 0.312	6.686 ± 0.274	4.404 ± 0.170	0.809 ± 0.013	59.444 ± 5.906
	EVMD-PMB-CMHA-TCN	9.068 ± 0.273	6.704 ± 0.284	4.417 ± 0.189	0.805 ± 0.012	55.556 ± 4.157
	SVMD-TCN	9.685 ± 0.240	7.405 ± 0.138	4.948 ± 0.085	0.778 ± 0.011	52.222 ± 1.571
	SVMD-CMHA-TCN	10.135 ± 0.878	7.725 ± 0.565	5.126 ± 0.334	0.755 ± 0.045	53.333 ± 2.722
	SVMD-PMB-TCN	9.564 ± 0.242	7.271 ± 0.175	4.865 ± 0.103	0.784 ± 0.011	55.556 ± 1.571
	SVMD-PMB-CMHA-TCN	9.379 ± 0.123	7.184 ± 0.105	4.809 ± 0.062	0.792 ± 0.005	54.444 ± 1.571
July 2021	TCN [27]	4.952 ± 0.386	4.283 ± 0.487	3.333 ± 0.377	0.725 ± 0.043	38.172 ± 8.207
	Diff-TCN [27]	**4.104** ± 0.004	**3.246** ± 0.005	**2.533** ± 0.005	**0.812** ± 0.000	**48.387** ± 0.000
	TCN	4.199 ± 0.054	3.415 ± 0.082	2.677 ± 0.067	0.803 ± 0.005	42.473 ± 4.335
	Diff-TCN	4.167 ± 0.012	3.341 ± 0.014	2.613 ± 0.012	0.806 ± 0.001	45.161 ± 0.000
	CMHA-TCN	4.236 ± 0.067	3.455 ± 0.073	2.710 ± 0.060	0.800 ± 0.006	41.935 ± 4.165
	Diff-CMHA-TCN	4.132 ± 0.023	3.309 ± 0.049	2.586 ± 0.041	0.809 ± 0.002	44.624 ± 5.403
	EVMD-TCN	4.165 ± 0.026	3.418 ± 0.035	2.671 ± 0.030	0.806 ± 0.003	40.323 ± 3.088
	EVMD-CMHA-TCN	4.155 ± 0.032	3.385 ± 0.028	2.645 ± 0.025	0.807 ± 0.003	40.860 ± 4.809
	EVMD-PMB-TCN	4.213 ± 0.129	3.476 ± 0.114	2.723 ± 0.092	0.802 ± 0.012	40.323 ± 3.088
	EVMD-PMB-CMHA-TCN	4.234 ± 0.033	3.479 ± 0.024	2.723 ± 0.020	0.800 ± 0.003	41.398 ± 4.335
	SVMD-TCN	4.406 ± 0.038	3.632 ± 0.041	2.852 ± 0.033	0.783 ± 0.004	35.484 ± 1.862
	SVMD-CMHA-TCN	4.319 ± 0.074	3.560 ± 0.036	2.790 ± 0.031	0.792 ± 0.007	32.258 ± 3.725
	SVMD-PMB-TCN	4.260 ± 0.045	3.488 ± 0.045	2.728 ± 0.038	0.797 ± 0.004	37.634 ± 5.157
	SVMD-PMB-CMHA-TCN	4.317 ± 0.059	3.576 ± 0.068	2.797 ± 0.056	0.792 ± 0.006	34.409 ± 5.483
August 2021	**TCN** [27]	**6.796** ± 0.115	5.356 ± 0.097	3.180 ± 0.054	**0.787** ± 0.007	68.280 ± 4.335
	Diff-TCN [27]	7.157 ± 0.006	5.657 ± 0.003	3.356 ± 0.001	0.764 ± 0.000	51.613 ± 0.000
	TCN	7.062 ± 0.032	5.540 ± 0.036	3.285 ± 0.021	0.770 ± 0.002	61.290 ± 4.562
	Diff-TCN	7.067 ± 0.044	5.522 ± 0.055	3.277 ± 0.032	0.770 ± 0.003	60.753 ± 2.217
	CMHA-TCN	7.064 ± 0.021	5.529 ± 0.025	3.277 ± 0.015	0.770 ± 0.001	60.753 ± 2.895
	Diff-CMHA-TCN	7.123 ± 0.043	5.602 ± 0.062	3.323 ± 0.036	0.766 ± 0.003	58.602 ± 2.895
	EVMD-TCN	7.139 ± 0.008	5.511 ± 0.009	3.277 ± 0.005	0.765 ± 0.001	59.677 ± 2.464
	EVMD-CMHA-TCN	7.159 ± 0.024	5.540 ± 0.039	3.294 ± 0.022	0.764 ± 0.002	56.989 ± 2.404
	EVMD-PMB-TCN	7.147 ± 0.082	5.603 ± 0.082	3.328 ± 0.047	0.765 ± 0.005	60.215 ± 3.041
	EVMD-PMB-CMHA-TCN	7.148 ± 0.029	5.564 ± 0.085	3.305 ± 0.046	0.765 ± 0.002	60.215 ± 1.521
	SVMD-TCN	6.902 ± 0.025	**5.277** ± 0.049	**3.133** ± 0.023	0.781 ± 0.002	62.903 ± 4.839
	SVMD-CMHA-TCN	6.942 ± 0.062	5.331 ± 0.070	3.159 ± 0.037	0.778 ± 0.004	66.129 ± 3.088
	SVMD-PMB-TCN	6.983 ± 0.036	5.388 ± 0.051	3.189 ± 0.026	0.775 ± 0.002	67.204 ± 2.217
	SVMD-PMB-CMHA-TCN	6.959 ± 0.079	5.360 ± 0.052	3.172 ± 0.028	0.777 ± 0.005	**70.968** ± 2.634
September 2021	TCN [27]	13.483 ± 0.349	10.051 ± 0.342	5.676 ± 0.177	0.642 ± 0.019	41.667 ± 2.546
	Diff-TCN [27]	**12.017** ± 0.006	**8.053** ± 0.002	**4.525** ± 0.001	**0.716** ± 0.000	50.000 ± 0.000
	TCN	12.082 ± 0.091	8.137 ± 0.110	4.576 ± 0.063	0.712 ± 0.004	53.333 ± 3.333
	Diff-TCN	12.225 ± 0.035	8.267 ± 0.074	4.666 ± 0.037	0.706 ± 0.002	50.000 ± 2.722
	CMHA-TCN	12.071 ± 0.058	8.156 ± 0.066	4.590 ± 0.040	0.713 ± 0.003	**53.889** ± 2.992
	Diff-CMHA-TCN	12.105 ± 0.037	8.155 ± 0.053	4.589 ± 0.034	0.711 ± 0.002	50.000 ± 0.000
	EVMD-TCN	12.400 ± 0.046	8.458 ± 0.062	4.776 ± 0.036	0.697 ± 0.002	50.556 ± 1.242
	EVMD-CMHA-TCN	12.393 ± 0.041	8.418 ± 0.074	4.755 ± 0.044	0.697 ± 0.002	51.667 ± 1.667
	EVMD-PMB-TCN	12.590 ± 0.080	8.760 ± 0.128	4.938 ± 0.077	0.688 ± 0.004	48.889 ± 3.143
	EVMD-PMB-CMHA-TCN	12.476 ± 0.105	8.533 ± 0.121	4.820 ± 0.073	0.693 ± 0.005	52.222 ± 1.571
	SVMD-TCN	12.430 ± 0.106	8.630 ± 0.102	4.879 ± 0.061	0.696 ± 0.005	44.444 ± 3.685
	SVMD-CMHA-TCN	12.388 ± 0.045	8.628 ± 0.057	4.863 ± 0.035	0.698 ± 0.002	47.778 ± 2.485
	SVMD-PMB-TCN	12.444 ± 0.080	8.677 ± 0.087	4.895 ± 0.050	0.695 ± 0.004	50.556 ± 2.992
	SVMD-PMB-CMHA-TCN	12.292 ± 0.108	8.481 ± 0.115	4.790 ± 0.063	0.702 ± 0.005	50.556 ± 3.557
October 2021	TCN [27]	7.554 ± 0.370	5.758 ± 0.439	3.141 ± 0.235	0.442 ± 0.056	53.763 ± 8.047
	Diff-TCN [27]	7.169 ± 0.006	5.696 ± 0.011	3.078 ± 0.006	0.498 ± 0.001	64.516 ± 0.000
	TCN	7.028 ± 0.010	5.587 ± 0.021	3.020 ± 0.011	0.518 ± 0.001	71.505 ± 6.011
	Diff-TCN	7.091 ± 0.007	5.611 ± 0.013	3.034 ± 0.007	0.509 ± 0.001	60.753 ± 1.202
	CMHA-TCN	7.035 ± 0.040	5.597 ± 0.042	3.028 ± 0.022	0.517 ± 0.005	**76.344** ± 3.566
	Diff-CMHA-TCN	7.063 ± 0.053	5.593 ± 0.062	3.026 ± 0.032	0.513 ± 0.007	63.441 ± 3.566
	EVMD-TCN	7.158 ± 0.047	5.651 ± 0.063	3.060 ± 0.033	0.500 ± 0.006	53.226 ± 2.464
	EVMD-CMHA-TCN	7.240 ± 0.080	5.762 ± 0.089	3.120 ± 0.048	0.488 ± 0.011	52.688 ± 3.566
	EVMD-PMB-TCN	7.240 ± 0.091	5.683 ± 0.101	3.083 ± 0.055	0.488 ± 0.013	55.376 ± 2.217
	EVMD-PMB-CMHA-TCN	7.179 ± 0.045	5.676 ± 0.057	3.075 ± 0.030	0.497 ± 0.006	52.688 ± 2.404
	SVMD-TCN	**6.874** ± 0.035	**5.221** ± 0.048	**2.826** ± 0.026	**0.539** ± 0.005	54.301 ± 2.217
	SVMD-CMHA-TCN	6.916 ± 0.094	5.295 ± 0.111	2.871 ± 0.060	0.533 ± 0.013	55.914 ± 1.521
	SVMD-PMB-TCN	6.949 ± 0.069	5.319 ± 0.092	2.878 ± 0.050	0.529 ± 0.009	52.688 ± 5.483
	SVMD-PMB-CMHA-TCN	6.949 ± 0.053	5.339 ± 0.068	2.889 ± 0.038	0.529 ± 0.007	54.839 ± 2.634
November 2021	TCN [27]	16.083 ± 0.537	12.072 ± 0.384	5.319 ± 0.157	0.573 ± 0.029	43.333 ± 3.333
	Diff-TCN [27]	14.145 ± 0.001	10.295 ± 0.009	4.557 ± 0.004	0.670 ± 0.000	53.333 ± 0.000
	TCN	13.990 ± 0.039	10.163 ± 0.020	4.489 ± 0.009	0.677 ± 0.002	62.778 ± 2.291
	Diff-TCN	14.240 ± 0.026	10.292 ± 0.035	4.563 ± 0.015	0.665 ± 0.001	55.556 ± 2.485
	CMHA-TCN	14.065 ± 0.015	10.213 ± 0.065	4.511 ± 0.024	0.673 ± 0.001	**64.444** ± 3.685

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	14.120 ± 0.035	10.198 ± 0.065	4.519 ± 0.026	0.671 ± 0.002	55.000 ± 3.191
	EVMD-TCN	14.366 ± 0.018	10.423 ± 0.038	4.593 ± 0.014	0.659 ± 0.001	51.667 ± 3.191
	EVMD-CMHA-TCN	14.380 ± 0.045	10.407 ± 0.057	4.593 ± 0.022	0.659 ± 0.002	53.333 ± 3.333
	EVMD-PMB-TCN	14.635 ± 0.043	10.779 ± 0.074	4.752 ± 0.032	0.646 ± 0.002	51.111 ± 3.143
	EVMD-PMB-CMHA-TCN	14.484 ± 0.100	10.519 ± 0.082	4.636 ± 0.034	0.654 ± 0.005	50.556 ± 2.291
	SVMD-TCN	**13.510** ± 0.068	**10.065** ± 0.106	**4.453** ± 0.042	**0.699** ± 0.003	63.333 ± 1.925
	SVMD-CMHA-TCN	13.604 ± 0.136	10.142 ± 0.107	4.476 ± 0.037	0.695 ± 0.006	57.778 ± 4.157
	SVMD-PMB-TCN	13.521 ± 0.113	10.073 ± 0.089	4.454 ± 0.034	0.698 ± 0.005	58.889 ± 2.485
	SVMD-PMB-CMHA-TCN	13.531 ± 0.104	10.132 ± 0.042	4.485 ± 0.020	0.698 ± 0.005	52.778 ± 4.479
December 2021	TCN [27]	9.356 ± 0.397	6.487 ± 0.195	4.101 ± 0.127	0.616 ± 0.032	52.151 ± 5.072
	Diff-TCN [27]	7.823 ± 0.019	5.397 ± 0.008	3.416 ± 0.005	0.732 ± 0.001	48.387 ± 0.000
	TCN	7.845 ± 0.042	5.488 ± 0.034	3.477 ± 0.023	0.730 ± 0.003	48.925 ± 1.202
	Diff-TCN	7.769 ± 0.120	5.355 ± 0.049	3.386 ± 0.033	0.735 ± 0.008	**53.763** ± 5.483
	CMHA-TCN	7.785 ± 0.149	5.474 ± 0.044	3.467 ± 0.028	0.734 ± 0.010	49.462 ± 1.521
	Diff-CMHA-TCN	**7.759** ± 0.067	**5.327** ± 0.097	**3.369** ± 0.063	**0.736** ± 0.005	52.688 ± 5.790
	EVMD-TCN	8.000 ± 0.084	5.721 ± 0.066	3.605 ± 0.043	0.720 ± 0.006	44.086 ± 1.521
	EVMD-CMHA-TCN	8.014 ± 0.078	5.712 ± 0.047	3.601 ± 0.030	0.719 ± 0.005	44.086 ± 3.041
	EVMD-PMB-TCN	8.085 ± 0.329	5.761 ± 0.154	3.630 ± 0.093	0.713 ± 0.024	51.075 ± 5.715
	EVMD-PMB-CMHA-TCN	7.933 ± 0.105	5.694 ± 0.095	3.578 ± 0.060	0.724 ± 0.007	50.000 ± 3.607
	SVMD-TCN	8.802 ± 0.124	6.306 ± 0.052	3.996 ± 0.033	0.660 ± 0.010	37.097 ± 3.088
	SVMD-CMHA-TCN	8.794 ± 0.247	6.316 ± 0.089	4.010 ± 0.054	0.661 ± 0.019	36.559 ± 4.433
	SVMD-PMB-TCN	8.806 ± 0.073	6.251 ± 0.067	3.965 ± 0.040	0.660 ± 0.006	37.097 ± 3.088
	SVMD-PMB-CMHA-TCN	8.773 ± 0.177	6.252 ± 0.068	3.967 ± 0.047	0.663 ± 0.013	38.710 ± 4.928
January 2022	TCN [27]	7.921 ± 0.357	6.058 ± 0.316	4.791 ± 0.256	0.751 ± 0.022	42.473 ± 2.217
	Diff-TCN [27]	**5.597** ± 0.012	**4.284** ± 0.009	**3.316** ± 0.008	**0.876** ± 0.001	41.935 ± 0.000
	TCN	6.144 ± 0.067	4.743 ± 0.042	3.707 ± 0.034	0.850 ± 0.003	42.473 ± 1.202
	Diff-TCN	5.672 ± 0.098	4.346 ± 0.080	3.367 ± 0.066	0.873 ± 0.004	43.011 ± 1.521
	CMHA-TCN	6.051 ± 0.110	4.648 ± 0.116	3.626 ± 0.103	0.855 ± 0.005	41.935 ± 0.000
	Diff-CMHA-TCN	5.874 ± 0.247	4.455 ± 0.157	3.453 ± 0.130	0.863 ± 0.011	**45.161** ± 1.862
	EVMD-TCN	6.067 ± 0.060	4.786 ± 0.062	3.717 ± 0.055	0.854 ± 0.003	39.247 ± 1.202
	EVMD-CMHA-TCN	6.226 ± 0.084	4.933 ± 0.085	3.847 ± 0.076	0.846 ± 0.004	40.860 ± 1.521
	EVMD-PMB-TCN	6.250 ± 0.206	4.892 ± 0.183	3.792 ± 0.163	0.845 ± 0.010	36.022 ± 4.718
	EVMD-PMB-CMHA-TCN	6.342 ± 0.074	4.966 ± 0.073	3.863 ± 0.066	0.841 ± 0.004	40.323 ± 1.613
	SVMD-TCN	6.345 ± 0.178	4.879 ± 0.172	3.832 ± 0.144	0.840 ± 0.009	40.323 ± 1.613
	SVMD-CMHA-TCN	6.386 ± 0.228	4.945 ± 0.232	3.871 ± 0.195	0.838 ± 0.012	40.860 ± 1.521
	SVMD-PMB-TCN	6.522 ± 0.129	5.015 ± 0.153	3.934 ± 0.132	0.831 ± 0.007	41.398 ± 1.202
	SVMD-PMB-CMHA-TCN	6.463 ± 0.207	5.033 ± 0.219	3.964 ± 0.186	0.834 ± 0.010	40.860 ± 1.521
February 2022	TCN [27]	7.679 ± 0.255	6.455 ± 0.203	5.398 ± 0.171	0.505 ± 0.033	41.667 ± 2.662
	Diff-TCN [27]	5.873 ± 0.001	4.874 ± 0.002	4.110 ± 0.002	0.711 ± 0.000	46.429 ± 0.000
	TCN	5.904 ± 0.016	4.977 ± 0.032	4.212 ± 0.030	0.708 ± 0.002	47.024 ± 1.331
	Diff-TCN	5.879 ± 0.006	4.855 ± 0.010	4.100 ± 0.010	0.710 ± 0.001	47.024 ± 1.331
	CMHA-TCN	5.907 ± 0.022	4.991 ± 0.040	4.226 ± 0.036	0.708 ± 0.002	46.429 ± 0.000
	Diff-CMHA-TCN	**5.833** ± 0.021	**4.822** ± 0.015	**4.066** ± 0.014	**0.715** ± 0.002	50.595 ± 4.799
	EVMD-TCN	6.205 ± 0.017	5.256 ± 0.041	4.447 ± 0.037	0.677 ± 0.002	43.452 ± 1.331
	EVMD-CMHA-TCN	6.203 ± 0.035	5.245 ± 0.063	4.442 ± 0.058	0.678 ± 0.004	45.238 ± 1.684
	EVMD-PMB-TCN	6.268 ± 0.045	5.290 ± 0.106	4.471 ± 0.099	0.671 ± 0.005	41.071 ± 4.494
	EVMD-PMB-CMHA-TCN	6.203 ± 0.034	5.220 ± 0.062	4.416 ± 0.055	0.678 ± 0.004	43.452 ± 2.454
	SVMD-TCN	6.045 ± 0.099	5.071 ± 0.159	4.278 ± 0.146	0.694 ± 0.010	**52.976** ± 3.205
	SVMD-CMHA-TCN	6.015 ± 0.096	5.088 ± 0.122	4.285 ± 0.113	0.697 ± 0.010	50.595 ± 3.811
	SVMD-PMB-TCN	5.964 ± 0.078	5.034 ± 0.109	4.254 ± 0.106	0.702 ± 0.008	51.786 ± 5.740
	SVMD-PMB-CMHA-TCN	6.059 ± 0.094	5.140 ± 0.104	4.344 ± 0.098	0.692 ± 0.010	51.191 ± 2.662
March 2022	TCN [27]	4.044 ± 0.125	3.204 ± 0.214	2.873 ± 0.189	0.836 ± 0.010	58.065 ± 4.562
	Diff-TCN [27]	3.895 ± 0.001	3.155 ± 0.002	2.829 ± 0.001	0.848 ± 0.000	58.065 ± 0.000
	TCN	3.868 ± 0.019	3.073 ± 0.049	2.759 ± 0.041	0.851 ± 0.001	60.753 ± 4.718
	Diff-TCN	3.827 ± 0.016	3.025 ± 0.031	2.714 ± 0.028	0.854 ± 0.001	66.129 ± 5.815
	CMHA-TCN	3.873 ± 0.015	3.022 ± 0.019	2.716 ± 0.016	0.850 ± 0.001	58.065 ± 0.000
	Diff-CMHA-TCN	3.835 ± 0.018	3.054 ± 0.038	2.740 ± 0.033	0.853 ± 0.001	65.054 ± 6.563
	EVMD-TCN	4.043 ± 0.010	3.229 ± 0.023	2.901 ± 0.019	0.837 ± 0.001	49.462 ± 5.157
	EVMD-CMHA-TCN	4.021 ± 0.006	3.201 ± 0.025	2.876 ± 0.021	0.838 ± 0.001	48.387 ± 8.329
	EVMD-PMB-TCN	4.086 ± 0.033	3.221 ± 0.070	2.897 ± 0.059	0.833 ± 0.003	52.688 ± 8.259
	EVMD-PMB-CMHA-TCN	4.019 ± 0.019	3.177 ± 0.053	2.855 ± 0.045	0.839 ± 0.002	51.613 ± 7.213
	SVMD-TCN	3.687 ± 0.058	2.861 ± 0.081	2.548 ± 0.069	0.864 ± 0.004	68.817 ± 6.628
	SVMD-CMHA-TCN	3.691 ± 0.021	2.771 ± 0.027	2.482 ± 0.020	**0.864** ± 0.002	**74.731** ± 4.718
	SVMD-PMB-TCN	3.726 ± 0.043	2.846 ± 0.100	2.538 ± 0.072	0.861 ± 0.003	65.054 ± 7.546
	SVMD-PMB-CMHA-TCN	**3.686** ± 0.016	**2.750** ± 0.061	**2.461** ± 0.047	**0.864** ± 0.001	73.656 ± 5.072
April 2022	**TCN** [27]	4.081 ± 0.089	**3.114** ± 0.091	**2.840** ± 0.078	0.750 ± 0.011	**58.889**± 4.581
	Diff-TCN [27]	3.985 ± 0.006	3.225 ± 0.005	2.966 ± 0.005	0.762 ± 0.001	40.000 ± 0.000
	TCN	4.044 ± 0.084	3.230 ± 0.049	2.982 ± 0.049	0.755 ± 0.010	43.889 ± 4.875
	Diff-TCN	4.029 ± 0.014	3.201 ± 0.012	2.949 ± 0.011	0.756 ± 0.002	42.778 ± 3.557
	CMHA-TCN	4.137 ± 0.042	3.273 ± 0.014	3.024 ± 0.015	0.743 ± 0.005	40.000 ± 0.000
	Diff-CMHA-TCN	**3.950** ± 0.058	3.167 ± 0.037	2.912 ± 0.037	**0.766** ± 0.007	52.222 ± 5.666
	EVMD-TCN	4.145 ± 0.030	3.191 ± 0.015	2.950 ± 0.014	0.742 ± 0.004	47.778 ± 1.571
	EVMD-CMHA-TCN	4.180 ± 0.058	3.196 ± 0.025	2.955 ± 0.025	0.738 ± 0.007	46.667 ± 0.000
	EVMD-PMB-TCN	4.130 ± 0.116	3.207 ± 0.053	2.964 ± 0.053	0.744 ± 0.014	47.222 ± 3.557
	EVMD-PMB-CMHA-TCN	4.177 ± 0.074	3.199 ± 0.041	2.958 ± 0.040	0.738 ± 0.009	43.889 ± 2.992
	SVMD-TCN	4.091 ± 0.145	3.158 ± 0.141	2.907 ± 0.139	0.749 ± 0.018	44.444 ± 10.304
	SVMD-CMHA-TCN	4.149 ± 0.188	3.219 ± 0.176	2.968 ± 0.166	0.741 ± 0.023	42.778 ± 8.032
	SVMD-PMB-TCN	4.113 ± 0.087	3.178 ± 0.092	2.929 ± 0.088	0.746 ± 0.011	42.778 ± 4.479
	SVMD-PMB-CMHA-TCN	4.143 ± 0.137	3.189 ± 0.118	2.938 ± 0.112	0.742 ± 0.017	42.778 ± 7.798

Month	Model	RMSE	MAE	MAPE	R2	DA
May 2022	**TCN** [27]	5.540 ± 0.127	3.794 ± 0.105	5.163 ± 0.162	0.834 ± 0.008	**62.903** ± 5.509
	Diff-TCN [27]	5.474 ± 0.000	3.890 ± 0.000	5.223 ± 0.000	0.838 ± 0.000	45.161 ± 6.177
	TCN	5.713 ± 0.152	4.007 ± 0.103	5.412 ± 0.158	0.824 ± 0.009	49.462 ± 1.521
	Diff-TCN	5.448 ± 0.036	3.841 ± 0.005	5.160 ± 0.007	0.840 ± 0.002	54.301 ± 6.293
	CMHA-TCN	5.727 ± 0.111	3.997 ± 0.091	5.400 ± 0.138	0.823 ± 0.007	48.387 ± 0.000
	Diff-CMHA-TCN	5.471 ± 0.062	3.871 ± 0.041	5.205 ± 0.054	0.839 ± 0.004	52.151 ± 7.072
	EVMD-TCN	5.804 ± 0.065	4.079 ± 0.068	5.505 ± 0.102	0.818 ± 0.004	45.699 ± 1.202
	EVMD-CMHA-TCN	5.700 ± 0.066	3.967 ± 0.055	5.345 ± 0.083	0.825 ± 0.004	48.925 ± 4.718
	EVMD-PMB-TCN	5.740 ± 0.086	4.062 ± 0.063	5.469 ± 0.097	0.822 ± 0.005	46.774 ± 2.464
	EVMD-PMB-CMHA-TCN	5.715 ± 0.071	4.011 ± 0.061	5.408 ± 0.093	0.824 ± 0.004	47.849 ± 2.895
	SVMD-TCN	5.548 ± 0.100	3.765 ± 0.071	5.138 ± 0.109	0.834 ± 0.006	54.301 ± 2.895
	SVMD-CMHA-TCN	5.516 ± 0.158	3.795 ± 0.123	5.176 ± 0.186	0.836 ± 0.009	56.989 ± 6.361
	SVMD-PMB-TCN	5.630 ± 0.105	3.874 ± 0.101	5.296 ± 0.157	0.829 ± 0.006	52.688 ± 1.521
	SVMD-PMB-CMHA-TCN	**5.427** ± 0.081	**3.655** ± 0.057	**4.978** ± 0.085	**0.841** ± 0.005	62.366 ± 1.521

Table 62: Average results of the *benchmark experiments* across 6 repetitions per split $M_1, \ldots, M_{12}$ corresponding to months June 2021 to May 2022 in relation to forecasting $\mathbf{S}_{\text{Close}}$ with respect to LTC/USD using the novel framework.

Month	Model	RMSE	MAE	MAPE	R2	DA
June 2022	Diff-TCN [27]	3.094 ± 0.002	2.488 ± 0.002	4.691 ± 0.003	0.748 ± 0.000	43.333 ± 0.000
	TCN	3.325 ± 0.089	2.694 ± 0.085	5.081 ± 0.158	0.708 ± 0.016	43.333 ± 0.000
	Diff-TCN	3.159 ± 0.037	2.565 ± 0.063	4.828 ± 0.114	0.737 ± 0.006	40.000 ± 7.201
	CMHA-TCN	3.345 ± 0.104	2.711 ± 0.097	5.112 ± 0.181	0.705 ± 0.018	43.333 ± 0.000
	Diff-CMHA-TCN	3.115 ± 0.044	2.514 ± 0.042	4.736 ± 0.079	0.744 ± 0.007	44.444 ± 4.969
	EVMD-TCN	3.135 ± 0.063	2.490 ± 0.051	4.705 ± 0.096	0.741 ± 0.010	50.556 ± 4.045
	EVMD-CMHA-TCN	3.141 ± 0.078	2.485 ± 0.073	4.696 ± 0.135	0.740 ± 0.013	49.444 ± 4.045
	EVMD-PMB-TCN	3.162 ± 0.071	2.527 ± 0.064	4.778 ± 0.118	0.736 ± 0.012	51.667 ± 5.000
	EVMD-PMB-CMHA-TCN	3.146 ± 0.066	2.495 ± 0.055	4.714 ± 0.102	0.739 ± 0.011	51.111 ± 3.685
	SVMD-TCN	**3.049** ± 0.035	2.417 ± 0.057	4.576 ± 0.098	**0.755** ± 0.006	60.000 ± 3.333
	SVMD-CMHA-TCN	3.051 ± 0.043	**2.404** ± 0.036	**4.550** ± 0.065	**0.755** ± 0.007	**61.111** ± 4.581
	SVMD-PMB-TCN	3.300 ± 0.135	2.630 ± 0.132	4.954 ± 0.235	0.712 ± 0.023	51.667 ± 4.194
	SVMD-PMB-CMHA-TCN	3.138 ± 0.068	2.446 ± 0.051	4.623 ± 0.098	0.740 ± 0.011	56.667 ± 1.925
July 2022	Diff-TCN [27]	2.239 ± 0.001	1.797 ± 0.001	3.292 ± 0.002	0.692 ± 0.000	52.151 ± 2.895
	TCN	2.253 ± 0.033	1.805 ± 0.018	3.305 ± 0.030	0.688 ± 0.009	49.462 ± 4.433
	Diff-TCN	2.244 ± 0.001	1.807 ± 0.001	3.311 ± 0.002	0.691 ± 0.000	**56.452** ± 2.464
	CMHA-TCN	2.273 ± 0.042	1.810 ± 0.027	3.313 ± 0.045	0.682 ± 0.012	48.387 ± 0.000
	Diff-CMHA-TCN	2.249 ± 0.015	1.821 ± 0.013	3.335 ± 0.023	0.689 ± 0.004	46.774 ± 5.509
	EVMD-TCN	2.257 ± 0.026	1.802 ± 0.019	3.301 ± 0.031	0.687 ± 0.007	53.226 ± 4.466
	EVMD-CMHA-TCN	2.247 ± 0.024	1.790 ± 0.018	3.283 ± 0.028	0.690 ± 0.006	55.914 ± 5.157
	EVMD-PMB-TCN	**2.227** ± 0.004	**1.782** ± 0.006	**3.265** ± 0.009	**0.695** ± 0.001	53.763 ± 2.404
	EVMD-PMB-CMHA-TCN	2.240 ± 0.011	1.788 ± 0.011	3.279 ± 0.017	0.692 ± 0.003	54.301 ± 5.715
	SVMD-TCN	2.525 ± 0.201	1.991 ± 0.156	3.639 ± 0.278	0.605 ± 0.065	47.849 ± 2.217
	SVMD-CMHA-TCN	2.425 ± 0.045	1.909 ± 0.022	3.494 ± 0.039	0.638 ± 0.013	47.849 ± 2.217
	SVMD-PMB-TCN	2.370 ± 0.040	1.882 ± 0.016	3.443 ± 0.029	0.655 ± 0.012	51.613 ± 1.862
	SVMD-PMB-CMHA-TCN	2.391 ± 0.049	1.887 ± 0.029	3.453 ± 0.051	0.648 ± 0.014	47.849 ± 3.442
August 2022	Diff-TCN [27]	1.967 ± 0.003	1.413 ± 0.001	2.457 ± 0.001	0.671 ± 0.001	54.839 ± 0.000
	TCN	1.958 ± 0.018	1.449 ± 0.039	2.513 ± 0.065	0.674 ± 0.006	49.462 ± 4.023
	Diff-TCN	1.968 ± 0.008	1.420 ± 0.029	2.470 ± 0.050	0.671 ± 0.003	53.763 ± 4.023
	CMHA-TCN	**1.945** ± 0.009	**1.406** ± 0.011	**2.441** ± 0.019	**0.678** ± 0.003	58.602 ± 6.011
	Diff-CMHA-TCN	1.972 ± 0.023	1.414 ± 0.016	2.460 ± 0.029	0.669 ± 0.008	54.301 ± 2.895
	EVMD-TCN	1.990 ± 0.029	1.412 ± 0.002	2.457 ± 0.005	0.663 ± 0.010	65.591 ± 3.041
	EVMD-CMHA-TCN	1.986 ± 0.028	1.411 ± 0.003	2.455 ± 0.008	0.664 ± 0.010	**67.204** ± 2.217
	EVMD-PMB-TCN	1.949 ± 0.021	1.425 ± 0.007	2.469 ± 0.014	0.677 ± 0.007	60.753 ± 5.072
	EVMD-PMB-CMHA-TCN	1.974 ± 0.032	1.417 ± 0.008	2.464 ± 0.013	0.668 ± 0.011	63.978 ± 3.442
	SVMD-TCN	2.043 ± 0.037	1.551 ± 0.065	2.693 ± 0.107	0.645 ± 0.013	46.774 ± 1.613
	SVMD-CMHA-TCN	2.022 ± 0.017	1.503 ± 0.014	2.610 ± 0.022	0.652 ± 0.006	51.613 ± 4.165
	SVMD-PMB-TCN	2.020 ± 0.010	1.500 ± 0.019	2.606 ± 0.031	0.653 ± 0.003	50.000 ± 6.106
	SVMD-PMB-CMHA-TCN	1.997 ± 0.009	1.474 ± 0.006	2.563 ± 0.010	0.661 ± 0.003	52.688 ± 2.404
September 2022	Diff-TCN [27]	2.333 ± 0.001	1.789 ± 0.000	3.172 ± 0.001	0.574 ± 0.000	50.000 ± 0.000
	TCN	2.334 ± 0.006	**1.748** ± 0.012	**3.096** ± 0.022	0.574 ± 0.002	53.889 ± 2.291
	Diff-TCN	2.329 ± 0.009	1.783 ± 0.010	3.160 ± 0.021	0.576 ± 0.003	51.111 ± 6.849
	CMHA-TCN	**2.325** ± 0.003	1.756 ± 0.007	3.111 ± 0.013	**0.577** ± 0.001	**58.889** ± 4.157
	Diff-CMHA-TCN	2.326 ± 0.009	1.770 ± 0.017	3.136 ± 0.032	0.576 ± 0.003	54.444 ± 4.581
	EVMD-TCN	2.451 ± 0.011	1.883 ± 0.007	3.349 ± 0.016	0.530 ± 0.004	42.222 ± 2.485
	EVMD-CMHA-TCN	2.425 ± 0.015	1.863 ± 0.014	3.310 ± 0.027	0.540 ± 0.005	43.333 ± 3.849
	EVMD-PMB-TCN	2.436 ± 0.009	1.852 ± 0.007	3.288 ± 0.015	0.536 ± 0.004	44.444 ± 4.157
	EVMD-PMB-CMHA-TCN	2.439 ± 0.009	1.874 ± 0.009	3.329 ± 0.021	0.534 ± 0.003	42.222 ± 5.329
	SVMD-TCN	2.548 ± 0.069	1.913 ± 0.051	3.367 ± 0.082	0.491 ± 0.028	50.000 ± 6.939
	SVMD-CMHA-TCN	2.471 ± 0.015	1.865 ± 0.020	3.300 ± 0.032	0.522 ± 0.006	47.778 ± 1.571
	SVMD-PMB-TCN	2.462 ± 0.006	1.873 ± 0.017	3.314 ± 0.031	0.526 ± 0.002	40.556 ± 4.045
	SVMD-PMB-CMHA-TCN	2.429 ± 0.009	1.862 ± 0.005	3.290 ± 0.007	0.538 ± 0.003	44.444 ± 3.143
October 2022	Diff-TCN [27]	1.177 ± 0.000	0.934 ± 0.000	1.741 ± 0.000	0.531 ± 0.000	50.538 ± 4.433
	TCN	1.168 ± 0.018	0.930 ± 0.018	1.735 ± 0.036	0.538 ± 0.015	56.989 ± 5.790
	Diff-TCN	1.182 ± 0.016	0.941 ± 0.007	1.753 ± 0.013	0.527 ± 0.013	50.000 ± 1.613
	CMHA-TCN	1.183 ± 0.023	0.925 ± 0.004	1.724 ± 0.008	0.526 ± 0.018	50.000 ± 2.464

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	1.188 ± 0.026	0.949 ± 0.036	1.770 ± 0.070	0.522 ± 0.021	50.538 ± 1.521
	EVMD-TCN	1.164 ± 0.013	0.932 ± 0.019	1.739 ± 0.038	0.541 ± 0.011	57.527 ± 3.442
	EVMD-CMHA-TCN	1.161 ± 0.007	0.923 ± 0.012	1.719 ± 0.025	0.544 ± 0.005	53.763 ± 3.041
	EVMD-PMB-TCN	1.154 ± 0.016	0.923 ± 0.022	1.722 ± 0.043	0.549 ± 0.013	**59.140** ± 6.083
	EVMD-PMB-CMHA-TCN	**1.152** ± 0.006	**0.916** ± 0.011	**1.707** ± 0.023	**0.550** ± 0.005	58.602 ± 3.442
	SVMD-TCN	1.289 ± 0.132	0.997 ± 0.073	1.855 ± 0.133	0.431 ± 0.120	46.237 ± 5.157
	SVMD-CMHA-TCN	1.208 ± 0.075	0.948 ± 0.036	1.764 ± 0.064	0.504 ± 0.064	50.000 ± 3.607
	SVMD-PMB-TCN	1.165 ± 0.012	0.926 ± 0.005	1.726 ± 0.009	0.541 ± 0.010	45.699 ± 2.895
	SVMD-PMB-CMHA-TCN	1.163 ± 0.008	0.925 ± 0.006	1.724 ± 0.010	0.542 ± 0.006	44.086 ± 3.041
November 2022	Diff-TCN [27]	4.317 ± 0.001	3.068 ± 0.000	4.761 ± 0.000	0.700 ± 0.000	50.000 ± 3.849
	TCN	4.349 ± 0.074	3.115 ± 0.060	4.835 ± 0.079	0.695 ± 0.010	50.000 ± 6.086
	Diff-TCN	4.334 ± 0.012	3.084 ± 0.010	4.791 ± 0.023	0.698 ± 0.002	45.556 ± 3.685
	CMHA-TCN	4.313 ± 0.032	**3.059** ± 0.010	**4.749** ± 0.010	**0.701** ± 0.004	52.222 ± 7.115
	Diff-CMHA-TCN	4.331 ± 0.096	3.083 ± 0.111	4.789 ± 0.169	0.698 ± 0.014	**56.667** ± 9.230
	EVMD-TCN	**4.312** ± 0.037	3.073 ± 0.016	4.752 ± 0.029	**0.701** ± 0.005	50.556 ± 4.479
	EVMD-CMHA-TCN	4.356 ± 0.034	3.121 ± 0.011	4.817 ± 0.008	0.695 ± 0.005	46.667 ± 1.925
	EVMD-PMB-TCN	4.343 ± 0.046	3.072 ± 0.046	4.753 ± 0.057	0.696 ± 0.006	48.333 ± 6.009
	EVMD-PMB-CMHA-TCN	4.428 ± 0.088	3.223 ± 0.073	4.983 ± 0.111	0.684 ± 0.013	43.889 ± 2.291
	SVMD-TCN	4.552 ± 0.026	3.400 ± 0.024	5.273 ± 0.032	0.666 ± 0.004	36.111 ± 2.992
	SVMD-CMHA-TCN	4.496 ± 0.036	3.384 ± 0.026	5.256 ± 0.033	0.675 ± 0.005	40.000 ± 3.333
	SVMD-PMB-TCN	4.518 ± 0.030	3.400 ± 0.023	5.265 ± 0.030	0.671 ± 0.004	35.000 ± 2.546
	SVMD-PMB-CMHA-TCN	4.580 ± 0.052	3.436 ± 0.036	5.318 ± 0.048	0.662 ± 0.008	40.000 ± 1.925
December 2022	Diff-TCN [27]	1.980 ± 0.002	1.496 ± 0.001	2.105 ± 0.002	0.870 ± 0.000	48.925 ± 4.718
	TCN	1.992 ± 0.021	1.509 ± 0.015	2.130 ± 0.021	0.868 ± 0.003	55.914 ± 2.404
	Diff-TCN	2.000 ± 0.007	**1.488** ± 0.005	**2.099** ± 0.006	0.867 ± 0.001	51.613 ± 2.634
	CMHA-TCN	**1.969** ± 0.010	1.490 ± 0.003	**2.099** ± 0.006	**0.871** ± 0.001	54.839 ± 6.177
	Diff-CMHA-TCN	1.990 ± 0.026	1.507 ± 0.015	2.122 ± 0.024	0.868 ± 0.003	50.000 ± 2.464
	EVMD-TCN	2.018 ± 0.014	1.531 ± 0.014	2.162 ± 0.021	0.865 ± 0.002	55.376 ± 3.442
	EVMD-CMHA-TCN	1.999 ± 0.027	1.523 ± 0.021	2.149 ± 0.034	0.867 ± 0.004	**59.140** ± 2.404
	EVMD-PMB-TCN	2.020 ± 0.021	1.530 ± 0.017	2.163 ± 0.026	0.864 ± 0.003	58.065 ± 4.165
	EVMD-PMB-CMHA-TCN	2.072 ± 0.049	1.572 ± 0.029	2.224 ± 0.047	0.857 ± 0.007	58.065 ± 2.634
	SVMD-TCN	2.078 ± 0.026	1.567 ± 0.021	2.218 ± 0.032	0.856 ± 0.004	51.075 ± 6.011
	SVMD-CMHA-TCN	2.038 ± 0.008	1.546 ± 0.016	2.187 ± 0.020	0.862 ± 0.001	52.688 ± 4.433
	SVMD-PMB-TCN	2.047 ± 0.009	1.568 ± 0.011	2.216 ± 0.014	0.861 ± 0.001	45.699 ± 4.335
	SVMD-PMB-CMHA-TCN	2.107 ± 0.025	1.571 ± 0.028	2.229 ± 0.042	0.852 ± 0.004	55.376 ± 5.072
January 2023	Diff-TCN [27]	2.487 ± 0.002	2.022 ± 0.002	2.367 ± 0.002	0.839 ± 0.000	35.484 ± 0.000
	TCN	2.551 ± 0.058	2.071 ± 0.056	2.428 ± 0.067	0.831 ± 0.008	36.022 ± 2.895
	Diff-TCN	2.508 ± 0.035	2.032 ± 0.037	2.384 ± 0.046	0.837 ± 0.004	43.011 ± 7.372
	CMHA-TCN	2.548 ± 0.054	2.068 ± 0.051	2.422 ± 0.060	0.831 ± 0.007	39.247 ± 8.415
	Diff-CMHA-TCN	**2.486** ± 0.041	**2.010** ± 0.039	**2.357** ± 0.047	**0.839** ± 0.005	**50.538** ± 9.972
	EVMD-TCN	2.642 ± 0.049	2.128 ± 0.052	2.496 ± 0.062	0.819 ± 0.007	39.247 ± 5.403
	EVMD-CMHA-TCN	2.586 ± 0.043	2.071 ± 0.045	2.429 ± 0.053	0.826 ± 0.006	43.548 ± 5.185
	EVMD-PMB-TCN	2.559 ± 0.037	2.056 ± 0.036	2.412 ± 0.043	0.830 ± 0.005	44.086 ± 5.790
	EVMD-PMB-CMHA-TCN	2.669 ± 0.056	2.154 ± 0.060	2.530 ± 0.070	0.815 ± 0.008	41.935 ± 3.226
	SVMD-TCN	2.631 ± 0.060	2.161 ± 0.064	2.544 ± 0.080	0.820 ± 0.008	46.774 ± 2.464
	SVMD-CMHA-TCN	2.622 ± 0.057	2.158 ± 0.062	2.541 ± 0.075	0.821 ± 0.008	48.925 ± 2.217
	SVMD-PMB-TCN	2.639 ± 0.078	2.165 ± 0.073	2.552 ± 0.088	0.819 ± 0.011	46.237 ± 6.628
	SVMD-PMB-CMHA-TCN	2.621 ± 0.079	2.166 ± 0.083	2.555 ± 0.100	0.822 ± 0.011	48.925 ± 3.442
February 2023	Diff-TCN [27]	3.050 ± 0.000	2.381 ± 0.002	2.460 ± 0.002	0.043 ± 0.000	44.048 ± 10.648
	TCN	3.067 ± 0.016	2.289 ± 0.024	2.360 ± 0.026	0.032 ± 0.010	59.524 ± 1.684
	Diff-TCN	**3.032** ± 0.016	2.329 ± 0.063	2.405 ± 0.067	**0.054** ± 0.010	60.714 ± 5.455
	CMHA-TCN	3.054 ± 0.011	**2.269** ± 0.054	**2.339** ± 0.058	0.040 ± 0.007	61.309 ± 1.331
	Diff-CMHA-TCN	3.034 ± 0.033	2.389 ± 0.028	2.469 ± 0.030	0.052 ± 0.021	48.809 ± 7.623
	EVMD-TCN	3.088 ± 0.019	2.335 ± 0.009	2.407 ± 0.010	0.018 ± 0.012	57.738 ± 2.454
	EVMD-CMHA-TCN	3.100 ± 0.025	2.336 ± 0.020	2.408 ± 0.023	0.011 ± 0.016	58.929 ± 3.419
	EVMD-PMB-TCN	3.087 ± 0.012	2.343 ± 0.029	2.415 ± 0.031	0.019 ± 0.007	53.571 ± 2.062
	EVMD-PMB-CMHA-TCN	3.073 ± 0.027	2.322 ± 0.051	2.395 ± 0.056	0.028 ± 0.017	57.143 ± 2.062
	SVMD-TCN	3.176 ± 0.033	2.274 ± 0.010	2.343 ± 0.012	−0.038 ± 0.022	**62.500** ± 1.786
	SVMD-CMHA-TCN	3.198 ± 0.061	2.349 ± 0.018	2.420 ± 0.020	−0.053 ± 0.041	55.357 ± 3.993
	SVMD-PMB-TCN	3.220 ± 0.032	2.368 ± 0.049	2.441 ± 0.054	−0.067 ± 0.021	48.809 ± 7.623
	SVMD-PMB-CMHA-TCN	3.131 ± 0.011	2.293 ± 0.029	2.363 ± 0.031	−0.009 ± 0.007	59.524 ± 6.411
March 2023	Diff-TCN [27]	3.958 ± 0.000	3.324 ± 0.000	3.998 ± 0.001	0.673 ± 0.000	52.151 ± 4.718
	TCN	3.948 ± 0.035	3.345 ± 0.043	4.026 ± 0.059	0.675 ± 0.006	52.151 ± 2.895
	Diff-TCN	3.988 ± 0.009	3.337 ± 0.008	4.013 ± 0.011	0.668 ± 0.002	54.301 ± 4.718
	CMHA-TCN	3.931 ± 0.003	**3.312** ± 0.006	**3.979** ± 0.009	0.678 ± 0.001	**54.839** ± 1.862
	Diff-CMHA-TCN	3.968 ± 0.018	3.336 ± 0.017	4.016 ± 0.021	0.672 ± 0.003	46.774 ± 9.811
	EVMD-TCN	**3.900** ± 0.006	3.317 ± 0.007	3.981 ± 0.009	**0.683** ± 0.001	49.462 ± 2.404
	EVMD-CMHA-TCN	3.915 ± 0.029	3.328 ± 0.042	3.994 ± 0.056	0.681 ± 0.005	52.688 ± 7.133
	EVMD-PMB-TCN	3.901 ± 0.021	3.339 ± 0.014	4.011 ± 0.019	0.683 ± 0.004	51.613 ± 3.226
	EVMD-PMB-CMHA-TCN	3.987 ± 0.028	3.356 ± 0.018	4.030 ± 0.025	0.669 ± 0.005	54.301 ± 5.715
	SVMD-TCN	4.068 ± 0.018	3.356 ± 0.025	4.042 ± 0.033	0.655 ± 0.003	50.538 ± 4.023
	SVMD-CMHA-TCN	4.051 ± 0.017	3.394 ± 0.009	4.092 ± 0.012	0.658 ± 0.003	53.226 ± 2.464
	SVMD-PMB-TCN	4.052 ± 0.009	3.390 ± 0.011	4.085 ± 0.017	0.658 ± 0.002	52.688 ± 2.404
	SVMD-PMB-CMHA-TCN	4.151 ± 0.086	3.412 ± 0.049	4.116 ± 0.063	0.641 ± 0.015	52.688 ± 2.404
April 2023	**Diff-TCN** [27]	2.883 ± 0.000	**1.905** ± 0.000	**2.079** ± 0.000	0.425 ± 0.000	43.333 ± 0.000
	TCN	2.918 ± 0.015	2.007 ± 0.044	2.185 ± 0.046	0.411 ± 0.006	40.556 ± 4.045
	Diff-TCN	2.871 ± 0.014	1.915 ± 0.018	2.091 ± 0.021	0.429 ± 0.006	50.556 ± 4.045
	CMHA-TCN	2.899 ± 0.014	2.024 ± 0.053	2.201 ± 0.055	0.418 ± 0.006	43.333 ± 0.000

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	2.936 ± 0.020	1.958 ± 0.021	2.140 ± 0.021	0.404 ± 0.008	41.111 ± 11.811
	EVMD-TCN	2.853 ± 0.014	1.924 ± 0.037	2.096 ± 0.040	0.437 ± 0.006	48.333 ± 4.615
	EVMD-CMHA-TCN	**2.847** ± 0.012	1.953 ± 0.046	2.125 ± 0.047	**0.439** ± 0.005	**51.111** ± 4.581
	EVMD-PMB-TCN	2.889 ± 0.020	2.000 ± 0.060	2.177 ± 0.064	0.422 ± 0.008	46.111 ± 3.557
	EVMD-PMB-CMHA-TCN	2.857 ± 0.025	1.964 ± 0.069	2.139 ± 0.072	0.435 ± 0.010	48.889 ± 3.685
	SVMD-TCN	2.871 ± 0.029	2.017 ± 0.076	2.196 ± 0.080	0.430 ± 0.011	46.667 ± 3.333
	SVMD-CMHA-TCN	2.913 ± 0.029	2.069 ± 0.065	2.253 ± 0.068	0.413 ± 0.012	44.444 ± 3.143
	SVMD-PMB-TCN	2.912 ± 0.009	2.031 ± 0.021	2.214 ± 0.022	0.413 ± 0.004	41.111 ± 4.969
	SVMD-PMB-CMHA-TCN	2.904 ± 0.040	2.071 ± 0.070	2.254 ± 0.073	0.416 ± 0.016	44.444 ± 5.329
May 2023	Diff-TCN [27]	2.458 ± 0.000	1.809 ± 0.000	2.093 ± 0.000	0.692 ± 0.000	58.065 ± 0.000
	TCN	2.470 ± 0.013	1.792 ± 0.031	2.072 ± 0.034	0.689 ± 0.003	52.151 ± 8.207
	Diff-TCN	2.460 ± 0.004	1.790 ± 0.006	2.071 ± 0.006	0.692 ± 0.001	52.688 ± 3.566
	CMHA-TCN	2.480 ± 0.036	1.809 ± 0.019	2.091 ± 0.021	0.686 ± 0.009	51.613 ± 8.736
	Diff-CMHA-TCN	2.482 ± 0.011	1.807 ± 0.018	2.092 ± 0.020	0.686 ± 0.003	57.527 ± 4.335
	EVMD-TCN	2.465 ± 0.003	1.792 ± 0.009	2.069 ± 0.009	0.690 ± 0.001	**59.140** ± 4.023
	EVMD-CMHA-TCN	2.464 ± 0.004	1.786 ± 0.007	2.062 ± 0.006	0.691 ± 0.001	54.839 ± 1.862
	EVMD-PMB-TCN	2.472 ± 0.004	**1.775** ± 0.011	**2.051** ± 0.011	0.689 ± 0.001	54.301 ± 2.895
	EVMD-PMB-CMHA-TCN	2.484 ± 0.015	1.783 ± 0.016	2.061 ± 0.017	0.685 ± 0.004	54.301 ± 3.914
	SVMD-TCN	2.445 ± 0.004	1.791 ± 0.013	2.073 ± 0.013	0.695 ± 0.001	48.387 ± 3.725
	SVMD-CMHA-TCN	**2.441** ± 0.004	1.800 ± 0.010	2.082 ± 0.010	**0.696** ± 0.001	48.925 ± 6.822
	SVMD-PMB-TCN	2.461 ± 0.035	1.813 ± 0.026	2.097 ± 0.029	0.691 ± 0.009	48.925 ± 3.914
	SVMD-PMB-CMHA-TCN	2.451 ± 0.011	1.796 ± 0.009	2.079 ± 0.010	0.694 ± 0.003	46.237 ± 2.404
June 2023	**Diff-TCN** [27]	5.529 ± 0.002	3.038 ± 0.003	3.407 ± 0.003	0.516 ± 0.000	**60.000** ± 0.000
	TCN	5.523 ± 0.009	3.037 ± 0.018	3.408 ± 0.020	0.517 ± 0.002	48.889 ± 8.315
	Diff-TCN	5.532 ± 0.007	3.022 ± 0.009	3.386 ± 0.011	0.516 ± 0.001	48.889 ± 4.969
	CMHA-TCN	5.532 ± 0.004	3.041 ± 0.008	3.408 ± 0.010	0.516 ± 0.001	46.111 ± 6.503
	Diff-CMHA-TCN	**5.519** ± 0.008	3.025 ± 0.019	3.392 ± 0.022	**0.518** ± 0.001	50.000 ± 6.383
	EVMD-TCN	5.587 ± 0.005	3.062 ± 0.002	3.432 ± 0.004	0.506 ± 0.001	47.222 ± 5.583
	EVMD-CMHA-TCN	5.589 ± 0.009	3.059 ± 0.011	3.427 ± 0.013	0.506 ± 0.002	51.667 ± 5.000
	EVMD-PMB-TCN	5.571 ± 0.005	3.058 ± 0.010	3.428 ± 0.012	0.509 ± 0.001	44.444 ± 3.143
	EVMD-PMB-CMHA-TCN	5.588 ± 0.007	3.059 ± 0.018	3.428 ± 0.023	0.506 ± 0.001	52.222 ± 5.666
	SVMD-TCN	5.601 ± 0.022	3.019 ± 0.021	3.370 ± 0.020	0.504 ± 0.004	54.444 ± 7.115
	SVMD-CMHA-TCN	5.578 ± 0.005	3.015 ± 0.004	3.371 ± 0.006	0.508 ± 0.001	51.111 ± 1.571
	SVMD-PMB-TCN	5.584 ± 0.009	3.053 ± 0.012	3.421 ± 0.013	0.506 ± 0.002	53.889 ± 2.992
	SVMD-PMB-CMHA-TCN	5.587 ± 0.013	**3.012** ± 0.012	**3.365** ± 0.015	0.506 ± 0.002	54.444 ± 2.485
July 2023	Diff-TCN [27]	3.070 ± 0.002	2.196 ± 0.003	2.235 ± 0.003	0.710 ± 0.000	41.935 ± 0.000
	TCN	3.020 ± 0.036	2.126 ± 0.012	2.163 ± 0.011	0.720 ± 0.007	56.989 ± 1.521
	Diff-TCN	3.058 ± 0.108	2.166 ± 0.090	2.207 ± 0.090	0.712 ± 0.021	58.602 ± 7.546
	CMHA-TCN	**2.999** ± 0.026	**2.109** ± 0.018	**2.147** ± 0.018	**0.723** ± 0.005	**58.602** ± 2.895
	Diff-CMHA-TCN	3.081 ± 0.016	2.194 ± 0.018	2.233 ± 0.018	0.708 ± 0.003	47.312 ± 5.483
	EVMD-TCN	3.005 ± 0.011	2.204 ± 0.016	2.247 ± 0.017	0.722 ± 0.002	44.624 ± 3.442
	EVMD-CMHA-TCN	3.013 ± 0.022	2.227 ± 0.019	2.272 ± 0.020	0.721 ± 0.004	42.473 ± 4.335
	EVMD-PMB-TCN	3.054 ± 0.016	2.214 ± 0.009	2.256 ± 0.009	0.713 ± 0.003	46.237 ± 3.041
	EVMD-PMB-CMHA-TCN	3.029 ± 0.041	2.252 ± 0.062	2.295 ± 0.060	0.718 ± 0.008	46.237 ± 4.809
	SVMD-TCN	3.104 ± 0.048	2.199 ± 0.012	2.243 ± 0.013	0.704 ± 0.009	54.301 ± 6.822
	SVMD-CMHA-TCN	3.184 ± 0.019	2.270 ± 0.007	2.314 ± 0.008	0.688 ± 0.004	42.473 ± 1.202
	SVMD-PMB-TCN	3.229 ± 0.036	2.283 ± 0.014	2.331 ± 0.014	0.679 ± 0.007	51.075 ± 3.442
	SVMD-PMB-CMHA-TCN	3.082 ± 0.033	2.208 ± 0.021	2.250 ± 0.021	0.708 ± 0.006	49.462 ± 3.566
August 2023	Diff-TCN [27]	2.811 ± 0.001	1.746 ± 0.000	2.388 ± 0.000	0.909 ± 0.000	45.161 ± 0.000
	TCN	2.810 ± 0.096	1.757 ± 0.069	2.405 ± 0.099	0.908 ± 0.006	55.914 ± 5.157
	Diff-TCN	2.849 ± 0.009	1.768 ± 0.003	2.420 ± 0.004	0.906 ± 0.001	52.688 ± 2.404
	CMHA-TCN	**2.789** ± 0.040	**1.739** ± 0.027	**2.380** ± 0.039	**0.910** ± 0.003	55.914 ± 9.060
	Diff-CMHA-TCN	2.841 ± 0.029	1.769 ± 0.016	2.421 ± 0.023	0.907 ± 0.002	44.086 ± 6.083
	EVMD-TCN	2.905 ± 0.027	1.848 ± 0.021	2.525 ± 0.030	0.902 ± 0.002	46.774 ± 2.464
	EVMD-CMHA-TCN	2.956 ± 0.043	1.890 ± 0.035	2.589 ± 0.051	0.899 ± 0.003	45.699 ± 2.217
	EVMD-PMB-TCN	2.929 ± 0.018	1.839 ± 0.009	2.518 ± 0.013	0.901 ± 0.001	48.925 ± 2.895
	EVMD-PMB-CMHA-TCN	2.981 ± 0.046	1.903 ± 0.043	2.606 ± 0.062	0.897 ± 0.003	46.774 ± 1.613
	SVMD-TCN	2.868 ± 0.054	1.762 ± 0.041	2.413 ± 0.058	0.905 ± 0.004	**56.452** ± 6.650
	SVMD-CMHA-TCN	3.000 ± 0.091	1.900 ± 0.103	2.606 ± 0.144	0.896 ± 0.006	51.075 ± 3.442
	SVMD-PMB-TCN	2.937 ± 0.028	1.841 ± 0.031	2.519 ± 0.046	0.900 ± 0.002	45.699 ± 2.217
	SVMD-PMB-CMHA-TCN	2.970 ± 0.028	1.844 ± 0.034	2.529 ± 0.048	0.898 ± 0.002	47.312 ± 2.404
September 2023	Diff-TCN [27]	1.366 ± 0.000	1.111 ± 0.000	1.747 ± 0.001	0.393 ± 0.000	50.000 ± 0.000
	TCN	**1.358** ± 0.003	1.102 ± 0.003	1.733 ± 0.005	**0.400** ± 0.003	52.222 ± 3.685
	Diff-TCN	1.367 ± 0.000	1.108 ± 0.001	1.742 ± 0.002	0.392 ± 0.000	49.444 ± 2.992
	CMHA-TCN	1.359 ± 0.002	1.104 ± 0.004	1.737 ± 0.006	0.399 ± 0.002	50.000 ± 0.000
	Diff-CMHA-TCN	1.365 ± 0.002	1.109 ± 0.004	1.743 ± 0.006	0.394 ± 0.002	51.111 ± 3.143
	EVMD-TCN	1.387 ± 0.002	1.088 ± 0.003	1.712 ± 0.004	0.374 ± 0.002	53.889 ± 2.992
	EVMD-CMHA-TCN	1.387 ± 0.002	1.087 ± 0.004	1.711 ± 0.006	0.374 ± 0.002	56.667 ± 1.925
	EVMD-PMB-TCN	1.368 ± 0.003	**1.074** ± 0.004	**1.690** ± 0.007	0.391 ± 0.003	**59.444** ± 3.557
	EVMD-PMB-CMHA-TCN	1.388 ± 0.003	1.088 ± 0.004	1.712 ± 0.005	0.373 ± 0.003	54.444 ± 3.685
	SVMD-TCN	1.450 ± 0.009	1.136 ± 0.005	1.789 ± 0.009	0.316 ± 0.008	44.444 ± 3.143
	SVMD-CMHA-TCN	1.465 ± 0.014	1.148 ± 0.010	1.808 ± 0.016	0.301 ± 0.013	43.333 ± 2.722
	SVMD-PMB-TCN	1.446 ± 0.010	1.130 ± 0.005	1.779 ± 0.009	0.320 ± 0.009	43.889 ± 4.479
	SVMD-PMB-CMHA-TCN	1.436 ± 0.004	1.128 ± 0.002	1.777 ± 0.004	0.329 ± 0.004	46.111 ± 5.241
October 2023	Diff-TCN [27]	1.337 ± 0.000	1.007 ± 0.000	1.554 ± 0.001	0.776 ± 0.000	58.065 ± 0.000
	TCN	**1.332** ± 0.001	1.003 ± 0.001	1.548 ± 0.002	**0.777** ± 0.000	**58.065** ± 0.000
	Diff-TCN	1.339 ± 0.001	1.012 ± 0.001	1.560 ± 0.002	0.775 ± 0.000	53.226 ± 5.509
	CMHA-TCN	1.337 ± 0.010	**1.002** ± 0.007	**1.547** ± 0.012	0.776 ± 0.003	57.527 ± 3.442

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	1.339 ± 0.003	1.009 ± 0.002	1.556 ± 0.003	0.775 ± 0.001	53.763 ± 4.809
	EVMD-TCN	1.384 ± 0.001	1.042 ± 0.001	1.607 ± 0.001	0.760 ± 0.000	50.538 ± 1.521
	EVMD-CMHA-TCN	1.384 ± 0.001	1.042 ± 0.001	1.607 ± 0.002	0.760 ± 0.000	48.925 ± 1.202
	EVMD-PMB-TCN	1.370 ± 0.001	1.026 ± 0.002	1.581 ± 0.003	0.764 ± 0.000	47.312 ± 2.404
	EVMD-PMB-CMHA-TCN	1.384 ± 0.001	1.042 ± 0.001	1.608 ± 0.001	0.759 ± 0.000	49.462 ± 2.404
	SVMD-TCN	1.409 ± 0.032	1.043 ± 0.042	1.612 ± 0.067	0.751 ± 0.011	54.301 ± 4.718
	SVMD-CMHA-TCN	1.389 ± 0.004	1.013 ± 0.004	1.563 ± 0.006	0.758 ± 0.002	51.613 ± 2.634
	SVMD-PMB-TCN	1.387 ± 0.003	1.006 ± 0.006	1.552 ± 0.009	0.758 ± 0.001	52.688 ± 5.790
	SVMD-PMB-CMHA-TCN	1.384 ± 0.003	1.016 ± 0.003	1.569 ± 0.004	0.759 ± 0.001	51.075 ± 2.895
November 2023	Diff-TCN [27]	1.653 ± 0.000	1.282 ± 0.001	1.805 ± 0.001	0.368 ± 0.000	50.000 ± 0.000
	TCN	1.635 ± 0.003	1.265 ± 0.003	1.782 ± 0.005	0.381 ± 0.002	55.000 ± 6.310
	Diff-TCN	1.643 ± 0.001	1.282 ± 0.001	1.805 ± 0.002	0.375 ± 0.001	54.444 ± 1.571
	CMHA-TCN	1.642 ± 0.023	1.267 ± 0.025	1.786 ± 0.039	0.376 ± 0.018	60.000 ± 7.454
	Diff-CMHA-TCN	1.650 ± 0.011	1.278 ± 0.007	1.800 ± 0.011	0.370 ± 0.009	55.556 ± 5.984
	EVMD-TCN	1.635 ± 0.001	1.239 ± 0.001	1.745 ± 0.002	0.381 ± 0.001	56.111 ± 1.242
	EVMD-CMHA-TCN	1.636 ± 0.002	1.242 ± 0.002	1.750 ± 0.003	0.380 ± 0.001	55.000 ± 2.546
	EVMD-PMB-TCN	1.631 ± 0.001	1.249 ± 0.003	1.760 ± 0.004	0.384 ± 0.001	52.222 ± 1.571
	EVMD-PMB-CMHA-TCN	1.632 ± 0.002	1.240 ± 0.002	1.747 ± 0.003	0.384 ± 0.002	56.111 ± 3.557
	SVMD-TCN	1.589 ± 0.027	1.240 ± 0.011	1.752 ± 0.018	0.416 ± 0.020	58.889 ± 4.969
	SVMD-CMHA-TCN	1.572 ± 0.005	1.237 ± 0.006	1.745 ± 0.009	0.428 ± 0.004	58.333 ± 4.194
	SVMD-PMB-TCN	1.571 ± 0.005	**1.235** ± 0.003	**1.742** ± 0.004	0.429 ± 0.003	**62.222** ± 3.143
	SVMD-PMB-CMHA-TCN	**1.569** ± 0.003	1.240 ± 0.003	1.749 ± 0.004	**0.430** ± 0.002	59.444 ± 2.291
December 2023	Diff-TCN [27]	1.793 ± 0.000	1.373 ± 0.000	1.867 ± 0.000	0.197 ± 0.000	51.613 ± 0.000
	TCN	1.769 ± 0.009	1.361 ± 0.004	1.849 ± 0.005	0.218 ± 0.008	57.527 ± 2.217
	Diff-TCN	1.784 ± 0.002	1.375 ± 0.001	1.869 ± 0.001	0.205 ± 0.001	48.925 ± 3.442
	CMHA-TCN	1.766 ± 0.007	1.364 ± 0.003	1.854 ± 0.004	0.221 ± 0.006	51.075 ± 3.914
	Diff-CMHA-TCN	1.788 ± 0.009	1.369 ± 0.003	1.861 ± 0.004	0.201 ± 0.008	53.763 ± 1.521
	EVMD-TCN	1.769 ± 0.002	1.404 ± 0.001	1.907 ± 0.002	0.218 ± 0.002	47.312 ± 2.404
	EVMD-CMHA-TCN	1.772 ± 0.002	1.403 ± 0.001	1.905 ± 0.002	0.216 ± 0.002	46.774 ± 1.613
	EVMD-PMB-TCN	**1.760** ± 0.002	1.393 ± 0.002	1.893 ± 0.002	**0.227** ± 0.002	47.849 ± 1.202
	EVMD-PMB-CMHA-TCN	1.768 ± 0.002	1.402 ± 0.003	1.904 ± 0.004	0.219 ± 0.002	47.312 ± 3.566
	SVMD-TCN	1.802 ± 0.022	1.346 ± 0.014	1.832 ± 0.019	0.189 ± 0.020	59.677 ± 1.613
	SVMD-CMHA-TCN	1.781 ± 0.007	1.335 ± 0.005	1.816 ± 0.006	0.207 ± 0.006	59.140 ± 2.404
	SVMD-PMB-TCN	1.782 ± 0.005	**1.334** ± 0.008	**1.814** ± 0.011	0.207 ± 0.005	**61.290** ± 0.000
	SVMD-PMB-CMHA-TCN	1.792 ± 0.004	1.349 ± 0.003	1.836 ± 0.004	0.198 ± 0.003	57.527 ± 1.202
January 2024	Diff-TCN [27]	2.156 ± 0.000	1.488 ± 0.000	2.182 ± 0.000	0.334 ± 0.000	51.613 ± 0.000
	TCN	2.147 ± 0.004	1.492 ± 0.009	2.188 ± 0.014	0.339 ± 0.003	52.151 ± 2.895
	Diff-TCN	2.159 ± 0.001	**1.486** ± 0.001	**2.177** ± 0.001	0.332 ± 0.001	48.387 ± 0.000
	CMHA-TCN	2.182 ± 0.077	1.538 ± 0.086	2.256 ± 0.132	0.316 ± 0.050	49.462 ± 2.404
	Diff-CMHA-TCN	2.164 ± 0.003	1.496 ± 0.004	2.192 ± 0.006	0.329 ± 0.002	50.538 ± 4.433
	EVMD-TCN	2.127 ± 0.002	1.493 ± 0.003	2.192 ± 0.004	0.351 ± 0.001	48.925 ± 1.202
	EVMD-CMHA-TCN	**2.121** ± 0.002	1.487 ± 0.003	2.181 ± 0.004	**0.355** ± 0.001	49.462 ± 1.521
	EVMD-PMB-TCN	2.143 ± 0.003	1.505 ± 0.003	2.207 ± 0.004	0.341 ± 0.002	**53.226** ± 4.466
	EVMD-PMB-CMHA-TCN	2.129 ± 0.002	1.490 ± 0.003	2.186 ± 0.004	0.350 ± 0.002	48.387 ± 0.000
	SVMD-TCN	2.298 ± 0.036	1.578 ± 0.048	2.322 ± 0.071	0.242 ± 0.024	46.237 ± 4.023
	SVMD-CMHA-TCN	2.290 ± 0.003	1.567 ± 0.004	2.305 ± 0.006	0.248 ± 0.002	38.710 ± 2.634
	SVMD-PMB-TCN	2.297 ± 0.013	1.565 ± 0.008	2.304 ± 0.012	0.243 ± 0.009	44.086 ± 3.041
	SVMD-PMB-CMHA-TCN	2.280 ± 0.012	1.552 ± 0.004	2.284 ± 0.007	0.254 ± 0.008	47.312 ± 2.404
February 2024	**Diff-TCN** [27]	1.566 ± 0.001	1.064 ± 0.002	1.486 ± 0.003	0.615 ± 0.001	**68.966** ± 0.000
	TCN	**1.561** ± 0.005	1.046 ± 0.008	1.459 ± 0.011	**0.618** ± 0.002	67.241 ± 2.634
	Diff-TCN	1.562 ± 0.002	1.060 ± 0.003	1.480 ± 0.004	0.617 ± 0.001	63.218 ± 2.570
	CMHA-TCN	1.573 ± 0.009	1.065 ± 0.015	1.485 ± 0.021	0.612 ± 0.005	60.919 ± 5.140
	Diff-CMHA-TCN	1.563 ± 0.009	1.063 ± 0.015	1.484 ± 0.021	0.617 ± 0.004	64.942 ± 4.184
	EVMD-TCN	1.583 ± 0.006	1.044 ± 0.014	1.455 ± 0.019	0.607 ± 0.003	60.345 ± 2.634
	EVMD-CMHA-TCN	1.578 ± 0.004	1.044 ± 0.008	1.455 ± 0.011	0.609 ± 0.002	60.345 ± 2.634
	EVMD-PMB-TCN	1.566 ± 0.006	**1.035** ± 0.011	**1.442** ± 0.015	0.615 ± 0.003	61.494 ± 4.184
	EVMD-PMB-CMHA-TCN	1.574 ± 0.007	1.035 ± 0.013	1.442 ± 0.019	0.611 ± 0.003	60.919 ± 2.570
	SVMD-TCN	1.569 ± 0.026	1.099 ± 0.042	1.534 ± 0.059	0.614 ± 0.013	43.678 ± 9.685
	SVMD-CMHA-TCN	1.568 ± 0.014	1.091 ± 0.023	1.523 ± 0.032	0.614 ± 0.007	45.977 ± 4.739
	SVMD-PMB-TCN	1.566 ± 0.011	1.088 ± 0.021	1.518 ± 0.030	0.615 ± 0.005	45.402 ± 3.095
	SVMD-PMB-CMHA-TCN	1.566 ± 0.006	1.086 ± 0.012	1.516 ± 0.018	0.615 ± 0.003	45.402 ± 2.370
March 2024	Diff-TCN [27]	5.755 ± 0.001	4.319 ± 0.001	4.670 ± 0.001	0.342 ± 0.000	58.065 ± 0.000
	TCN	5.750 ± 0.007	4.298 ± 0.007	4.643 ± 0.007	0.343 ± 0.002	52.151 ± 7.313
	Diff-TCN	5.689 ± 0.005	4.261 ± 0.005	4.612 ± 0.005	0.357 ± 0.001	54.839 ± 0.000
	CMHA-TCN	5.719 ± 0.033	4.237 ± 0.052	4.577 ± 0.054	0.350 ± 0.007	51.075 ± 3.442
	Diff-CMHA-TCN	5.758 ± 0.017	4.331 ± 0.020	4.684 ± 0.021	0.341 ± 0.004	**61.828** ± 4.718
	EVMD-TCN	5.708 ± 0.008	4.281 ± 0.009	4.647 ± 0.010	0.352 ± 0.002	42.473 ± 1.202
	EVMD-CMHA-TCN	5.696 ± 0.007	4.275 ± 0.010	4.641 ± 0.011	0.355 ± 0.002	43.011 ± 1.521
	EVMD-PMB-TCN	5.666 ± 0.005	4.225 ± 0.008	4.579 ± 0.009	0.362 ± 0.001	46.237 ± 1.521
	EVMD-PMB-CMHA-TCN	5.689 ± 0.009	4.277 ± 0.010	4.644 ± 0.011	0.357 ± 0.002	43.011 ± 2.404
	SVMD-TCN	**5.548** ± 0.044	3.966 ± 0.015	4.288 ± 0.016	**0.388** ± 0.010	54.839 ± 6.715
	SVMD-CMHA-TCN	5.590 ± 0.010	3.985 ± 0.020	4.307 ± 0.023	0.379 ± 0.002	51.075 ± 3.442
	SVMD-PMB-TCN	5.555 ± 0.030	4.007 ± 0.007	4.331 ± 0.006	0.387 ± 0.007	53.226 ± 3.088
	SVMD-PMB-CMHA-TCN	5.561 ± 0.009	**3.958** ± 0.004	**4.277** ± 0.005	0.386 ± 0.002	52.688 ± 2.404
April 2024	Diff-TCN [27]	4.289 ± 0.000	2.927 ± 0.001	3.272 ± 0.001	0.766 ± 0.000	50.000 ± 0.000
	TCN	4.176 ± 0.012	2.857 ± 0.005	3.192 ± 0.006	0.778 ± 0.001	63.333 ± 3.849
	Diff-TCN	4.261 ± 0.009	2.904 ± 0.007	3.249 ± 0.007	0.769 ± 0.001	63.889 ± 3.557
	CMHA-TCN	4.169 ± 0.026	2.837 ± 0.017	3.175 ± 0.020	0.779 ± 0.003	58.333 ± 2.546

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	4.303 ± 0.027	2.949 ± 0.028	3.294 ± 0.030	0.764 ± 0.003	50.556 ± 7.798
	EVMD-TCN	4.124 ± 0.021	2.859 ± 0.004	3.221 ± 0.006	0.783 ± 0.002	66.667 ± 3.333
	EVMD-CMHA-TCN	4.125 ± 0.011	2.857 ± 0.005	3.219 ± 0.005	0.783 ± 0.001	66.667 ± 3.849
	EVMD-PMB-TCN	4.147 ± 0.013	2.842 ± 0.004	3.199 ± 0.005	0.781 ± 0.001	**71.667** ± 1.667
	EVMD-PMB-CMHA-TCN	4.116 ± 0.016	2.840 ± 0.027	3.199 ± 0.032	0.784 ± 0.002	70.000 ± 3.333
	SVMD-TCN	4.189 ± 0.071	2.841 ± 0.052	3.163 ± 0.058	0.776 ± 0.008	61.111 ± 3.143
	SVMD-CMHA-TCN	4.168 ± 0.043	2.824 ± 0.029	3.145 ± 0.035	0.779 ± 0.005	63.889 ± 2.992
	SVMD-PMB-TCN	4.135 ± 0.015	2.813 ± 0.018	3.129 ± 0.019	0.782 ± 0.002	62.778 ± 2.291
	SVMD-PMB-CMHA-TCN	**4.081** ± 0.017	**2.774** ± 0.007	**3.086** ± 0.009	**0.788** ± 0.002	58.333 ± 4.194
May 2024	Diff-TCN [27]	1.726 ± 0.000	1.199 ± 0.001	1.436 ± 0.001	0.432 ± 0.000	41.935 ± 0.000
	TCN	1.711 ± 0.010	1.142 ± 0.013	1.367 ± 0.016	0.443 ± 0.006	63.441 ± 4.023
	Diff-TCN	1.696 ± 0.013	1.163 ± 0.018	1.391 ± 0.022	0.452 ± 0.008	51.613 ± 5.889
	CMHA-TCN	1.674 ± 0.012	**1.121** ± 0.012	**1.342** ± 0.015	0.466 ± 0.008	64.516 ± 5.268
	Diff-CMHA-TCN	1.713 ± 0.010	1.192 ± 0.015	1.427 ± 0.019	0.441 ± 0.006	43.011 ± 1.521
	EVMD-TCN	1.676 ± 0.006	1.145 ± 0.005	1.370 ± 0.005	0.465 ± 0.004	66.667 ± 1.521
	EVMD-CMHA-TCN	1.674 ± 0.005	1.146 ± 0.004	1.371 ± 0.005	0.466 ± 0.003	**68.817** ± 4.023
	EVMD-PMB-TCN	1.674 ± 0.003	1.124 ± 0.003	1.344 ± 0.004	0.466 ± 0.002	66.129 ± 1.613
	EVMD-PMB-CMHA-TCN	**1.666** ± 0.004	1.140 ± 0.002	1.364 ± 0.003	**0.471** ± 0.003	68.280 ± 1.202
	SVMD-TCN	1.740 ± 0.048	1.239 ± 0.031	1.485 ± 0.038	0.423 ± 0.031	60.215 ± 6.628
	SVMD-CMHA-TCN	1.764 ± 0.009	1.226 ± 0.009	1.469 ± 0.011	0.407 ± 0.006	55.914 ± 4.023
	SVMD-PMB-TCN	1.775 ± 0.004	1.234 ± 0.013	1.480 ± 0.016	0.400 ± 0.002	59.140 ± 1.521
	SVMD-PMB-CMHA-TCN	1.761 ± 0.011	1.209 ± 0.003	1.449 ± 0.004	0.409 ± 0.007	60.753 ± 1.202
June 2024	Diff-TCN [27]	1.713 ± 0.001	1.312 ± 0.000	1.723 ± 0.000	0.840 ± 0.000	46.667 ± 0.000
	TCN	**1.701** ± 0.006	1.286 ± 0.005	1.688 ± 0.007	**0.842** ± 0.001	50.000 ± 4.303
	Diff-TCN	1.716 ± 0.005	1.295 ± 0.001	1.700 ± 0.002	0.840 ± 0.001	52.778 ± 2.291
	CMHA-TCN	1.703 ± 0.008	**1.269** ± 0.010	**1.667** ± 0.014	**0.842** ± 0.002	53.333 ± 3.849
	Diff-CMHA-TCN	1.721 ± 0.006	1.303 ± 0.007	1.710 ± 0.010	0.839 ± 0.001	50.000 ± 3.849
	EVMD-TCN	1.758 ± 0.014	1.290 ± 0.006	1.694 ± 0.008	0.832 ± 0.003	53.889 ± 2.992
	EVMD-CMHA-TCN	1.752 ± 0.009	1.287 ± 0.005	1.690 ± 0.006	0.833 ± 0.002	56.111 ± 2.291
	EVMD-PMB-TCN	1.730 ± 0.007	1.284 ± 0.004	1.685 ± 0.005	0.837 ± 0.001	55.556 ± 2.485
	EVMD-PMB-CMHA-TCN	1.759 ± 0.007	1.284 ± 0.005	1.685 ± 0.007	0.831 ± 0.001	55.556 ± 3.143
	SVMD-TCN	1.778 ± 0.054	1.351 ± 0.031	1.774 ± 0.040	0.828 ± 0.011	56.667 ± 3.333
	SVMD-CMHA-TCN	1.750 ± 0.010	1.326 ± 0.011	1.741 ± 0.014	0.833 ± 0.002	**58.889** ± 4.581
	SVMD-PMB-TCN	1.761 ± 0.007	1.340 ± 0.007	1.760 ± 0.009	0.831 ± 0.001	51.667 ± 6.009
	SVMD-PMB-CMHA-TCN	1.744 ± 0.005	1.306 ± 0.004	1.716 ± 0.005	0.834 ± 0.001	56.667 ± 1.925
July 2024	Diff-TCN [27]	2.333 ± 0.000	1.848 ± 0.000	2.688 ± 0.000	0.564 ± 0.000	58.065 ± 0.000
	TCN	2.333 ± 0.005	1.808 ± 0.002	2.632 ± 0.004	0.564 ± 0.002	58.065 ± 0.000
	Diff-TCN	2.332 ± 0.002	1.845 ± 0.004	2.686 ± 0.005	0.565 ± 0.001	58.602 ± 2.217
	CMHA-TCN	2.376 ± 0.056	1.817 ± 0.023	2.651 ± 0.035	0.548 ± 0.022	59.140 ± 1.521
	Diff-CMHA-TCN	2.335 ± 0.004	1.845 ± 0.002	2.685 ± 0.003	0.564 ± 0.001	56.452 ± 3.088
	EVMD-TCN	2.395 ± 0.005	1.890 ± 0.010	2.752 ± 0.014	0.541 ± 0.002	50.538 ± 7.828
	EVMD-CMHA-TCN	2.391 ± 0.007	1.882 ± 0.004	2.741 ± 0.005	0.542 ± 0.003	54.301 ± 2.217
	EVMD-PMB-TCN	2.379 ± 0.003	1.864 ± 0.005	2.717 ± 0.008	0.547 ± 0.001	55.376 ± 2.217
	EVMD-PMB-CMHA-TCN	2.392 ± 0.009	1.877 ± 0.008	2.734 ± 0.011	0.542 ± 0.003	54.301 ± 1.202
	SVMD-TCN	2.419 ± 0.143	1.811 ± 0.053	2.651 ± 0.079	0.530 ± 0.058	56.452 ± 5.509
	SVMD-CMHA-TCN	2.334 ± 0.011	1.784 ± 0.021	2.609 ± 0.030	0.564 ± 0.004	57.527 ± 7.546
	SVMD-PMB-TCN	2.328 ± 0.009	1.788 ± 0.003	2.614 ± 0.004	0.566 ± 0.003	57.527 ± 2.895
	SVMD-PMB-CMHA-TCN	**2.315** ± 0.003	**1.752** ± 0.006	**2.560** ± 0.009	**0.571** ± 0.001	**61.290** ± 4.562
August 2024	**Diff-TCN** [27]	**2.207** ± 0.001	1.659 ± 0.001	2.681 ± 0.001	**0.496** ± 0.000	**48.387** ± 0.000
	TCN	2.255 ± 0.030	1.673 ± 0.015	2.707 ± 0.024	0.474 ± 0.014	47.312 ± 2.404
	Diff-TCN	2.211 ± 0.006	1.670 ± 0.003	2.695 ± 0.005	0.494 ± 0.003	40.323 ± 5.185
	CMHA-TCN	2.226 ± 0.018	1.660 ± 0.008	2.686 ± 0.013	0.488 ± 0.009	48.387 ± 0.000
	Diff-CMHA-TCN	2.221 ± 0.010	1.675 ± 0.007	2.706 ± 0.011	0.490 ± 0.005	45.161 ± 3.725
	EVMD-TCN	2.216 ± 0.007	**1.630** ± 0.005	**2.632** ± 0.008	0.492 ± 0.003	40.860 ± 1.521
	EVMD-CMHA-TCN	2.219 ± 0.008	1.631 ± 0.003	2.632 ± 0.005	0.491 ± 0.004	42.473 ± 1.202
	EVMD-PMB-TCN	2.231 ± 0.017	1.661 ± 0.005	2.679 ± 0.008	0.485 ± 0.008	41.398 ± 3.442
	EVMD-PMB-CMHA-TCN	2.223 ± 0.005	1.652 ± 0.005	2.664 ± 0.008	0.489 ± 0.003	40.323 ± 2.464
	SVMD-TCN	2.317 ± 0.113	1.706 ± 0.079	2.751 ± 0.131	0.444 ± 0.056	43.548 ± 6.384
	SVMD-CMHA-TCN	2.274 ± 0.022	1.670 ± 0.013	2.692 ± 0.022	0.465 ± 0.010	44.624 ± 3.442
	SVMD-PMB-TCN	2.268 ± 0.021	1.676 ± 0.009	2.701 ± 0.016	0.468 ± 0.010	41.398 ± 2.895
	SVMD-PMB-CMHA-TCN	2.276 ± 0.026	1.683 ± 0.017	2.713 ± 0.028	0.464 ± 0.012	40.323 ± 3.088
September 2024	Diff-TCN [27]	1.445 ± 0.000	1.208 ± 0.000	1.844 ± 0.000	0.691 ± 0.000	53.333 ± 0.000
	TCN	1.452 ± 0.014	1.193 ± 0.004	1.822 ± 0.006	0.688 ± 0.006	54.444 ± 2.485
	Diff-TCN	1.454 ± 0.002	1.224 ± 0.003	1.869 ± 0.005	0.687 ± 0.001	52.778 ± 4.479
	CMHA-TCN	1.436 ± 0.005	1.190 ± 0.002	1.818 ± 0.003	0.695 ± 0.002	**57.222** ± 3.557
	Diff-CMHA-TCN	1.454 ± 0.004	1.213 ± 0.012	1.851 ± 0.018	0.687 ± 0.002	53.333 ± 1.925
	EVMD-TCN	**1.421** ± 0.005	**1.169** ± 0.003	**1.788** ± 0.004	**0.701** ± 0.002	55.000 ± 1.667
	EVMD-CMHA-TCN	1.426 ± 0.006	1.173 ± 0.003	1.795 ± 0.004	0.699 ± 0.003	53.333 ± 3.333
	EVMD-PMB-TCN	1.442 ± 0.005	1.190 ± 0.003	1.819 ± 0.004	0.692 ± 0.002	53.333 ± 3.333
	EVMD-PMB-CMHA-TCN	1.436 ± 0.011	1.183 ± 0.009	1.810 ± 0.014	0.695 ± 0.005	53.333 ± 1.925
	SVMD-TCN	1.523 ± 0.013	1.270 ± 0.007	1.941 ± 0.007	0.656 ± 0.006	45.000 ± 5.693
	SVMD-CMHA-TCN	1.520 ± 0.007	1.271 ± 0.003	1.941 ± 0.004	0.657 ± 0.003	46.111 ± 3.557
	SVMD-PMB-TCN	1.503 ± 0.004	1.263 ± 0.007	1.928 ± 0.011	0.665 ± 0.002	43.889 ± 4.045
	SVMD-PMB-CMHA-TCN	1.549 ± 0.010	1.300 ± 0.012	1.985 ± 0.018	0.644 ± 0.005	45.556 ± 2.485
October 2024	Diff-TCN [27]	1.861 ± 0.000	1.513 ± 0.000	2.198 ± 0.000	0.717 ± 0.000	48.387 ± 0.000
	TCN	1.867 ± 0.014	1.515 ± 0.011	2.204 ± 0.018	0.716 ± 0.004	50.000 ± 2.464
	Diff-TCN	1.872 ± 0.005	1.522 ± 0.005	2.214 ± 0.007	0.714 ± 0.002	50.000 ± 5.509
	CMHA-TCN	1.862 ± 0.008	1.510 ± 0.008	2.197 ± 0.013	0.717 ± 0.003	52.151 ± 2.217

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	**1.861** ± 0.002	1.512 ± 0.003	2.198 ± 0.004	**0.717** ± 0.001	48.387 ± 0.000
	EVMD-TCN	1.881 ± 0.006	1.539 ± 0.006	2.244 ± 0.010	0.711 ± 0.002	50.000 ± 1.613
	EVMD-CMHA-TCN	1.881 ± 0.004	1.534 ± 0.005	2.237 ± 0.008	0.711 ± 0.001	**53.763** ± 3.566
	EVMD-PMB-TCN	1.893 ± 0.004	1.545 ± 0.003	2.252 ± 0.004	0.708 ± 0.001	50.000 ± 1.613
	EVMD-PMB-CMHA-TCN	1.896 ± 0.006	1.549 ± 0.004	2.259 ± 0.005	0.707 ± 0.002	52.151 ± 3.442
	SVMD-TCN	1.881 ± 0.041	1.502 ± 0.028	2.190 ± 0.044	0.711 ± 0.013	50.000 ± 4.059
	SVMD-CMHA-TCN	1.878 ± 0.006	1.514 ± 0.008	2.205 ± 0.011	0.712 ± 0.002	47.312 ± 3.566
	SVMD-PMB-TCN	1.868 ± 0.004	**1.491** ± 0.007	**2.174** ± 0.011	0.715 ± 0.001	47.312 ± 3.566
	SVMD-PMB-CMHA-TCN	1.869 ± 0.008	1.499 ± 0.013	2.184 ± 0.019	0.715 ± 0.003	47.312 ± 1.521
November 2024	Diff-TCN [27]	4.422 ± 0.001	3.407 ± 0.001	3.918 ± 0.001	0.855 ± 0.000	56.667 ± 0.000
	TCN	4.429 ± 0.021	3.371 ± 0.013	3.890 ± 0.012	0.855 ± 0.001	52.222 ± 3.143
	Diff-TCN	4.370 ± 0.022	3.369 ± 0.017	3.885 ± 0.013	0.859 ± 0.001	**57.222** ± 4.045
	CMHA-TCN	4.416 ± 0.018	3.374 ± 0.013	3.893 ± 0.013	0.856 ± 0.001	48.889 ± 8.089
	Diff-CMHA-TCN	4.419 ± 0.024	3.399 ± 0.020	3.912 ± 0.016	0.855 ± 0.002	53.333 ± 3.333
	EVMD-TCN	4.402 ± 0.031	3.291 ± 0.008	3.797 ± 0.007	0.857 ± 0.002	50.556 ± 2.992
	EVMD-CMHA-TCN	4.412 ± 0.018	3.288 ± 0.011	3.795 ± 0.011	0.856 ± 0.001	52.222 ± 2.485
	EVMD-PMB-TCN	**4.352** ± 0.016	3.309 ± 0.007	3.827 ± 0.008	**0.860** ± 0.001	48.333 ± 3.191
	EVMD-PMB-CMHA-TCN	4.391 ± 0.014	**3.282** ± 0.005	**3.790** ± 0.004	0.857 ± 0.001	51.111 ± 1.571
	SVMD-TCN	4.454 ± 0.041	3.400 ± 0.013	3.939 ± 0.022	0.853 ± 0.003	46.667 ± 3.849
	SVMD-CMHA-TCN	4.462 ± 0.044	3.404 ± 0.009	3.946 ± 0.009	0.853 ± 0.003	38.889 ± 1.571
	SVMD-PMB-TCN	4.433 ± 0.019	3.422 ± 0.008	3.964 ± 0.009	0.855 ± 0.001	40.000 ± 2.722
	SVMD-PMB-CMHA-TCN	4.458 ± 0.028	3.392 ± 0.019	3.928 ± 0.020	0.853 ± 0.002	42.778 ± 2.291
December 2024	**Diff-TCN** [27]	7.639 ± 0.001	5.047 ± 0.002	4.429 ± 0.002	0.648 ± 0.000	**61.290** ± 0.000
	TCN	7.641 ± 0.037	5.260 ± 0.122	4.584 ± 0.092	0.648 ± 0.003	39.247 ± 1.202
	Diff-TCN	7.677 ± 0.024	5.105 ± 0.023	4.484 ± 0.022	0.645 ± 0.002	56.452 ± 5.185
	CMHA-TCN	7.692 ± 0.066	5.289 ± 0.120	4.605 ± 0.091	0.644 ± 0.006	44.624 ± 2.895
	Diff-CMHA-TCN	**7.636** ± 0.006	**5.043** ± 0.009	**4.425** ± 0.009	**0.649** ± 0.001	59.140 ± 7.828
	EVMD-TCN	7.643 ± 0.005	5.298 ± 0.007	4.636 ± 0.005	0.648 ± 0.001	45.699 ± 2.217
	EVMD-CMHA-TCN	7.663 ± 0.007	5.325 ± 0.020	4.659 ± 0.012	0.646 ± 0.001	42.473 ± 4.335
	EVMD-PMB-TCN	7.683 ± 0.014	5.265 ± 0.012	4.622 ± 0.006	0.644 ± 0.001	46.774 ± 6.906
	EVMD-PMB-CMHA-TCN	7.674 ± 0.026	5.347 ± 0.060	4.674 ± 0.038	0.645 ± 0.002	45.699 ± 3.914
	SVMD-TCN	7.863 ± 0.139	5.897 ± 0.143	5.132 ± 0.113	0.627 ± 0.013	29.032 ± 2.634
	SVMD-CMHA-TCN	7.817 ± 0.043	5.887 ± 0.112	5.124 ± 0.081	0.632 ± 0.004	26.882 ± 1.521
	SVMD-PMB-TCN	7.769 ± 0.038	5.697 ± 0.014	4.988 ± 0.014	0.636 ± 0.004	34.409 ± 2.404
	SVMD-PMB-CMHA-TCN	7.770 ± 0.029	5.715 ± 0.073	4.991 ± 0.058	0.636 ± 0.003	30.108 ± 3.041
January 2025	Diff-TCN [27]	6.444 ± 0.001	4.867 ± 0.001	4.161 ± 0.001	0.531 ± 0.000	54.839 ± 0.000
	TCN	6.498 ± 0.045	4.874 ± 0.049	4.158 ± 0.042	0.523 ± 0.007	48.387 ± 4.928
	Diff-TCN	6.518 ± 0.023	4.875 ± 0.012	4.170 ± 0.010	0.520 ± 0.003	50.000 ± 5.509
	CMHA-TCN	6.479 ± 0.029	4.837 ± 0.021	4.128 ± 0.018	0.526 ± 0.004	48.925 ± 4.335
	Diff-CMHA-TCN	6.443 ± 0.025	4.869 ± 0.003	4.163 ± 0.002	0.531 ± 0.004	56.989 ± 3.041
	EVMD-TCN	6.534 ± 0.026	4.778 ± 0.025	4.073 ± 0.020	0.518 ± 0.004	**58.065** ± 2.634
	EVMD-CMHA-TCN	6.549 ± 0.022	4.793 ± 0.022	4.087 ± 0.018	0.515 ± 0.003	57.527 ± 1.202
	EVMD-PMB-TCN	6.559 ± 0.064	4.849 ± 0.036	4.139 ± 0.027	0.514 ± 0.009	53.226 ± 3.088
	EVMD-PMB-CMHA-TCN	6.598 ± 0.034	4.832 ± 0.035	4.124 ± 0.028	0.508 ± 0.005	56.452 ± 3.607
	SVMD-TCN	6.604 ± 0.289	4.853 ± 0.311	4.136 ± 0.264	0.506 ± 0.045	53.226 ± 2.464
	SVMD-CMHA-TCN	6.472 ± 0.034	4.725 ± 0.023	4.026 ± 0.018	0.527 ± 0.005	52.151 ± 2.895
	SVMD-PMB-TCN	**6.417** ± 0.042	**4.720** ± 0.018	**4.022** ± 0.014	**0.535** ± 0.006	55.376 ± 2.217
	SVMD-PMB-CMHA-TCN	6.531 ± 0.033	4.763 ± 0.035	4.061 ± 0.031	0.518 ± 0.005	50.538 ± 3.041
February 2025	Diff-TCN [27]	6.155 ± 0.001	4.798 ± 0.001	4.007 ± 0.001	0.653 ± 0.000	50.000 ± 0.000
	TCN	6.147 ± 0.018	4.785 ± 0.009	3.991 ± 0.012	0.654 ± 0.002	49.405 ± 4.333
	Diff-TCN	6.181 ± 0.014	4.849 ± 0.024	4.052 ± 0.021	0.650 ± 0.002	50.595 ± 6.655
	CMHA-TCN	**6.129** ± 0.009	4.798 ± 0.019	4.006 ± 0.018	**0.656** ± 0.001	47.024 ± 3.811
	Diff-CMHA-TCN	6.151 ± 0.008	4.790 ± 0.011	4.002 ± 0.010	0.653 ± 0.001	53.571 ± 5.832
	EVMD-TCN	6.142 ± 0.006	**4.685** ± 0.012	**3.917** ± 0.009	0.654 ± 0.001	55.357 ± 3.993
	EVMD-CMHA-TCN	6.138 ± 0.007	4.698 ± 0.013	3.930 ± 0.010	0.655 ± 0.001	**55.952** ± 4.909
	EVMD-PMB-TCN	6.164 ± 0.016	4.779 ± 0.044	4.000 ± 0.036	0.652 ± 0.002	55.952 ± 4.909
	EVMD-PMB-CMHA-TCN	6.144 ± 0.011	4.736 ± 0.017	3.963 ± 0.013	0.654 ± 0.001	52.976 ± 8.096
	SVMD-TCN	6.392 ± 0.004	5.223 ± 0.009	4.388 ± 0.008	0.626 ± 0.001	38.691 ± 1.331
	SVMD-CMHA-TCN	6.404 ± 0.018	5.241 ± 0.011	4.406 ± 0.009	0.624 ± 0.002	43.452 ± 2.454
	SVMD-PMB-TCN	6.416 ± 0.011	5.216 ± 0.011	4.386 ± 0.009	0.623 ± 0.001	45.238 ± 3.948
	SVMD-PMB-CMHA-TCN	6.391 ± 0.004	5.237 ± 0.007	4.402 ± 0.007	0.626 ± 0.001	41.071 ± 2.728
March 2025	Diff-TCN [27]	4.547 ± 0.004	3.011 ± 0.002	3.101 ± 0.002	0.797 ± 0.000	48.387 ± 0.000
	TCN	**4.434** ± 0.049	**2.943** ± 0.027	**3.030** ± 0.030	**0.807** ± 0.004	**56.989** ± 4.023
	Diff-TCN	4.561 ± 0.028	3.005 ± 0.015	3.096 ± 0.016	0.796 ± 0.003	50.000 ± 3.088
	CMHA-TCN	4.489 ± 0.104	2.959 ± 0.046	3.048 ± 0.046	0.803 ± 0.009	54.839 ± 4.928
	Diff-CMHA-TCN	4.568 ± 0.024	3.015 ± 0.012	3.106 ± 0.013	0.796 ± 0.002	50.538 ± 2.404
	EVMD-TCN	4.722 ± 0.034	3.039 ± 0.012	3.149 ± 0.012	0.782 ± 0.003	44.624 ± 2.895
	EVMD-CMHA-TCN	4.736 ± 0.034	3.032 ± 0.008	3.140 ± 0.008	0.780 ± 0.003	47.312 ± 1.521
	EVMD-PMB-TCN	4.747 ± 0.067	3.038 ± 0.029	3.140 ± 0.028	0.779 ± 0.006	52.688 ± 5.483
	EVMD-PMB-CMHA-TCN	4.827 ± 0.061	3.059 ± 0.026	3.168 ± 0.025	0.772 ± 0.006	54.839 ± 4.165
	SVMD-TCN	4.639 ± 0.079	3.066 ± 0.028	3.167 ± 0.028	0.789 ± 0.007	50.000 ± 4.059
	SVMD-CMHA-TCN	4.636 ± 0.088	3.058 ± 0.032	3.158 ± 0.032	0.789 ± 0.008	49.462 ± 1.521
	SVMD-PMB-TCN	4.694 ± 0.033	3.085 ± 0.017	3.185 ± 0.018	0.784 ± 0.003	49.462 ± 2.404
	SVMD-PMB-CMHA-TCN	4.738 ± 0.084	3.092 ± 0.047	3.195 ± 0.050	0.780 ± 0.008	51.075 ± 2.217
April 2025	Diff-TCN [27]	3.069 ± 0.001	1.945 ± 0.000	2.517 ± 0.001	0.636 ± 0.000	56.667 ± 0.000
	TCN	3.054 ± 0.010	1.967 ± 0.018	2.546 ± 0.023	0.640 ± 0.002	50.556 ± 5.906
	Diff-TCN	3.067 ± 0.007	1.928 ± 0.012	2.496 ± 0.015	0.637 ± 0.002	62.222 ± 4.157
	CMHA-TCN	3.064 ± 0.007	1.955 ± 0.013	2.534 ± 0.020	0.638 ± 0.002	55.000 ± 3.191

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	3.074 ± 0.005	1.946 ± 0.017	2.519 ± 0.021	0.635 ± 0.001	57.222 ± 4.479
	EVMD-TCN	**2.992** ± 0.007	1.964 ± 0.013	2.542 ± 0.015	**0.654** ± 0.002	53.333 ± 7.201
	EVMD-CMHA-TCN	3.002 ± 0.007	1.968 ± 0.008	2.549 ± 0.008	0.652 ± 0.002	50.000 ± 6.383
	EVMD-PMB-TCN	3.008 ± 0.012	1.965 ± 0.009	2.545 ± 0.013	0.651 ± 0.003	47.778 ± 8.315
	EVMD-PMB-CMHA-TCN	3.012 ± 0.008	1.973 ± 0.017	2.556 ± 0.021	0.650 ± 0.002	51.667 ± 6.310
	SVMD-TCN	3.048 ± 0.014	1.836 ± 0.017	2.370 ± 0.021	0.641 ± 0.003	62.222 ± 2.485
	SVMD-CMHA-TCN	3.051 ± 0.018	1.845 ± 0.009	2.385 ± 0.016	0.640 ± 0.004	61.111 ± 4.157
	SVMD-PMB-TCN	3.038 ± 0.011	**1.818** ± 0.008	**2.347** ± 0.011	0.644 ± 0.003	**62.778** ± 2.291
	SVMD-PMB-CMHA-TCN	3.056 ± 0.011	1.829 ± 0.013	2.368 ± 0.021	0.640 ± 0.003	62.222 ± 3.685
May 2025	Diff-TCN [27]	3.625 ± 0.000	2.917 ± 0.001	3.079 ± 0.001	0.615 ± 0.000	41.935 ± 0.000
	TCN	3.596 ± 0.018	2.828 ± 0.029	2.979 ± 0.031	0.621 ± 0.004	62.903 ± 3.088
	Diff-TCN	3.601 ± 0.005	2.869 ± 0.015	3.028 ± 0.016	0.620 ± 0.001	51.613 ± 3.725
	CMHA-TCN	3.591 ± 0.012	2.837 ± 0.035	2.991 ± 0.037	0.622 ± 0.003	62.366 ± 8.669
	Diff-CMHA-TCN	3.619 ± 0.012	2.913 ± 0.024	3.075 ± 0.026	0.616 ± 0.003	40.860 ± 5.790
	EVMD-TCN	3.669 ± 0.005	2.884 ± 0.007	3.036 ± 0.006	0.605 ± 0.001	46.774 ± 3.088
	EVMD-CMHA-TCN	3.656 ± 0.007	2.867 ± 0.008	3.018 ± 0.008	0.608 ± 0.002	48.387 ± 2.634
	EVMD-PMB-TCN	3.637 ± 0.012	2.847 ± 0.013	2.998 ± 0.013	0.612 ± 0.003	59.677 ± 2.464
	EVMD-PMB-CMHA-TCN	3.664 ± 0.014	2.860 ± 0.020	3.010 ± 0.021	0.606 ± 0.003	50.538 ± 4.023
	SVMD-TCN	**3.590** ± 0.006	2.820 ± 0.009	2.971 ± 0.011	**0.622** ± 0.001	61.290 ± 0.000
	SVMD-CMHA-TCN	3.600 ± 0.012	2.816 ± 0.021	2.964 ± 0.024	0.620 ± 0.003	**65.054** ± 2.217
	SVMD-PMB-TCN	3.608 ± 0.010	2.851 ± 0.015	3.005 ± 0.016	0.618 ± 0.002	65.054 ± 3.442
	SVMD-PMB-CMHA-TCN	3.591 ± 0.010	**2.811** ± 0.019	**2.962** ± 0.021	**0.622** ± 0.002	64.516 ± 1.862

Table 63: Average results of the *extended experiments* across 6 repetitions per split $M_1, \ldots, M_{36}$ corresponding to months June 2022 to May 2025 in relation to forecasting $\mathbf{S}_{\text{Close}}$ with respect to LTC/USD using the novel framework.

F.2.4 *XMR/USD*

Month	Model	RMSE	MAE	MAPE	R2	DA
June 2021	TCN [27]	19.314 ± 0.228	14.479 ± 0.359	6.016 ± 0.151	0.598 ± 0.009	52.778 ± 5.241
	Diff-TCN [27]	18.495 ± 0.034	13.547 ± 0.025	5.577 ± 0.009	0.631 ± 0.001	60.000 ± 0.000
	TCN	**18.242** ± 0.104	**13.158** ± 0.068	**5.449** ± 0.031	**0.641** ± 0.004	**67.778** ± 3.685
	Diff-TCN	18.529 ± 0.081	13.789 ± 0.095	5.692 ± 0.042	0.630 ± 0.003	55.000 ± 2.546
	CMHA-TCN	18.538 ± 0.201	13.416 ± 0.083	5.548 ± 0.036	0.629 ± 0.008	61.667 ± 3.191
	Diff-CMHA-TCN	18.820 ± 0.253	14.007 ± 0.205	5.784 ± 0.092	0.618 ± 0.010	50.000 ± 6.383
	EVMD-TCN	19.627 ± 0.484	14.545 ± 0.353	6.092 ± 0.154	0.584 ± 0.021	59.444 ± 2.291
	EVMD-CMHA-TCN	19.336 ± 0.245	14.554 ± 0.079	6.062 ± 0.039	0.597 ± 0.010	58.333 ± 2.546
	EVMD-PMB-TCN	20.761 ± 1.135	15.681 ± 0.921	6.575 ± 0.399	0.534 ± 0.051	53.889 ± 4.479
	EVMD-PMB-CMHA-TCN	22.529 ± 2.230	17.077 ± 2.007	7.181 ± 0.879	0.447 ± 0.110	58.889 ± 4.157
	SVMD-TCN	19.276 ± 0.131	13.928 ± 0.087	5.773 ± 0.040	0.599 ± 0.005	59.444 ± 2.992
	SVMD-CMHA-TCN	19.807 ± 0.559	14.364 ± 0.455	6.003 ± 0.202	0.577 ± 0.024	62.222 ± 2.485
	SVMD-PMB-TCN	19.047 ± 0.151	13.722 ± 0.106	5.696 ± 0.049	0.609 ± 0.006	61.667 ± 1.667
	SVMD-PMB-CMHA-TCN	19.179 ± 0.324	13.972 ± 0.287	5.815 ± 0.126	0.603 ± 0.013	59.444 ± 3.557
July 2021	**TCN** [27]	6.991 ± 0.225	**5.565** ± 0.246	**2.683** ± 0.115	0.770 ± 0.015	**59.140** ± 4.433
	Diff-TCN [27]	6.844 ± 0.031	5.577 ± 0.011	2.686 ± 0.003	0.780 ± 0.002	58.065 ± 0.000
	TCN	6.893 ± 0.080	5.634 ± 0.070	2.707 ± 0.032	0.777 ± 0.005	48.925 ± 4.335
	Diff-TCN	6.839 ± 0.053	5.643 ± 0.056	2.717 ± 0.022	0.780 ± 0.003	53.226 ± 3.088
	CMHA-TCN	6.873 ± 0.074	5.662 ± 0.090	2.723 ± 0.037	0.778 ± 0.005	50.538 ± 7.603
	Diff-CMHA-TCN	**6.790** ± 0.042	5.597 ± 0.017	2.698 ± 0.008	**0.783** ± 0.003	55.914 ± 3.041
	EVMD-TCN	7.037 ± 0.189	5.868 ± 0.096	2.834 ± 0.038	0.767 ± 0.013	48.925 ± 7.772
	EVMD-CMHA-TCN	7.130 ± 0.106	5.913 ± 0.226	2.850 ± 0.092	0.761 ± 0.007	48.387 ± 8.118
	EVMD-PMB-TCN	7.623 ± 0.647	6.058 ± 0.283	2.938 ± 0.144	0.725 ± 0.047	54.839 ± 8.932
	EVMD-PMB-CMHA-TCN	7.476 ± 0.222	6.129 ± 0.268	2.950 ± 0.106	0.737 ± 0.016	48.387 ± 6.715
	SVMD-TCN	7.450 ± 0.169	5.931 ± 0.059	2.868 ± 0.032	0.739 ± 0.012	58.065 ± 2.634
	SVMD-CMHA-TCN	7.691 ± 0.192	6.011 ± 0.083	2.911 ± 0.042	0.722 ± 0.014	59.140 ± 2.404
	SVMD-PMB-TCN	7.238 ± 0.046	5.828 ± 0.018	2.817 ± 0.009	0.754 ± 0.003	55.914 ± 2.404
	SVMD-PMB-CMHA-TCN	7.491 ± 0.215	5.933 ± 0.064	2.872 ± 0.035	0.736 ± 0.015	54.839 ± 3.226
August 2021	TCN [27]	13.352 ± 0.642	11.326 ± 0.346	4.166 ± 0.133	0.688 ± 0.030	48.387 ± 2.634
	Diff-TCN [27]	11.488 ± 0.008	9.871 ± 0.009	3.575 ± 0.006	0.769 ± 0.000	51.613 ± 0.000
	TCN	11.563 ± 0.046	10.056 ± 0.073	3.649 ± 0.033	0.766 ± 0.002	46.774 ± 3.088
	Diff-TCN	**11.340** ± 0.027	**9.800** ± 0.011	**3.561** ± 0.005	**0.775** ± 0.001	50.000 ± 1.613
	CMHA-TCN	11.557 ± 0.039	10.068 ± 0.101	3.657 ± 0.044	0.767 ± 0.002	45.699 ± 4.718
	Diff-CMHA-TCN	11.361 ± 0.045	9.802 ± 0.048	3.561 ± 0.019	**0.775** ± 0.002	**53.226** ± 1.613
	EVMD-TCN	11.976 ± 0.150	10.528 ± 0.133	3.838 ± 0.054	0.750 ± 0.006	45.161 ± 3.226
	EVMD-CMHA-TCN	11.680 ± 0.123	10.304 ± 0.107	3.749 ± 0.047	0.762 ± 0.005	51.613 ± 5.268
	EVMD-PMB-TCN	11.977 ± 0.071	10.495 ± 0.081	3.827 ± 0.035	0.749 ± 0.003	41.398 ± 2.217
	EVMD-PMB-CMHA-TCN	11.797 ± 0.282	10.232 ± 0.225	3.704 ± 0.087	0.757 ± 0.012	48.387 ± 4.928
	SVMD-TCN	11.546 ± 0.066	10.026 ± 0.071	3.657 ± 0.035	0.767 ± 0.003	45.161 ± 3.226
	SVMD-CMHA-TCN	11.456 ± 0.067	10.072 ± 0.043	3.672 ± 0.015	0.771 ± 0.003	43.011 ± 4.023
	SVMD-PMB-TCN	11.567 ± 0.089	10.072 ± 0.061	3.679 ± 0.025	0.766 ± 0.004	45.699 ± 2.895
	SVMD-PMB-CMHA-TCN	11.516 ± 0.035	10.022 ± 0.025	3.657 ± 0.009	0.768 ± 0.001	45.699 ± 2.217
September 2021	TCN [27]	17.069 ± 0.448	12.127 ± 0.471	4.742 ± 0.177	0.591 ± 0.022	46.667 ± 4.303
	Diff-TCN [27]	**14.300** ± 0.065	**9.160** ± 0.052	**3.616** ± 0.022	**0.713** ± 0.003	56.667 ± 0.000
	TCN	14.714 ± 0.259	9.645 ± 0.206	3.803 ± 0.087	0.697 ± 0.011	46.111 ± 7.798
	Diff-TCN	14.617 ± 0.143	9.547 ± 0.141	3.778 ± 0.058	0.701 ± 0.006	56.111 ± 2.291
	CMHA-TCN	14.606 ± 0.148	9.673 ± 0.115	3.825 ± 0.048	0.701 ± 0.006	51.111 ± 5.666
	Diff-CMHA-TCN	14.886 ± 0.125	9.798 ± 0.105	3.869 ± 0.045	0.689 ± 0.005	51.111 ± 2.485
	EVMD-TCN	14.802 ± 0.142	9.916 ± 0.187	3.924 ± 0.079	0.693 ± 0.006	61.111 ± 4.157
	EVMD-CMHA-TCN	14.917 ± 0.291	10.035 ± 0.179	3.982 ± 0.077	0.688 ± 0.012	**63.333** ± 4.303
	EVMD-PMB-TCN	14.736 ± 0.096	9.999 ± 0.218	3.925 ± 0.074	0.696 ± 0.004	50.556 ± 8.032
	EVMD-PMB-CMHA-TCN	14.556 ± 0.256	9.991 ± 0.141	3.936 ± 0.077	0.703 ± 0.011	58.333 ± 7.876
	SVMD-TCN	15.276 ± 0.245	10.514 ± 0.227	4.143 ± 0.093	0.673 ± 0.010	49.444 ± 4.479
	SVMD-CMHA-TCN	15.501 ± 0.111	10.784 ± 0.070	4.259 ± 0.028	0.663 ± 0.005	47.222 ± 2.992
	SVMD-PMB-TCN	15.336 ± 0.137	10.564 ± 0.147	4.170 ± 0.062	0.670 ± 0.006	53.889 ± 1.242
	SVMD-PMB-CMHA-TCN	14.976 ± 0.083	10.240 ± 0.065	4.047 ± 0.031	0.686 ± 0.004	58.333 ± 4.194
October 2021	TCN [27]	10.189 ± 0.537	7.696 ± 0.498	2.861 ± 0.184	−0.136 ± 0.121	58.065 ± 3.226
	Diff-TCN [27]	8.842 ± 0.013	6.964 ± 0.041	2.582 ± 0.016	0.146 ± 0.003	54.839 ± 0.000
	TCN	8.823 ± 0.062	6.822 ± 0.175	2.535 ± 0.065	0.150 ± 0.012	58.602 ± 3.442
	Diff-TCN	8.838 ± 0.026	6.900 ± 0.027	2.562 ± 0.011	0.147 ± 0.005	56.989 ± 1.521
	CMHA-TCN	8.807 ± 0.033	6.826 ± 0.094	2.536 ± 0.035	0.153 ± 0.006	60.753 ± 1.202
	Diff-CMHA-TCN	8.934 ± 0.081	7.017 ± 0.121	2.605 ± 0.046	0.129 ± 0.016	54.301 ± 2.217
	EVMD-TCN	9.134 ± 0.048	7.050 ± 0.049	2.621 ± 0.019	0.089 ± 0.009	59.140 ± 3.041
	EVMD-CMHA-TCN	9.127 ± 0.074	6.985 ± 0.080	2.596 ± 0.031	0.091 ± 0.015	57.527 ± 2.217
	EVMD-PMB-TCN	9.289 ± 0.079	7.151 ± 0.101	2.662 ± 0.039	0.058 ± 0.016	53.763 ± 2.404
	EVMD-PMB-CMHA-TCN	9.115 ± 0.188	6.932 ± 0.226	2.572 ± 0.085	0.093 ± 0.037	58.065 ± 7.679
	SVMD-TCN	8.781 ± 0.104	6.500 ± 0.077	2.416 ± 0.029	0.158 ± 0.020	61.828 ± 2.895
	SVMD-CMHA-TCN	8.845 ± 0.041	6.523 ± 0.029	2.423 ± 0.012	0.146 ± 0.008	63.441 ± 1.521
	SVMD-PMB-TCN	**8.712** ± 0.040	6.432 ± 0.051	2.391 ± 0.020	**0.172** ± 0.008	**67.742** ± 1.862
	SVMD-PMB-CMHA-TCN	8.741 ± 0.033	**6.417** ± 0.044	**2.384** ± 0.017	0.166 ± 0.006	60.753 ± 5.072
November 2021	TCN [27]	11.178 ± 0.203	9.178 ± 0.320	3.678 ± 0.122	0.562 ± 0.016	48.889 ± 4.157
	Diff-TCN [27]	10.903 ± 0.041	8.339 ± 0.016	3.341 ± 0.006	0.583 ± 0.003	56.667 ± 0.000
	TCN	10.672 ± 0.126	**8.204** ± 0.067	**3.290** ± 0.026	0.601 ± 0.009	**60.000** ± 3.849
	Diff-TCN	10.883 ± 0.102	8.571 ± 0.072	3.430 ± 0.029	0.585 ± 0.008	48.889 ± 6.573
	CMHA-TCN	**10.656** ± 0.104	8.281 ± 0.043	3.319 ± 0.017	**0.602** ± 0.008	58.333 ± 1.667

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	10.980 ± 0.080	8.549 ± 0.117	3.422 ± 0.045	0.577 ± 0.006	54.444 ± 8.089
	EVMD-TCN	11.400 ± 0.192	9.354 ± 0.141	3.731 ± 0.057	0.544 ± 0.015	56.667 ± 0.000
	EVMD-CMHA-TCN	11.312 ± 0.074	9.098 ± 0.063	3.635 ± 0.026	0.551 ± 0.006	56.667 ± 0.000
	EVMD-PMB-TCN	11.184 ± 0.118	9.279 ± 0.079	3.703 ± 0.032	0.561 ± 0.009	55.000 ± 2.546
	EVMD-PMB-CMHA-TCN	11.275 ± 0.221	9.190 ± 0.131	3.664 ± 0.052	0.554 ± 0.018	52.222 ± 4.969
	SVMD-TCN	11.263 ± 0.150	8.844 ± 0.208	3.556 ± 0.080	0.555 ± 0.012	48.333 ± 5.358
	SVMD-CMHA-TCN	11.102 ± 0.150	8.482 ± 0.105	3.413 ± 0.043	0.568 ± 0.012	58.333 ± 1.667
	SVMD-PMB-TCN	11.151 ± 0.067	8.736 ± 0.050	3.509 ± 0.018	0.564 ± 0.005	51.111 ± 2.485
	SVMD-PMB-CMHA-TCN	11.307 ± 0.158	8.972 ± 0.050	3.602 ± 0.020	0.552 ± 0.013	49.444 ± 3.557
December 2021	TCN [27]	9.189 ± 0.124	7.258 ± 0.182	3.585 ± 0.079	0.668 ± 0.009	62.366 ± 6.361
	Diff-TCN [27]	**8.872** ± 0.007	**6.424** ± 0.002	**3.135** ± 0.001	**0.691** ± 0.001	58.065 ± 0.000
	TCN	9.031 ± 0.058	6.673 ± 0.079	3.266 ± 0.044	0.680 ± 0.004	58.602 ± 3.442
	Diff-TCN	9.071 ± 0.034	6.608 ± 0.032	3.233 ± 0.017	0.677 ± 0.002	**64.516** ± 0.000
	CMHA-TCN	9.097 ± 0.103	6.702 ± 0.093	3.275 ± 0.049	0.675 ± 0.007	54.301 ± 3.914
	Diff-CMHA-TCN	8.909 ± 0.062	6.488 ± 0.048	3.168 ± 0.026	0.688 ± 0.004	60.215 ± 2.404
	EVMD-TCN	9.666 ± 0.299	7.259 ± 0.234	3.587 ± 0.126	0.633 ± 0.023	59.677 ± 3.088
	EVMD-CMHA-TCN	9.758 ± 0.171	7.399 ± 0.157	3.661 ± 0.092	0.626 ± 0.013	58.065 ± 2.634
	EVMD-PMB-TCN	9.607 ± 0.173	7.355 ± 0.115	3.623 ± 0.056	0.637 ± 0.013	51.075 ± 2.217
	EVMD-PMB-CMHA-TCN	9.860 ± 0.228	7.504 ± 0.216	3.715 ± 0.124	0.618 ± 0.018	54.301 ± 5.403
	SVMD-TCN	9.710 ± 0.179	7.049 ± 0.102	3.462 ± 0.058	0.630 ± 0.014	55.914 ± 2.404
	SVMD-CMHA-TCN	9.896 ± 0.191	7.228 ± 0.190	3.553 ± 0.098	0.615 ± 0.015	55.914 ± 4.433
	SVMD-PMB-TCN	9.732 ± 0.079	7.023 ± 0.078	3.457 ± 0.041	0.628 ± 0.006	58.602 ± 3.914
	SVMD-PMB-CMHA-TCN	9.826 ± 0.309	7.175 ± 0.257	3.538 ± 0.138	0.621 ± 0.024	56.452 ± 2.464
January 2022	TCN [27]	14.067 ± 0.616	11.979 ± 0.603	6.166 ± 0.350	0.809 ± 0.016	33.871 ± 6.106
	Diff-TCN [27]	**11.136** ± 0.014	**9.454** ± 0.011	**4.939** ± 0.006	**0.881** ± 0.000	35.484 ± 0.000
	TCN	11.966 ± 0.197	10.082 ± 0.162	5.300 ± 0.112	0.862 ± 0.004	37.097 ± 1.613
	Diff-TCN	11.653 ± 0.032	9.749 ± 0.027	5.084 ± 0.015	0.869 ± 0.001	33.333 ± 1.521
	CMHA-TCN	12.018 ± 0.138	10.053 ± 0.119	5.282 ± 0.074	0.861 ± 0.003	37.097 ± 1.613
	Diff-CMHA-TCN	11.538 ± 0.238	9.678 ± 0.173	5.047 ± 0.093	0.872 ± 0.005	**37.097** ± 2.464
	EVMD-TCN	12.786 ± 0.231	10.540 ± 0.211	5.531 ± 0.118	0.843 ± 0.006	33.333 ± 2.404
	EVMD-CMHA-TCN	13.204 ± 0.279	10.892 ± 0.248	5.753 ± 0.141	0.832 ± 0.007	32.796 ± 1.202
	EVMD-PMB-TCN	13.527 ± 0.265	11.240 ± 0.245	5.890 ± 0.142	0.824 ± 0.007	31.183 ± 1.521
	EVMD-PMB-CMHA-TCN	13.309 ± 0.754	11.042 ± 0.789	5.824 ± 0.475	0.829 ± 0.020	33.333 ± 2.404
	SVMD-TCN	12.461 ± 0.142	10.471 ± 0.149	5.454 ± 0.083	0.851 ± 0.003	32.796 ± 3.442
	SVMD-CMHA-TCN	12.432 ± 0.196	10.457 ± 0.204	5.441 ± 0.114	0.851 ± 0.005	32.258 ± 3.226
	SVMD-PMB-TCN	12.431 ± 0.044	10.466 ± 0.039	5.445 ± 0.022	0.851 ± 0.001	32.258 ± 2.634
	SVMD-PMB-CMHA-TCN	12.864 ± 0.184	10.790 ± 0.171	5.630 ± 0.093	0.841 ± 0.005	32.258 ± 3.226
February 2022	TCN [27]	9.841 ± 0.266	8.065 ± 0.169	4.907 ± 0.108	0.439 ± 0.030	35.119 ± 2.454
	Diff-TCN [27]	7.716 ± 0.002	5.983 ± 0.001	3.613 ± 0.001	0.655 ± 0.000	50.000 ± 0.000
	TCN	7.995 ± 0.211	6.314 ± 0.133	3.817 ± 0.076	0.630 ± 0.020	45.833 ± 3.811
	Diff-TCN	7.699 ± 0.040	5.980 ± 0.026	3.613 ± 0.019	0.657 ± 0.004	51.191 ± 2.662
	CMHA-TCN	7.909 ± 0.086	6.088 ± 0.047	3.659 ± 0.031	0.638 ± 0.008	47.024 ± 4.799
	Diff-CMHA-TCN	**7.635** ± 0.029	**5.912** ± 0.027	**3.566** ± 0.016	**0.663** ± 0.003	52.381 ± 4.909
	EVMD-TCN	8.263 ± 0.256	6.281 ± 0.239	3.785 ± 0.141	0.605 ± 0.025	48.809 ± 2.662
	EVMD-CMHA-TCN	8.090 ± 0.094	6.260 ± 0.052	3.795 ± 0.043	0.621 ± 0.009	**54.167** ± 3.205
	EVMD-PMB-TCN	8.297 ± 0.170	6.535 ± 0.138	3.972 ± 0.087	0.602 ± 0.016	49.405 ± 4.333
	EVMD-PMB-CMHA-TCN	9.560 ± 0.699	7.674 ± 0.683	4.728 ± 0.442	0.468 ± 0.076	47.619 ± 1.684
	SVMD-TCN	8.069 ± 0.138	6.309 ± 0.049	3.813 ± 0.026	0.623 ± 0.013	47.024 ± 1.331
	SVMD-CMHA-TCN	8.334 ± 0.067	6.545 ± 0.146	3.950 ± 0.095	0.598 ± 0.006	44.643 ± 2.728
	SVMD-PMB-TCN	8.075 ± 0.130	6.141 ± 0.049	3.693 ± 0.028	0.623 ± 0.012	53.571 ± 5.051
	SVMD-PMB-CMHA-TCN	8.034 ± 0.180	6.275 ± 0.276	3.788 ± 0.180	0.626 ± 0.017	52.976 ± 6.655
March 2022	TCN [27]	11.040 ± 0.280	7.722 ± 0.357	4.126 ± 0.204	0.607 ± 0.020	49.462 ± 3.041
	Diff-TCN [27]	10.735 ± 0.000	7.470 ± 0.004	3.970 ± 0.003	0.629 ± 0.000	48.387 ± 0.000
	TCN	**10.436** ± 0.061	7.198 ± 0.131	3.835 ± 0.076	**0.649** ± 0.004	52.688 ± 2.404
	Diff-TCN	10.482 ± 0.071	7.168 ± 0.064	3.819 ± 0.032	0.646 ± 0.005	53.226 ± 2.464
	CMHA-TCN	10.562 ± 0.050	7.199 ± 0.115	3.816 ± 0.072	0.641 ± 0.003	**59.677** ± 8.065
	Diff-CMHA-TCN	10.618 ± 0.076	7.353 ± 0.089	3.917 ± 0.049	0.637 ± 0.005	52.688 ± 1.521
	EVMD-TCN	10.984 ± 0.211	7.223 ± 0.121	3.839 ± 0.071	0.611 ± 0.015	52.151 ± 5.072
	EVMD-CMHA-TCN	10.866 ± 0.098	7.090 ± 0.069	3.757 ± 0.029	0.620 ± 0.007	55.914 ± 2.404
	EVMD-PMB-TCN	10.751 ± 0.081	7.142 ± 0.087	3.815 ± 0.052	0.628 ± 0.006	51.075 ± 1.202
	EVMD-PMB-CMHA-TCN	10.685 ± 0.197	**7.027** ± 0.133	**3.746** ± 0.065	0.632 ± 0.014	54.839 ± 5.268
	SVMD-TCN	10.777 ± 0.028	7.567 ± 0.025	4.046 ± 0.013	0.626 ± 0.002	50.538 ± 1.521
	SVMD-CMHA-TCN	10.868 ± 0.113	7.519 ± 0.057	3.995 ± 0.024	0.619 ± 0.008	45.699 ± 2.217
	SVMD-PMB-TCN	10.886 ± 0.046	7.502 ± 0.022	3.992 ± 0.019	0.618 ± 0.003	44.624 ± 3.442
	SVMD-PMB-CMHA-TCN	10.784 ± 0.104	7.444 ± 0.040	3.970 ± 0.021	0.625 ± 0.007	50.000 ± 2.464
April 2022	TCN [27]	10.979 ± 0.190	8.574 ± 0.183	3.571 ± 0.082	0.647 ± 0.012	57.222 ± 6.211
	Diff-TCN [27]	10.642 ± 0.005	8.598 ± 0.006	3.603 ± 0.003	0.668 ± 0.000	46.667 ± 0.000
	TCN	10.523 ± 0.066	8.443 ± 0.070	3.536 ± 0.030	0.676 ± 0.004	56.111 ± 5.241
	Diff-TCN	10.312 ± 0.036	8.235 ± 0.025	3.447 ± 0.010	0.689 ± 0.002	60.556 ± 1.242
	CMHA-TCN	10.587 ± 0.050	8.487 ± 0.081	3.555 ± 0.036	0.672 ± 0.003	60.556 ± 4.479
	Diff-CMHA-TCN	10.351 ± 0.092	8.271 ± 0.094	3.459 ± 0.041	0.686 ± 0.006	62.778 ± 6.781
	EVMD-TCN	**9.950** ± 0.087	**7.862** ± 0.086	**3.288** ± 0.037	**0.710** ± 0.005	**66.111** ± 2.992
	EVMD-CMHA-TCN	10.030 ± 0.132	7.882 ± 0.107	3.297 ± 0.048	0.705 ± 0.008	62.222 ± 4.157
	EVMD-PMB-TCN	9.983 ± 0.043	7.894 ± 0.046	3.299 ± 0.019	0.708 ± 0.003	65.556 ± 4.581
	EVMD-PMB-CMHA-TCN	10.158 ± 0.178	7.994 ± 0.115	3.343 ± 0.048	0.698 ± 0.011	62.778 ± 4.045
	SVMD-TCN	10.323 ± 0.013	8.303 ± 0.024	3.476 ± 0.011	0.688 ± 0.001	55.000 ± 3.727
	SVMD-CMHA-TCN	10.409 ± 0.017	8.338 ± 0.025	3.483 ± 0.013	0.683 ± 0.001	58.333 ± 3.191
	SVMD-PMB-TCN	10.391 ± 0.031	8.287 ± 0.054	3.464 ± 0.024	0.684 ± 0.002	56.111 ± 2.992
	SVMD-PMB-CMHA-TCN	10.330 ± 0.039	8.211 ± 0.058	3.430 ± 0.026	0.687 ± 0.002	61.111 ± 3.685

Month	Model	RMSE	MAE	MAPE	R2	DA
May 2022	TCN [27]	14.668 ± 0.336	11.729 ± 0.227	6.644 ± 0.140	0.604 ± 0.018	60.753 ± 5.072
	Diff-TCN [27]	14.094 ± 0.002	11.687 ± 0.004	6.479 ± 0.002	0.635 ± 0.000	51.613 ± 0.000
	TCN	14.202 ± 0.132	11.543 ± 0.048	6.446 ± 0.031	0.629 ± 0.007	55.376 ± 3.442
	Diff-TCN	13.988 ± 0.046	11.662 ± 0.049	6.500 ± 0.019	0.640 ± 0.002	54.301 ± 1.202
	CMHA-TCN	14.168 ± 0.116	**11.479** ± 0.060	**6.420** ± 0.032	0.631 ± 0.006	**62.366** ± 7.603
	Diff-CMHA-TCN	**13.853** ± 0.108	11.590 ± 0.056	6.447 ± 0.028	**0.647** ± 0.005	55.376 ± 4.335
	EVMD-TCN	14.219 ± 0.185	11.903 ± 0.162	6.724 ± 0.093	0.628 ± 0.010	52.151 ± 2.895
	EVMD-CMHA-TCN	14.269 ± 0.199	11.870 ± 0.063	6.720 ± 0.041	0.625 ± 0.011	53.763 ± 1.521
	EVMD-PMB-TCN	13.943 ± 0.051	11.770 ± 0.120	6.621 ± 0.059	0.642 ± 0.003	52.151 ± 3.442
	EVMD-PMB-CMHA-TCN	14.171 ± 0.222	11.988 ± 0.127	6.773 ± 0.080	0.630 ± 0.012	52.688 ± 5.157
	SVMD-TCN	14.432 ± 0.069	11.919 ± 0.074	6.671 ± 0.038	0.617 ± 0.004	51.613 ± 6.452
	SVMD-CMHA-TCN	14.553 ± 0.078	11.835 ± 0.125	6.632 ± 0.064	0.610 ± 0.004	53.763 ± 4.433
	SVMD-PMB-TCN	14.473 ± 0.172	11.931 ± 0.106	6.683 ± 0.043	0.615 ± 0.009	51.613 ± 5.889
	SVMD-PMB-CMHA-TCN	14.712 ± 0.073	11.927 ± 0.092	6.698 ± 0.044	0.602 ± 0.004	54.839 ± 4.165

Table 64: Average results of the *benchmark experiments* across 6 repetitions per split $M_1, \ldots, M_{12}$ corresponding to months June 2021 to May 2022 in relation to forecasting $\mathbf{S}_{\text{Close}}$ with respect to XMR/USD using the novel framework.

Month	Model	RMSE	MAE	MAPE	R2	DA
June 2022	**Diff-TCN** [27]	**8.108** ± 0.001	**5.890** ± 0.001	**4.516** ± 0.001	**0.943** ± 0.000	40.000 ± 0.000
	TCN	9.045 ± 0.162	6.724 ± 0.169	5.136 ± 0.126	0.929 ± 0.003	40.000 ± 0.000
	Diff-TCN	8.532 ± 0.147	6.301 ± 0.096	4.786 ± 0.066	0.937 ± 0.002	35.556 ± 2.485
	CMHA-TCN	8.873 ± 0.082	6.558 ± 0.076	5.004 ± 0.056	0.932 ± 0.001	40.000 ± 0.000
	Diff-CMHA-TCN	8.287 ± 0.052	6.072 ± 0.044	4.636 ± 0.030	0.940 ± 0.001	33.889 ± 1.242
	EVMD-TCN	9.808 ± 0.499	7.231 ± 0.496	5.375 ± 0.352	0.916 ± 0.008	44.444 ± 3.143
	EVMD-CMHA-TCN	10.189 ± 0.166	7.396 ± 0.151	5.514 ± 0.105	0.910 ± 0.003	42.222 ± 3.143
	EVMD-PMB-TCN	9.981 ± 1.366	7.369 ± 1.087	5.477 ± 0.827	0.912 ± 0.026	**46.667** ± 5.774
	EVMD-PMB-CMHA-TCN	10.480 ± 0.597	7.761 ± 0.451	5.716 ± 0.333	0.904 ± 0.011	38.889 ± 2.485
	SVMD-TCN	9.313 ± 0.138	7.127 ± 0.117	5.433 ± 0.088	0.925 ± 0.002	36.667 ± 2.722
	SVMD-CMHA-TCN	9.080 ± 0.203	6.851 ± 0.096	5.239 ± 0.073	0.928 ± 0.003	43.333 ± 3.849
	SVMD-PMB-TCN	9.063 ± 0.196	6.940 ± 0.151	5.297 ± 0.104	0.929 ± 0.003	38.889 ± 1.571
	SVMD-PMB-CMHA-TCN	9.533 ± 0.535	7.250 ± 0.442	5.534 ± 0.318	0.921 ± 0.009	37.222 ± 6.503
July 2022	Diff-TCN [27]	4.815 ± 0.004	3.750 ± 0.002	2.686 ± 0.002	0.886 ± 0.000	58.065 ± 0.000
	TCN	**4.685** ± 0.055	**3.681** ± 0.011	**2.630** ± 0.009	**0.892** ± 0.003	58.065 ± 0.000
	Diff-TCN	4.810 ± 0.040	3.744 ± 0.030	2.669 ± 0.024	0.886 ± 0.002	55.376 ± 4.718
	CMHA-TCN	4.832 ± 0.241	3.745 ± 0.117	2.678 ± 0.086	0.885 ± 0.012	54.839 ± 5.889
	Diff-CMHA-TCN	4.843 ± 0.016	3.755 ± 0.009	2.689 ± 0.006	0.885 ± 0.001	52.688 ± 2.404
	EVMD-TCN	5.006 ± 0.088	3.968 ± 0.052	2.805 ± 0.043	0.877 ± 0.004	54.839 ± 3.226
	EVMD-CMHA-TCN	4.897 ± 0.130	3.922 ± 0.053	2.777 ± 0.043	0.882 ± 0.006	55.914 ± 4.023
	EVMD-PMB-TCN	5.125 ± 0.121	3.961 ± 0.113	2.793 ± 0.085	0.871 ± 0.006	55.376 ± 4.335
	EVMD-PMB-CMHA-TCN	5.138 ± 0.187	3.961 ± 0.129	2.796 ± 0.091	0.870 ± 0.009	59.677 ± 4.059
	SVMD-TCN	4.912 ± 0.019	4.144 ± 0.049	3.000 ± 0.041	0.881 ± 0.001	**60.753** ± 2.895
	SVMD-CMHA-TCN	4.956 ± 0.041	4.068 ± 0.054	2.925 ± 0.052	0.879 ± 0.002	52.151 ± 3.442
	SVMD-PMB-TCN	4.975 ± 0.068	4.089 ± 0.082	2.945 ± 0.076	0.878 ± 0.003	52.688 ± 6.885
	SVMD-PMB-CMHA-TCN	5.275 ± 0.608	4.248 ± 0.336	3.047 ± 0.238	0.861 ± 0.035	52.688 ± 4.809
August 2022	Diff-TCN [27]	6.038 ± 0.001	4.436 ± 0.000	2.869 ± 0.000	0.372 ± 0.000	51.613 ± 0.000
	TCN	6.035 ± 0.015	4.400 ± 0.008	2.846 ± 0.005	0.373 ± 0.003	51.613 ± 0.000
	Diff-TCN	5.910 ± 0.037	4.176 ± 0.044	2.704 ± 0.029	0.398 ± 0.007	63.441 ± 4.433
	CMHA-TCN	6.043 ± 0.005	4.396 ± 0.006	2.844 ± 0.004	0.371 ± 0.001	51.613 ± 0.000
	Diff-CMHA-TCN	5.997 ± 0.021	4.371 ± 0.021	2.828 ± 0.014	0.380 ± 0.004	61.290 ± 3.725
	EVMD-TCN	5.857 ± 0.043	4.153 ± 0.074	2.696 ± 0.044	0.409 ± 0.009	67.204 ± 2.895
	EVMD-CMHA-TCN	5.831 ± 0.023	**4.024** ± 0.025	**2.618** ± 0.015	0.414 ± 0.005	65.054 ± 3.442
	EVMD-PMB-TCN	5.893 ± 0.022	4.204 ± 0.049	2.729 ± 0.029	0.402 ± 0.004	66.667 ± 2.404
	EVMD-PMB-CMHA-TCN	5.826 ± 0.126	4.341 ± 0.321	2.803 ± 0.198	0.415 ± 0.026	67.742 ± 5.268
	SVMD-TCN	5.856 ± 0.015	4.288 ± 0.034	2.775 ± 0.019	0.409 ± 0.003	**68.817** ± 4.809
	SVMD-CMHA-TCN	**5.770** ± 0.042	4.273 ± 0.049	2.758 ± 0.030	**0.426** ± 0.008	66.129 ± 1.613
	SVMD-PMB-TCN	5.837 ± 0.076	4.324 ± 0.083	2.796 ± 0.050	0.413 ± 0.015	65.054 ± 3.914
	SVMD-PMB-CMHA-TCN	5.816 ± 0.023	4.229 ± 0.049	2.735 ± 0.029	0.417 ± 0.005	66.667 ± 2.404
September 2022	Diff-TCN [27]	5.756 ± 0.000	4.096 ± 0.000	2.772 ± 0.000	0.303 ± 0.000	56.667 ± 0.000
	TCN	5.732 ± 0.014	4.043 ± 0.004	2.742 ± 0.002	0.309 ± 0.003	56.667 ± 0.000
	Diff-TCN	5.535 ± 0.035	3.818 ± 0.055	2.586 ± 0.036	0.356 ± 0.008	**72.778** ± 2.992
	CMHA-TCN	5.753 ± 0.010	4.055 ± 0.009	2.751 ± 0.005	0.304 ± 0.003	56.667 ± 0.000
	Diff-CMHA-TCN	5.691 ± 0.020	4.021 ± 0.025	2.721 ± 0.017	0.319 ± 0.005	71.111 ± 5.666
	EVMD-TCN	5.533 ± 0.015	3.662 ± 0.030	2.491 ± 0.018	0.356 ± 0.004	62.778 ± 1.242
	EVMD-CMHA-TCN	5.454 ± 0.059	**3.633** ± 0.050	**2.470** ± 0.030	0.374 ± 0.013	67.778 ± 2.485
	EVMD-PMB-TCN	5.502 ± 0.014	3.658 ± 0.062	2.480 ± 0.037	0.363 ± 0.003	65.556 ± 1.571
	EVMD-PMB-CMHA-TCN	5.497 ± 0.064	3.676 ± 0.117	2.498 ± 0.071	0.364 ± 0.015	63.889 ± 5.241
	SVMD-TCN	5.443 ± 0.046	3.748 ± 0.034	2.548 ± 0.019	0.377 ± 0.011	66.667 ± 3.849
	SVMD-CMHA-TCN	5.367 ± 0.036	3.720 ± 0.082	2.525 ± 0.045	0.394 ± 0.008	63.889 ± 2.291
	SVMD-PMB-TCN	5.425 ± 0.058	3.716 ± 0.042	2.521 ± 0.027	0.381 ± 0.013	71.667 ± 6.310
	SVMD-PMB-CMHA-TCN	**5.328** ± 0.032	3.731 ± 0.103	2.526 ± 0.060	**0.403** ± 0.007	65.556 ± 3.685
October 2022	**Diff-TCN** [27]	**2.699** ± 0.000	2.261 ± 0.000	1.573 ± 0.000	**0.177** ± 0.000	48.387 ± 0.000
	TCN	2.776 ± 0.014	2.289 ± 0.031	1.596 ± 0.021	0.129 ± 0.009	48.925 ± 1.202
	Diff-TCN	2.748 ± 0.014	**2.251** ± 0.005	**1.568** ± 0.004	0.146 ± 0.009	**55.376** ± 5.072
	CMHA-TCN	2.733 ± 0.025	2.255 ± 0.018	1.572 ± 0.013	0.156 ± 0.016	48.925 ± 1.202

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	2.726 ± 0.028	2.260 ± 0.005	1.573 ± 0.004	0.160 ± 0.017	48.925 ± 4.335
	EVMD-TCN	3.112 ± 0.162	2.438 ± 0.098	1.703 ± 0.070	−0.098 ± 0.118	47.312 ± 2.404
	EVMD-CMHA-TCN	2.995 ± 0.051	2.355 ± 0.009	1.645 ± 0.007	−0.014 ± 0.035	51.075 ± 2.895
	EVMD-PMB-TCN	3.153 ± 0.146	2.455 ± 0.092	1.715 ± 0.066	−0.126 ± 0.108	49.462 ± 2.404
	EVMD-PMB-CMHA-TCN	3.096 ± 0.150	2.424 ± 0.075	1.692 ± 0.054	−0.086 ± 0.108	49.462 ± 3.566
	SVMD-TCN	3.127 ± 0.077	2.536 ± 0.042	1.772 ± 0.030	−0.105 ± 0.054	46.237 ± 2.404
	SVMD-CMHA-TCN	2.969 ± 0.061	2.448 ± 0.023	1.706 ± 0.019	0.004 ± 0.041	46.774 ± 1.613
	SVMD-PMB-TCN	3.040 ± 0.042	2.493 ± 0.023	1.740 ± 0.017	−0.044 ± 0.029	45.699 ± 1.202
	SVMD-PMB-CMHA-TCN	3.030 ± 0.122	2.471 ± 0.067	1.725 ± 0.049	−0.039 ± 0.085	49.462 ± 4.809
November 2022	Diff-TCN [27]	6.202 ± 0.001	3.882 ± 0.003	2.892 ± 0.002	0.603 ± 0.000	56.667 ± 0.000
	TCN	6.185 ± 0.060	3.851 ± 0.072	2.879 ± 0.054	0.605 ± 0.008	59.444 ± 2.291
	Diff-TCN	6.223 ± 0.017	3.849 ± 0.034	2.873 ± 0.023	0.600 ± 0.002	52.778 ± 4.875
	CMHA-TCN	6.221 ± 0.038	3.832 ± 0.021	2.870 ± 0.013	0.600 ± 0.005	60.000 ± 1.925
	Diff-CMHA-TCN	6.217 ± 0.016	3.899 ± 0.035	2.904 ± 0.025	0.601 ± 0.002	50.556 ± 6.503
	EVMD-TCN	6.192 ± 0.052	3.798 ± 0.021	2.850 ± 0.018	0.604 ± 0.007	60.556 ± 6.503
	EVMD-CMHA-TCN	6.264 ± 0.047	3.805 ± 0.021	2.856 ± 0.017	0.595 ± 0.006	62.222 ± 6.285
	EVMD-PMB-TCN	6.228 ± 0.043	3.858 ± 0.040	2.894 ± 0.030	0.600 ± 0.006	55.000 ± 4.615
	EVMD-PMB-CMHA-TCN	6.314 ± 0.044	3.857 ± 0.052	2.899 ± 0.041	0.588 ± 0.006	57.222 ± 6.781
	SVMD-TCN	6.146 ± 0.029	3.740 ± 0.018	2.803 ± 0.014	0.610 ± 0.004	70.556 ± 2.291
	SVMD-CMHA-TCN	**6.087** ± 0.023	**3.665** ± 0.018	**2.747** ± 0.013	**0.617** ± 0.003	**72.222** ± 1.571
	SVMD-PMB-TCN	6.134 ± 0.059	3.746 ± 0.027	2.805 ± 0.020	0.612 ± 0.007	65.556 ± 5.329
	SVMD-PMB-CMHA-TCN	6.222 ± 0.090	3.793 ± 0.079	2.840 ± 0.054	0.600 ± 0.012	57.222 ± 8.259
December 2022	Diff-TCN [27]	2.090 ± 0.002	1.530 ± 0.004	1.053 ± 0.003	0.324 ± 0.002	64.516 ± 0.000
	TCN	2.103 ± 0.030	1.475 ± 0.025	1.017 ± 0.016	0.315 ± 0.020	62.903 ± 2.464
	Diff-TCN	2.095 ± 0.004	1.500 ± 0.008	1.033 ± 0.005	0.321 ± 0.003	54.839 ± 4.165
	CMHA-TCN	2.104 ± 0.036	1.469 ± 0.025	1.013 ± 0.018	0.315 ± 0.023	61.828 ± 3.914
	Diff-CMHA-TCN	2.089 ± 0.002	1.529 ± 0.012	1.052 ± 0.008	0.324 ± 0.001	59.140 ± 4.809
	EVMD-TCN	**2.052** ± 0.023	**1.460** ± 0.016	**1.005** ± 0.011	**0.348** ± 0.015	65.591 ± 1.521
	EVMD-CMHA-TCN	2.102 ± 0.067	1.508 ± 0.059	1.038 ± 0.042	0.315 ± 0.044	59.140 ± 7.133
	EVMD-PMB-TCN	2.070 ± 0.020	1.465 ± 0.019	1.009 ± 0.013	0.336 ± 0.013	**66.129** ± 2.464
	EVMD-PMB-CMHA-TCN	2.177 ± 0.249	1.596 ± 0.237	1.099 ± 0.164	0.257 ± 0.185	59.140 ± 5.483
	SVMD-TCN	2.182 ± 0.020	1.501 ± 0.007	1.035 ± 0.005	0.263 ± 0.013	59.140 ± 3.041
	SVMD-CMHA-TCN	2.223 ± 0.047	1.560 ± 0.094	1.074 ± 0.063	0.235 ± 0.033	55.914 ± 6.885
	SVMD-PMB-TCN	2.229 ± 0.085	1.518 ± 0.043	1.047 ± 0.030	0.230 ± 0.060	61.290 ± 3.226
	SVMD-PMB-CMHA-TCN	2.207 ± 0.026	1.535 ± 0.070	1.058 ± 0.047	0.246 ± 0.018	63.441 ± 3.041
January 2023	Diff-TCN [27]	4.431 ± 0.002	3.468 ± 0.002	2.046 ± 0.001	0.829 ± 0.000	64.516 ± 0.000
	TCN	4.371 ± 0.068	3.445 ± 0.081	2.026 ± 0.047	0.834 ± 0.005	57.527 ± 8.818
	Diff-TCN	4.418 ± 0.018	3.359 ± 0.035	1.980 ± 0.021	0.830 ± 0.001	64.516 ± 5.587
	CMHA-TCN	4.434 ± 0.088	3.523 ± 0.132	2.070 ± 0.076	0.829 ± 0.007	53.226 ± 11.594
	Diff-CMHA-TCN	4.401 ± 0.033	3.343 ± 0.080	1.971 ± 0.048	0.831 ± 0.003	**66.129**± 1.613
	EVMD-TCN	4.476 ± 0.084	3.388 ± 0.113	1.989 ± 0.067	0.825 ± 0.007	62.366 ± 7.372
	EVMD-CMHA-TCN	4.434 ± 0.033	3.369 ± 0.041	1.977 ± 0.023	0.829 ± 0.003	66.129 ± 4.059
	EVMD-PMB-TCN	4.418 ± 0.056	3.338 ± 0.072	1.963 ± 0.042	0.830 ± 0.004	60.215 ± 4.809
	EVMD-PMB-CMHA-TCN	4.489 ± 0.103	3.462 ± 0.106	2.031 ± 0.062	0.824 ± 0.008	58.065 ± 6.177
	SVMD-TCN	4.332 ± 0.055	3.312 ± 0.075	1.947 ± 0.043	0.837 ± 0.004	61.290 ± 6.452
	SVMD-CMHA-TCN	**4.284** ± 0.034	**3.275** ± 0.062	**1.926** ± 0.035	**0.840** ± 0.003	64.516 ± 6.968
	SVMD-PMB-TCN	4.300 ± 0.067	3.305 ± 0.074	1.943 ± 0.043	0.839 ± 0.005	60.753 ± 5.715
	SVMD-PMB-CMHA-TCN	4.337 ± 0.079	3.306 ± 0.116	1.940 ± 0.068	0.836 ± 0.006	62.366 ± 3.566
February 2023	Diff-TCN [27]	4.470 ± 0.003	3.321 ± 0.002	2.089 ± 0.001	0.662 ± 0.000	42.857 ± 0.000
	TCN	4.365 ± 0.076	3.239 ± 0.036	2.039 ± 0.024	0.678 ± 0.011	54.167 ± 10.797
	Diff-TCN	4.502 ± 0.045	3.304 ± 0.034	2.077 ± 0.021	0.657 ± 0.007	47.024 ± 4.333
	CMHA-TCN	4.303 ± 0.052	3.192 ± 0.044	2.009 ± 0.028	0.687 ± 0.008	**57.143**± 4.124
	Diff-CMHA-TCN	4.437 ± 0.073	3.263 ± 0.085	2.050 ± 0.054	0.667 ± 0.011	43.452 ± 4.799
	EVMD-TCN	4.316 ± 0.067	3.179 ± 0.075	2.003 ± 0.048	0.685 ± 0.010	46.429 ± 5.051
	EVMD-CMHA-TCN	4.362 ± 0.072	3.238 ± 0.087	2.040 ± 0.056	0.678 ± 0.011	47.619 ± 3.367
	EVMD-PMB-TCN	**4.257** ± 0.083	**3.113** ± 0.089	**1.958** ± 0.057	**0.694** ± 0.012	50.595 ± 2.454
	EVMD-PMB-CMHA-TCN	4.352 ± 0.213	3.248 ± 0.195	2.048 ± 0.125	0.679 ± 0.032	49.405 ± 4.333
	SVMD-TCN	4.388 ± 0.041	3.282 ± 0.036	2.062 ± 0.024	0.674 ± 0.006	47.619 ± 3.948
	SVMD-CMHA-TCN	4.370 ± 0.075	3.265 ± 0.075	2.052 ± 0.049	0.677 ± 0.011	45.833 ± 5.982
	SVMD-PMB-TCN	4.314 ± 0.050	3.216 ± 0.041	2.022 ± 0.026	0.685 ± 0.007	51.191 ± 2.662
	SVMD-PMB-CMHA-TCN	4.366 ± 0.163	3.269 ± 0.157	2.055 ± 0.100	0.677 ± 0.024	47.619 ± 10.241
March 2023	Diff-TCN [27]	4.643 ± 0.000	4.002 ± 0.002	2.666 ± 0.001	0.394 ± 0.000	54.839 ± 0.000
	TCN	4.551 ± 0.038	3.903 ± 0.058	2.601 ± 0.037	0.418 ± 0.010	59.677 ± 3.088
	Diff-TCN	4.707 ± 0.078	3.930 ± 0.044	2.620 ± 0.028	0.377 ± 0.021	55.376 ± 6.822
	CMHA-TCN	**4.548** ± 0.039	**3.877** ± 0.047	**2.585** ± 0.030	**0.419** ± 0.010	**63.978** ± 7.546
	Diff-CMHA-TCN	4.723 ± 0.050	3.984 ± 0.046	2.655 ± 0.030	0.373 ± 0.013	55.914 ± 4.023
	EVMD-TCN	4.846 ± 0.019	3.990 ± 0.024	2.663 ± 0.017	0.340 ± 0.005	53.226 ± 4.059
	EVMD-CMHA-TCN	4.832 ± 0.031	3.947 ± 0.029	2.638 ± 0.021	0.344 ± 0.008	50.538 ± 4.809
	EVMD-PMB-TCN	4.854 ± 0.017	3.979 ± 0.025	2.655 ± 0.017	0.338 ± 0.005	54.839 ± 6.452
	EVMD-PMB-CMHA-TCN	4.885 ± 0.060	3.962 ± 0.064	2.646 ± 0.046	0.329 ± 0.016	54.301 ± 7.313
	SVMD-TCN	4.814 ± 0.035	4.010 ± 0.035	2.677 ± 0.023	0.349 ± 0.009	48.387 ± 1.862
	SVMD-CMHA-TCN	4.819 ± 0.022	4.014 ± 0.026	2.679 ± 0.017	0.348 ± 0.006	50.000 ± 3.088
	SVMD-PMB-TCN	4.795 ± 0.021	3.989 ± 0.013	2.663 ± 0.009	0.354 ± 0.005	50.000 ± 1.613
	SVMD-PMB-CMHA-TCN	4.852 ± 0.050	3.983 ± 0.059	2.661 ± 0.037	0.339 ± 0.014	55.376 ± 4.718
April 2023	Diff-TCN [27]	2.897 ± 0.003	1.992 ± 0.002	1.268 ± 0.001	0.210 ± 0.001	56.667 ± 0.000
	TCN	2.850 ± 0.042	1.977 ± 0.042	1.259 ± 0.028	0.235 ± 0.022	59.444 ± 2.992
	Diff-TCN	2.834 ± 0.035	1.981 ± 0.029	1.262 ± 0.019	0.244 ± 0.019	57.778 ± 3.685
	CMHA-TCN	2.829 ± 0.031	**1.966** ± 0.018	**1.251** ± 0.011	0.247 ± 0.017	61.111 ± 5.329

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	2.850 ± 0.042	1.977 ± 0.030	1.259 ± 0.020	0.235 ± 0.023	57.222 ± 5.906
	EVMD-TCN	2.740 ± 0.026	1.992 ± 0.017	1.270 ± 0.009	0.293 ± 0.013	53.333 ± 5.092
	EVMD-CMHA-TCN	**2.698** ± 0.015	1.969 ± 0.009	1.255 ± 0.005	**0.315** ± 0.008	50.556 ± 4.045
	EVMD-PMB-TCN	2.747 ± 0.019	2.005 ± 0.021	1.278 ± 0.012	0.290 ± 0.010	55.000 ± 3.191
	EVMD-PMB-CMHA-TCN	2.730 ± 0.058	2.041 ± 0.122	1.299 ± 0.073	0.299 ± 0.030	56.111 ± 4.045
	SVMD-TCN	2.826 ± 0.006	1.983 ± 0.008	1.262 ± 0.005	0.248 ± 0.003	**72.222** ± 2.485
	SVMD-CMHA-TCN	2.821 ± 0.012	1.990 ± 0.014	1.266 ± 0.009	0.251 ± 0.006	68.333 ± 2.546
	SVMD-PMB-TCN	2.838 ± 0.011	2.011 ± 0.022	1.279 ± 0.013	0.242 ± 0.006	66.667 ± 7.454
	SVMD-PMB-CMHA-TCN	2.781 ± 0.032	1.989 ± 0.010	1.267 ± 0.006	0.272 ± 0.017	65.000 ± 4.194
May 2023	Diff-TCN [27]	2.078 ± 0.002	1.489 ± 0.002	0.978 ± 0.001	0.260 ± 0.001	38.710 ± 0.000
	TCN	2.037 ± 0.038	1.460 ± 0.037	0.958 ± 0.025	0.288 ± 0.027	41.398 ± 2.895
	Diff-TCN	2.056 ± 0.033	**1.452** ± 0.026	**0.954** ± 0.018	0.275 ± 0.024	41.398 ± 3.442
	CMHA-TCN	2.098 ± 0.090	1.511 ± 0.083	0.994 ± 0.056	0.244 ± 0.066	41.398 ± 3.442
	Diff-CMHA-TCN	2.146 ± 0.096	1.531 ± 0.082	1.007 ± 0.055	0.209 ± 0.072	39.247 ± 1.202
	EVMD-TCN	2.070 ± 0.054	1.436 ± 0.047	0.946 ± 0.032	0.265 ± 0.038	**50.538** ± 3.041
	EVMD-CMHA-TCN	2.117 ± 0.033	1.468 ± 0.028	0.967 ± 0.018	0.231 ± 0.024	48.387 ± 0.000
	EVMD-PMB-TCN	2.112 ± 0.029	1.471 ± 0.025	0.969 ± 0.017	0.235 ± 0.021	47.849 ± 1.202
	EVMD-PMB-CMHA-TCN	2.146 ± 0.148	1.514 ± 0.147	0.997 ± 0.098	0.206 ± 0.112	47.312 ± 3.041
	SVMD-TCN	2.063 ± 0.041	1.524 ± 0.042	1.001 ± 0.028	0.270 ± 0.029	44.624 ± 4.718
	SVMD-CMHA-TCN	2.067 ± 0.019	1.526 ± 0.020	1.002 ± 0.013	0.267 ± 0.013	40.860 ± 3.566
	SVMD-PMB-TCN	**2.007** ± 0.039	1.467 ± 0.040	0.963 ± 0.027	**0.309** ± 0.027	48.387 ± 5.268
	SVMD-PMB-CMHA-TCN	2.106 ± 0.086	1.540 ± 0.090	1.013 ± 0.060	0.238 ± 0.062	43.011 ± 5.157
June 2023	Diff-TCN [27]	3.255 ± 0.003	2.524 ± 0.005	1.702 ± 0.003	0.906 ± 0.000	66.667 ± 0.000
	TCN	3.374 ± 0.084	2.617 ± 0.107	1.765 ± 0.074	0.899 ± 0.005	57.778 ± 3.685
	Diff-TCN	3.284 ± 0.003	2.594 ± 0.006	1.749 ± 0.004	0.904 ± 0.000	60.000 ± 3.333
	CMHA-TCN	3.302 ± 0.037	2.558 ± 0.070	1.727 ± 0.052	0.903 ± 0.002	60.556 ± 4.045
	Diff-CMHA-TCN	3.241 ± 0.028	2.530 ± 0.033	1.707 ± 0.022	0.907 ± 0.002	57.778 ± 8.089
	EVMD-TCN	3.318 ± 0.048	2.663 ± 0.031	1.795 ± 0.019	0.902 ± 0.003	59.444 ± 9.510
	EVMD-CMHA-TCN	3.401 ± 0.019	2.750 ± 0.019	1.854 ± 0.013	0.897 ± 0.001	56.111 ± 2.291
	EVMD-PMB-TCN	3.309 ± 0.020	2.647 ± 0.013	1.784 ± 0.008	0.903 ± 0.001	57.778 ± 8.535
	EVMD-PMB-CMHA-TCN	3.502 ± 0.059	2.826 ± 0.041	1.903 ± 0.026	0.891 ± 0.004	53.333 ± 3.333
	SVMD-TCN	3.261 ± 0.043	2.505 ± 0.047	1.683 ± 0.032	0.906 ± 0.003	61.667 ± 3.727
	SVMD-CMHA-TCN	3.234 ± 0.017	**2.495** ± 0.012	**1.678** ± 0.008	0.907 ± 0.001	65.556 ± 4.157
	SVMD-PMB-TCN	**3.209** ± 0.071	2.497 ± 0.109	1.683 ± 0.073	**0.909** ± 0.004	**72.222** ± 8.535
	SVMD-PMB-CMHA-TCN	3.218 ± 0.038	2.533 ± 0.031	1.705 ± 0.019	0.908 ± 0.002	67.778 ± 6.849
July 2023	Diff-TCN [27]	2.029 ± 0.004	1.619 ± 0.002	0.987 ± 0.001	0.255 ± 0.003	51.613 ± 0.000
	TCN	1.916 ± 0.024	1.560 ± 0.036	0.950 ± 0.022	0.336 ± 0.016	57.527 ± 9.752
	Diff-TCN	1.931 ± 0.017	1.526 ± 0.011	0.930 ± 0.007	0.325 ± 0.012	56.452 ± 4.466
	CMHA-TCN	1.905 ± 0.020	1.556 ± 0.038	0.948 ± 0.023	0.343 ± 0.014	53.763 ± 9.796
	Diff-CMHA-TCN	1.953 ± 0.039	1.553 ± 0.024	0.947 ± 0.015	0.310 ± 0.028	55.914 ± 7.828
	EVMD-TCN	1.839 ± 0.003	1.485 ± 0.012	0.904 ± 0.007	0.388 ± 0.002	57.527 ± 3.442
	EVMD-CMHA-TCN	**1.827** ± 0.017	1.477 ± 0.032	0.899 ± 0.019	**0.396** ± 0.011	**59.677** ± 4.839
	EVMD-PMB-TCN	1.865 ± 0.015	1.519 ± 0.020	0.925 ± 0.012	0.370 ± 0.011	53.763 ± 5.790
	EVMD-PMB-CMHA-TCN	1.862 ± 0.064	1.508 ± 0.081	0.918 ± 0.049	0.372 ± 0.044	54.839 ± 5.587
	SVMD-TCN	1.866 ± 0.015	**1.470** ± 0.017	**0.895** ± 0.010	0.370 ± 0.010	59.140 ± 1.521
	SVMD-CMHA-TCN	1.886 ± 0.014	1.495 ± 0.030	0.911 ± 0.018	0.356 ± 0.010	59.677 ± 4.059
	SVMD-PMB-TCN	1.968 ± 0.065	1.540 ± 0.053	0.939 ± 0.033	0.299 ± 0.047	56.989 ± 3.566
	SVMD-PMB-CMHA-TCN	1.878 ± 0.020	1.522 ± 0.028	0.927 ± 0.017	0.362 ± 0.014	59.677 ± 2.464
August 2023	Diff-TCN [27]	3.082 ± 0.002	1.981 ± 0.000	1.351 ± 0.000	0.830 ± 0.000	54.839 ± 0.000
	TCN	**2.997** ± 0.026	**1.856** ± 0.029	**1.266** ± 0.021	**0.839** ± 0.003	58.065 ± 2.634
	Diff-TCN	3.118 ± 0.016	1.945 ± 0.002	1.327 ± 0.001	0.826 ± 0.002	51.613 ± 2.634
	CMHA-TCN	3.030 ± 0.050	1.864 ± 0.029	1.271 ± 0.020	0.836 ± 0.005	**58.602** ± 4.335
	Diff-CMHA-TCN	3.112 ± 0.042	1.988 ± 0.018	1.356 ± 0.012	0.826 ± 0.005	49.462 ± 4.433
	EVMD-TCN	3.518 ± 0.054	2.322 ± 0.040	1.590 ± 0.027	0.778 ± 0.007	38.710 ± 4.928
	EVMD-CMHA-TCN	3.511 ± 0.052	2.289 ± 0.034	1.567 ± 0.023	0.779 ± 0.006	45.161 ± 4.928
	EVMD-PMB-TCN	3.497 ± 0.052	2.329 ± 0.037	1.593 ± 0.024	0.781 ± 0.006	40.860 ± 3.041
	EVMD-PMB-CMHA-TCN	3.499 ± 0.085	2.306 ± 0.059	1.578 ± 0.039	0.780 ± 0.011	44.086 ± 4.809
	SVMD-TCN	3.109 ± 0.024	1.935 ± 0.011	1.321 ± 0.008	0.827 ± 0.003	52.688 ± 2.404
	SVMD-CMHA-TCN	3.121 ± 0.039	1.946 ± 0.016	1.328 ± 0.011	0.826 ± 0.004	53.763 ± 3.041
	SVMD-PMB-TCN	3.088 ± 0.053	1.946 ± 0.026	1.327 ± 0.018	0.829 ± 0.006	48.387 ± 2.634
	SVMD-PMB-CMHA-TCN	3.185 ± 0.061	2.015 ± 0.022	1.375 ± 0.015	0.818 ± 0.007	49.462 ± 4.023
September 2023	Diff-TCN [27]	1.979 ± 0.001	1.497 ± 0.000	1.046 ± 0.000	0.439 ± 0.001	56.667 ± 0.000
	TCN	2.030 ± 0.060	1.521 ± 0.042	1.064 ± 0.031	0.409 ± 0.035	56.667 ± 0.000
	Diff-TCN	1.956 ± 0.001	1.508 ± 0.004	1.053 ± 0.003	0.452 ± 0.001	45.000 ± 3.191
	CMHA-TCN	1.976 ± 0.027	1.475 ± 0.012	1.031 ± 0.009	0.440 ± 0.015	56.667 ± 0.000
	Diff-CMHA-TCN	1.977 ± 0.013	1.519 ± 0.016	1.061 ± 0.011	0.440 ± 0.007	52.778 ± 3.557
	EVMD-TCN	1.889 ± 0.018	1.432 ± 0.015	1.002 ± 0.010	0.489 ± 0.010	52.778 ± 2.291
	EVMD-CMHA-TCN	1.892 ± 0.032	**1.428** ± 0.018	**0.999** ± 0.012	0.487 ± 0.017	**57.222** ± 2.291
	EVMD-PMB-TCN	**1.876** ± 0.023	1.430 ± 0.011	1.000 ± 0.007	**0.496** ± 0.012	53.889 ± 1.242
	EVMD-PMB-CMHA-TCN	1.904 ± 0.044	1.461 ± 0.049	1.021 ± 0.033	0.480 ± 0.024	54.444 ± 7.370
	SVMD-TCN	2.013 ± 0.021	1.551 ± 0.015	1.085 ± 0.011	0.419 ± 0.012	50.000 ± 0.000
	SVMD-CMHA-TCN	1.996 ± 0.035	1.550 ± 0.014	1.083 ± 0.011	0.429 ± 0.020	51.111 ± 1.571
	SVMD-PMB-TCN	2.019 ± 0.031	1.553 ± 0.029	1.087 ± 0.021	0.416 ± 0.018	51.111 ± 2.485
	SVMD-PMB-CMHA-TCN	2.026 ± 0.025	1.570 ± 0.009	1.098 ± 0.008	0.412 ± 0.015	50.556 ± 2.992
October 2023	Diff-TCN [27]	2.834 ± 0.000	2.003 ± 0.000	1.269 ± 0.000	0.831 ± 0.000	58.065 ± 0.000
	TCN	2.872 ± 0.025	1.973 ± 0.013	1.251 ± 0.009	0.827 ± 0.003	58.065 ± 5.889
	Diff-TCN	**2.828** ± 0.011	**1.961** ± 0.005	**1.243** ± 0.003	**0.832** ± 0.001	58.602 ± 2.895
	CMHA-TCN	2.920 ± 0.062	2.016 ± 0.048	1.274 ± 0.028	0.821 ± 0.008	53.226 ± 2.464

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	2.856 ± 0.035	1.996 ± 0.009	1.264 ± 0.006	0.828 ± 0.004	58.065 ± 8.118
	EVMD-TCN	2.995 ± 0.026	2.167 ± 0.018	1.370 ± 0.011	0.811 ± 0.003	48.925 ± 4.335
	EVMD-CMHA-TCN	3.026 ± 0.056	2.173 ± 0.036	1.372 ± 0.022	0.807 ± 0.007	50.000 ± 2.464
	EVMD-PMB-TCN	2.928 ± 0.027	2.127 ± 0.019	1.345 ± 0.012	0.820 ± 0.003	55.914 ± 3.566
	EVMD-PMB-CMHA-TCN	3.013 ± 0.054	2.180 ± 0.029	1.377 ± 0.017	0.809 ± 0.007	54.301 ± 6.293
	SVMD-TCN	2.926 ± 0.066	2.019 ± 0.063	1.276 ± 0.037	0.820 ± 0.008	60.753 ± 5.072
	SVMD-CMHA-TCN	2.893 ± 0.025	1.993 ± 0.019	1.261 ± 0.011	0.824 ± 0.003	56.989 ± 4.023
	SVMD-PMB-TCN	2.877 ± 0.040	1.983 ± 0.030	1.255 ± 0.018	0.826 ± 0.005	**62.366** ± 1.521
	SVMD-PMB-CMHA-TCN	2.976 ± 0.098	2.056 ± 0.075	1.298 ± 0.045	0.814 ± 0.012	55.376 ± 8.415
November 2023	Diff-TCN [27]	2.928 ± 0.000	2.330 ± 0.000	1.407 ± 0.000	0.400 ± 0.000	50.000 ± 0.000
	TCN	2.875 ± 0.009	2.288 ± 0.009	1.380 ± 0.005	0.422 ± 0.004	50.556 ± 4.479
	Diff-TCN	2.900 ± 0.005	2.303 ± 0.002	1.390 ± 0.002	0.412 ± 0.002	42.222 ± 1.571
	CMHA-TCN	2.883 ± 0.032	2.293 ± 0.029	1.381 ± 0.016	0.418 ± 0.013	62.222 ± 4.581
	Diff-CMHA-TCN	2.925 ± 0.020	2.315 ± 0.012	1.397 ± 0.007	0.402 ± 0.008	52.778 ± 5.241
	EVMD-TCN	2.970 ± 0.026	2.257 ± 0.021	1.361 ± 0.013	0.383 ± 0.011	58.889 ± 6.285
	EVMD-CMHA-TCN	2.953 ± 0.016	2.253 ± 0.037	1.359 ± 0.022	0.390 ± 0.006	63.889 ± 4.479
	EVMD-PMB-TCN	2.995 ± 0.019	2.323 ± 0.032	1.400 ± 0.018	0.373 ± 0.008	60.000 ± 6.383
	EVMD-PMB-CMHA-TCN	2.920 ± 0.030	**2.240** ± 0.021	**1.351** ± 0.013	0.403 ± 0.012	**68.333** ± 2.546
	SVMD-TCN	**2.873** ± 0.019	2.288 ± 0.021	1.378 ± 0.012	**0.422** ± 0.008	52.222 ± 3.685
	SVMD-CMHA-TCN	2.881 ± 0.006	2.287 ± 0.006	1.377 ± 0.004	0.419 ± 0.003	51.111 ± 3.685
	SVMD-PMB-TCN	2.918 ± 0.016	2.350 ± 0.015	1.415 ± 0.009	0.404 ± 0.006	46.667 ± 2.722
	SVMD-PMB-CMHA-TCN	2.892 ± 0.011	2.315 ± 0.013	1.394 ± 0.008	0.415 ± 0.004	45.000 ± 3.727
December 2023	Diff-TCN [27]	2.808 ± 0.000	1.997 ± 0.001	1.165 ± 0.000	0.257 ± 0.000	48.387 ± 0.000
	TCN	2.760 ± 0.024	2.034 ± 0.038	1.184 ± 0.023	0.282 ± 0.013	50.538 ± 1.521
	Diff-TCN	2.781 ± 0.004	1.998 ± 0.003	1.166 ± 0.002	0.272 ± 0.002	50.538 ± 1.521
	CMHA-TCN	2.800 ± 0.059	2.098 ± 0.096	1.219 ± 0.054	0.262 ± 0.031	47.849 ± 2.217
	Diff-CMHA-TCN	2.788 ± 0.013	1.969 ± 0.014	1.148 ± 0.008	0.268 ± 0.007	54.301 ± 2.217
	EVMD-TCN	2.804 ± 0.018	2.085 ± 0.030	1.213 ± 0.017	0.260 ± 0.009	52.688 ± 2.404
	EVMD-CMHA-TCN	2.800 ± 0.023	2.108 ± 0.048	1.226 ± 0.026	0.262 ± 0.012	51.613 ± 1.862
	EVMD-PMB-TCN	2.806 ± 0.031	2.068 ± 0.053	1.203 ± 0.029	0.258 ± 0.016	52.151 ± 2.895
	EVMD-PMB-CMHA-TCN	2.802 ± 0.046	2.124 ± 0.065	1.235 ± 0.037	0.261 ± 0.025	51.613 ± 3.725
	SVMD-TCN	2.716 ± 0.052	1.956 ± 0.084	1.136 ± 0.048	0.305 ± 0.027	58.065 ± 3.226
	SVMD-CMHA-TCN	**2.689** ± 0.006	**1.894** ± 0.021	**1.101** ± 0.011	**0.319** ± 0.003	**61.290** ± 2.634
	SVMD-PMB-TCN	2.718 ± 0.016	1.907 ± 0.043	1.109 ± 0.024	0.304 ± 0.008	60.753 ± 3.914
	SVMD-PMB-CMHA-TCN	2.769 ± 0.132	2.034 ± 0.186	1.181 ± 0.106	0.276 ± 0.072	54.301 ± 2.895
January 2024	Diff-TCN [27]	5.035 ± 0.001	3.855 ± 0.000	2.465 ± 0.000	0.316 ± 0.000	58.065 ± 0.000
	TCN	4.893 ± 0.032	3.749 ± 0.028	2.398 ± 0.018	0.354 ± 0.009	**67.204** ± 4.335
	Diff-TCN	4.815 ± 0.008	3.689 ± 0.007	2.362 ± 0.004	0.374 ± 0.002	63.441 ± 2.404
	CMHA-TCN	4.901 ± 0.095	3.776 ± 0.049	2.415 ± 0.030	0.351 ± 0.025	62.903 ± 5.185
	Diff-CMHA-TCN	4.900 ± 0.053	3.753 ± 0.041	2.402 ± 0.025	0.352 ± 0.014	62.366 ± 2.404
	EVMD-TCN	4.691 ± 0.018	3.573 ± 0.014	2.286 ± 0.009	0.406 ± 0.005	60.215 ± 1.521
	EVMD-CMHA-TCN	**4.667** ± 0.016	**3.543** ± 0.015	**2.269** ± 0.009	**0.412** ± 0.004	61.828 ± 2.895
	EVMD-PMB-TCN	4.717 ± 0.028	3.590 ± 0.034	2.295 ± 0.020	0.399 ± 0.007	58.065 ± 3.226
	EVMD-PMB-CMHA-TCN	4.698 ± 0.017	3.616 ± 0.025	2.315 ± 0.014	0.404 ± 0.004	57.527 ± 2.895
	SVMD-TCN	4.762 ± 0.021	3.738 ± 0.020	2.389 ± 0.011	0.388 ± 0.005	52.688 ± 4.023
	SVMD-CMHA-TCN	4.797 ± 0.023	3.739 ± 0.012	2.391 ± 0.008	0.379 ± 0.006	56.452 ± 3.088
	SVMD-PMB-TCN	4.784 ± 0.038	3.723 ± 0.021	2.380 ± 0.014	0.382 ± 0.010	57.527 ± 5.072
	SVMD-PMB-CMHA-TCN	4.739 ± 0.045	3.714 ± 0.040	2.375 ± 0.025	0.394 ± 0.012	56.452 ± 3.088
February 2024	Diff-TCN [27]	12.429 ± 0.000	4.783 ± 0.001	4.100 ± 0.001	0.518 ± 0.000	48.276 ± 0.000
	TCN	12.225 ± 0.071	5.092 ± 0.228	4.364 ± 0.191	0.533 ± 0.005	51.149 ± 3.095
	Diff-TCN	11.996 ± 0.022	**4.606** ± 0.008	**3.960** ± 0.006	0.551 ± 0.002	41.954 ± 1.285
	CMHA-TCN	12.183 ± 0.123	5.169 ± 0.163	4.431 ± 0.136	0.536 ± 0.009	49.425 ± 2.570
	Diff-CMHA-TCN	12.152 ± 0.105	4.753 ± 0.061	4.074 ± 0.048	0.539 ± 0.008	41.954 ± 4.633
	EVMD-TCN	11.993 ± 0.008	4.997 ± 0.124	4.274 ± 0.106	0.551 ± 0.001	**58.621** ± 3.982
	EVMD-CMHA-TCN	11.847 ± 0.049	4.882 ± 0.141	4.188 ± 0.121	0.562 ± 0.004	52.874 ± 3.812
	EVMD-PMB-TCN	12.007 ± 0.038	4.936 ± 0.089	4.218 ± 0.075	0.550 ± 0.003	55.172 ± 5.267
	EVMD-PMB-CMHA-TCN	**11.817** ± 0.041	4.780 ± 0.165	4.104 ± 0.140	**0.564** ± 0.003	54.023 ± 4.301
	SVMD-TCN	12.113 ± 0.057	5.149 ± 0.159	4.416 ± 0.138	0.542 ± 0.004	48.276 ± 5.267
	SVMD-CMHA-TCN	12.047 ± 0.050	5.011 ± 0.085	4.301 ± 0.073	0.547 ± 0.004	50.000 ± 1.724
	SVMD-PMB-TCN	12.094 ± 0.036	5.005 ± 0.083	4.294 ± 0.071	0.543 ± 0.003	45.977 ± 3.812
	SVMD-PMB-CMHA-TCN	12.001 ± 0.089	5.072 ± 0.084	4.351 ± 0.067	0.550 ± 0.007	48.276 ± 2.816
March 2024	**Diff-TCN** [27]	4.458 ± 0.000	**2.312** ± 0.002	**1.702** ± 0.002	0.783 ± 0.000	51.613 ± 0.000
	TCN	4.457 ± 0.012	2.597 ± 0.102	1.934 ± 0.087	0.783 ± 0.001	52.688 ± 1.521
	Diff-TCN	4.447 ± 0.002	2.317 ± 0.007	1.705 ± 0.006	0.784 ± 0.000	57.527 ± 1.202
	CMHA-TCN	4.440 ± 0.019	2.630 ± 0.178	1.970 ± 0.154	0.785 ± 0.002	51.613 ± 0.000
	Diff-CMHA-TCN	4.463 ± 0.026	2.314 ± 0.067	1.704 ± 0.050	0.783 ± 0.003	55.376 ± 2.895
	EVMD-TCN	4.523 ± 0.018	2.484 ± 0.101	1.844 ± 0.087	0.777 ± 0.002	50.538 ± 5.483
	EVMD-CMHA-TCN	4.518 ± 0.023	2.504 ± 0.080	1.857 ± 0.069	0.777 ± 0.002	53.226 ± 5.185
	EVMD-PMB-TCN	4.510 ± 0.008	2.532 ± 0.064	1.886 ± 0.055	0.778 ± 0.001	52.151 ± 1.202
	EVMD-PMB-CMHA-TCN	4.557 ± 0.063	2.671 ± 0.198	1.993 ± 0.167	0.773 ± 0.006	54.839 ± 1.862
	SVMD-TCN	4.471 ± 0.078	2.703 ± 0.344	2.037 ± 0.290	0.782 ± 0.008	55.914 ± 6.885
	SVMD-CMHA-TCN	4.440 ± 0.030	2.672 ± 0.161	2.011 ± 0.136	0.785 ± 0.003	57.527 ± 2.895
	SVMD-PMB-TCN	4.430 ± 0.014	2.554 ± 0.097	1.911 ± 0.081	0.786 ± 0.001	57.527 ± 2.217
	SVMD-PMB-CMHA-TCN	**4.423** ± 0.028	2.627 ± 0.152	1.972 ± 0.131	**0.787** ± 0.003	**61.290** ± 4.562
April 2024	Diff-TCN [27]	4.463 ± 0.001	3.520 ± 0.003	2.854 ± 0.002	0.428 ± 0.000	53.333 ± 0.000
	TCN	4.443 ± 0.026	3.495 ± 0.022	2.836 ± 0.018	0.433 ± 0.007	54.444 ± 1.571
	Diff-TCN	4.462 ± 0.002	3.537 ± 0.002	2.871 ± 0.002	0.428 ± 0.000	53.889 ± 1.242
	CMHA-TCN	4.435 ± 0.011	3.504 ± 0.020	2.842 ± 0.014	0.435 ± 0.003	52.778 ± 9.702

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	4.508 ± 0.022	3.589 ± 0.020	2.913 ± 0.015	0.417 ± 0.006	48.889 ± 3.143
	EVMD-TCN	**4.413** ± 0.011	**3.481** ± 0.014	**2.833** ± 0.011	**0.441** ± 0.003	60.000 ± 3.333
	EVMD-CMHA-TCN	4.426 ± 0.015	3.484 ± 0.016	2.834 ± 0.011	0.438 ± 0.004	58.889 ± 2.485
	EVMD-PMB-TCN	4.470 ± 0.037	3.499 ± 0.012	2.848 ± 0.011	0.426 ± 0.009	56.667 ± 3.333
	EVMD-PMB-CMHA-TCN	4.518 ± 0.081	3.523 ± 0.033	2.873 ± 0.030	0.414 ± 0.021	55.556 ± 3.685
	SVMD-TCN	4.444 ± 0.075	3.575 ± 0.059	2.908 ± 0.053	0.433 ± 0.019	55.556 ± 4.969
	SVMD-CMHA-TCN	4.413 ± 0.017	3.548 ± 0.016	2.885 ± 0.014	0.441 ± 0.004	60.000 ± 1.925
	SVMD-PMB-TCN	4.418 ± 0.009	3.553 ± 0.008	2.890 ± 0.008	0.440 ± 0.002	58.333 ± 3.191
	SVMD-PMB-CMHA-TCN	4.417 ± 0.019	3.539 ± 0.014	2.879 ± 0.012	0.440 ± 0.005	**61.667** ± 3.191
May 2024	Diff-TCN [27]	2.980 ± 0.003	2.096 ± 0.003	1.563 ± 0.002	0.768 ± 0.000	64.516 ± 0.000
	TCN	2.923 ± 0.009	2.071 ± 0.013	1.542 ± 0.009	0.777 ± 0.001	58.065 ± 7.679
	Diff-TCN	2.828 ± 0.011	1.987 ± 0.009	1.474 ± 0.007	0.791 ± 0.002	63.441 ± 2.404
	CMHA-TCN	2.985 ± 0.054	2.110 ± 0.053	1.571 ± 0.038	0.768 ± 0.009	55.376 ± 11.986
	Diff-CMHA-TCN	2.879 ± 0.039	2.028 ± 0.039	1.509 ± 0.029	0.784 ± 0.006	61.828 ± 6.293
	EVMD-TCN	2.749 ± 0.063	1.913 ± 0.062	1.414 ± 0.045	0.803 ± 0.009	61.828 ± 4.718
	EVMD-CMHA-TCN	2.736 ± 0.032	1.892 ± 0.031	1.396 ± 0.022	0.805 ± 0.004	60.753 ± 5.072
	EVMD-PMB-TCN	**2.670** ± 0.027	1.832 ± 0.021	1.356 ± 0.015	0.814 ± 0.004	**67.742** ± 3.725
	EVMD-PMB-CMHA-TCN	**2.670** ± 0.118	**1.821** ± 0.092	**1.343** ± 0.065	**0.814** ± 0.017	64.516 ± 6.968
	SVMD-TCN	2.750 ± 0.080	1.933 ± 0.058	1.430 ± 0.041	0.803 ± 0.011	58.602 ± 3.442
	SVMD-CMHA-TCN	2.693 ± 0.028	1.892 ± 0.024	1.401 ± 0.017	0.811 ± 0.004	59.140 ± 4.809
	SVMD-PMB-TCN	2.686 ± 0.035	1.895 ± 0.022	1.401 ± 0.017	0.812 ± 0.005	55.376 ± 2.895
	SVMD-PMB-CMHA-TCN	2.724 ± 0.042	1.919 ± 0.038	1.418 ± 0.029	0.806 ± 0.006	53.763 ± 2.404
June 2024	**Diff-TCN** [27]	5.318 ± 0.001	4.193 ± 0.004	2.519 ± 0.002	0.524 ± 0.000	**63.333** ± 0.000
	TCN	5.257 ± 0.024	4.193 ± 0.035	2.520 ± 0.022	0.535 ± 0.004	54.444 ± 11.166
	Diff-TCN	5.174 ± 0.008	4.215 ± 0.007	2.532 ± 0.004	0.550 ± 0.001	49.444 ± 1.242
	CMHA-TCN	5.276 ± 0.064	4.196 ± 0.011	2.521 ± 0.007	0.532 ± 0.011	53.333 ± 8.607
	Diff-CMHA-TCN	5.244 ± 0.019	4.175 ± 0.014	2.506 ± 0.009	0.537 ± 0.003	58.333 ± 4.194
	EVMD-TCN	5.151 ± 0.021	4.228 ± 0.050	2.537 ± 0.030	0.554 ± 0.004	46.667 ± 6.939
	EVMD-CMHA-TCN	5.185 ± 0.024	4.320 ± 0.046	2.593 ± 0.028	0.548 ± 0.004	46.111 ± 2.291
	EVMD-PMB-TCN	5.115 ± 0.032	4.163 ± 0.063	2.498 ± 0.038	0.560 ± 0.005	55.000 ± 6.872
	EVMD-PMB-CMHA-TCN	5.179 ± 0.048	4.259 ± 0.082	2.556 ± 0.049	0.549 ± 0.008	49.444 ± 2.291
	SVMD-TCN	4.832 ± 0.029	**3.960** ± 0.043	**2.380** ± 0.026	**0.607** ± 0.005	57.222 ± 4.045
	SVMD-CMHA-TCN	4.851 ± 0.010	3.983 ± 0.013	2.395 ± 0.008	0.604 ± 0.002	57.778 ± 2.485
	SVMD-PMB-TCN	**4.830** ± 0.015	3.982 ± 0.014	2.394 ± 0.008	**0.607** ± 0.002	57.778 ± 2.485
	SVMD-PMB-CMHA-TCN	4.857 ± 0.032	3.992 ± 0.024	2.400 ± 0.015	0.603 ± 0.005	54.444 ± 3.143
July 2024	Diff-TCN [27]	3.333 ± 0.002	2.331 ± 0.001	1.478 ± 0.000	0.347 ± 0.001	51.613 ± 0.000
	TCN	3.313 ± 0.016	2.323 ± 0.011	1.472 ± 0.007	0.355 ± 0.006	47.849 ± 5.715
	Diff-TCN	3.293 ± 0.003	2.328 ± 0.001	1.476 ± 0.001	0.362 ± 0.001	61.290 ± 0.000
	CMHA-TCN	3.307 ± 0.021	2.315 ± 0.011	1.467 ± 0.007	0.357 ± 0.008	56.452 ± 5.185
	Diff-CMHA-TCN	3.314 ± 0.017	2.323 ± 0.009	1.473 ± 0.006	0.354 ± 0.007	53.226 ± 6.106
	EVMD-TCN	3.291 ± 0.021	2.366 ± 0.015	1.498 ± 0.009	0.363 ± 0.008	51.075 ± 6.011
	EVMD-CMHA-TCN	3.279 ± 0.056	2.370 ± 0.042	1.500 ± 0.025	0.368 ± 0.022	51.613 ± 8.118
	EVMD-PMB-TCN	3.325 ± 0.040	2.362 ± 0.027	1.497 ± 0.017	0.350 ± 0.016	55.376 ± 5.403
	EVMD-PMB-CMHA-TCN	3.316 ± 0.082	2.317 ± 0.040	1.468 ± 0.025	0.353 ± 0.032	59.677 ± 5.185
	SVMD-TCN	3.204 ± 0.051	2.270 ± 0.030	1.437 ± 0.019	0.396 ± 0.019	59.140 ± 4.433
	SVMD-CMHA-TCN	**3.161** ± 0.022	2.255 ± 0.009	**1.427** ± 0.005	**0.413** ± 0.008	63.441 ± 3.041
	SVMD-PMB-TCN	3.181 ± 0.006	2.253 ± 0.013	1.427 ± 0.008	0.405 ± 0.002	64.516 ± 1.862
	SVMD-PMB-CMHA-TCN	3.170 ± 0.015	**2.253** ± 0.019	**1.427** ± 0.012	0.409 ± 0.006	**65.054** ± 3.442
August 2024	Diff-TCN [27]	4.483 ± 0.001	3.419 ± 0.002	2.180 ± 0.001	0.686 ± 0.000	58.065 ± 0.000
	TCN	**4.472** ± 0.007	**3.393** ± 0.015	2.163 ± 0.011	**0.688** ± 0.001	54.301 ± 3.914
	Diff-TCN	4.475 ± 0.002	3.398 ± 0.003	**2.161** ± 0.002	0.687 ± 0.000	50.538 ± 2.404
	CMHA-TCN	4.490 ± 0.020	3.410 ± 0.014	2.170 ± 0.008	0.685 ± 0.003	51.075 ± 2.217
	Diff-CMHA-TCN	4.477 ± 0.023	3.412 ± 0.040	2.174 ± 0.026	0.687 ± 0.003	**59.140** ± 4.433
	EVMD-TCN	4.484 ± 0.012	3.463 ± 0.007	2.196 ± 0.004	0.686 ± 0.002	52.688 ± 2.404
	EVMD-CMHA-TCN	4.516 ± 0.009	3.467 ± 0.009	2.197 ± 0.006	0.681 ± 0.001	55.376 ± 2.217
	EVMD-PMB-TCN	4.527 ± 0.017	3.515 ± 0.014	2.229 ± 0.008	0.680 ± 0.002	55.376 ± 2.217
	EVMD-PMB-CMHA-TCN	4.672 ± 0.045	3.561 ± 0.030	2.253 ± 0.019	0.659 ± 0.007	50.000 ± 3.088
	SVMD-TCN	4.554 ± 0.013	3.465 ± 0.012	2.202 ± 0.006	0.676 ± 0.002	54.839 ± 1.862
	SVMD-CMHA-TCN	4.572 ± 0.017	3.486 ± 0.017	2.216 ± 0.010	0.673 ± 0.003	56.452 ± 1.613
	SVMD-PMB-TCN	4.556 ± 0.009	3.467 ± 0.006	2.202 ± 0.003	0.676 ± 0.001	53.226 ± 3.088
	SVMD-PMB-CMHA-TCN	4.607 ± 0.022	3.513 ± 0.023	2.230 ± 0.014	0.668 ± 0.003	51.613 ± 2.634
September 2024	Diff-TCN [27]	3.124 ± 0.001	2.419 ± 0.002	1.446 ± 0.001	0.698 ± 0.000	50.000 ± 0.000
	TCN	3.138 ± 0.026	2.426 ± 0.013	1.450 ± 0.009	0.696 ± 0.005	50.000 ± 5.774
	Diff-TCN	3.148 ± 0.026	2.380 ± 0.007	1.424 ± 0.005	0.694 ± 0.005	58.889 ± 3.685
	CMHA-TCN	3.150 ± 0.026	2.433 ± 0.014	1.455 ± 0.009	0.693 ± 0.005	51.111 ± 6.849
	Diff-CMHA-TCN	3.126 ± 0.016	2.391 ± 0.014	1.430 ± 0.008	0.698 ± 0.003	52.778 ± 2.291
	EVMD-TCN	3.145 ± 0.012	2.327 ± 0.007	1.391 ± 0.004	0.694 ± 0.002	56.667 ± 2.722
	EVMD-CMHA-TCN	3.126 ± 0.029	2.343 ± 0.027	1.400 ± 0.015	0.698 ± 0.006	53.333 ± 3.333
	EVMD-PMB-TCN	3.103 ± 0.013	2.314 ± 0.008	1.384 ± 0.005	0.702 ± 0.003	54.444 ± 2.485
	EVMD-PMB-CMHA-TCN	3.130 ± 0.035	2.384 ± 0.019	1.425 ± 0.010	0.697 ± 0.007	51.667 ± 4.615
	SVMD-TCN	**3.098** ± 0.031	2.282 ± 0.016	1.366 ± 0.010	**0.703** ± 0.006	**61.667** ± 3.191
	SVMD-CMHA-TCN	3.109 ± 0.015	**2.277** ± 0.005	**1.363** ± 0.004	0.701 ± 0.003	60.000 ± 2.722
	SVMD-PMB-TCN	3.147 ± 0.030	2.336 ± 0.026	1.399 ± 0.016	0.694 ± 0.006	53.333 ± 5.092
	SVMD-PMB-CMHA-TCN	3.141 ± 0.017	2.304 ± 0.015	1.380 ± 0.009	0.695 ± 0.003	57.222 ± 2.291
October 2024	Diff-TCN [27]	4.371 ± 0.000	3.393 ± 0.001	2.252 ± 0.001	0.551 ± 0.000	54.839 ± 0.000
	TCN	4.335 ± 0.016	3.359 ± 0.012	2.230 ± 0.008	0.559 ± 0.003	55.914 ± 1.521
	Diff-TCN	4.355 ± 0.004	3.326 ± 0.009	2.211 ± 0.005	0.555 ± 0.001	57.527 ± 5.072
	CMHA-TCN	4.338 ± 0.018	3.349 ± 0.017	2.224 ± 0.012	0.558 ± 0.004	59.140 ± 3.041

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	4.390 ± 0.015	3.408 ± 0.021	2.263 ± 0.013	0.547 ± 0.003	53.763 ± 4.809
	EVMD-TCN	4.433 ± 0.009	3.386 ± 0.010	2.250 ± 0.007	0.539 ± 0.002	50.000 ± 1.613
	EVMD-CMHA-TCN	4.442 ± 0.020	3.374 ± 0.009	2.240 ± 0.005	0.537 ± 0.004	44.624 ± 2.895
	EVMD-PMB-TCN	4.450 ± 0.007	3.438 ± 0.018	2.280 ± 0.011	0.535 ± 0.002	43.548 ± 4.059
	EVMD-PMB-CMHA-TCN	4.496 ± 0.047	3.444 ± 0.061	2.285 ± 0.039	0.525 ± 0.010	45.161 ± 5.587
	SVMD-TCN	**4.232** ± 0.010	**3.251** ± 0.009	**2.155** ± 0.006	**0.579** ± 0.002	67.742 ± 2.634
	SVMD-CMHA-TCN	4.235 ± 0.006	3.262 ± 0.013	2.164 ± 0.008	0.579 ± 0.001	62.366 ± 4.809
	SVMD-PMB-TCN	4.263 ± 0.004	3.264 ± 0.008	2.164 ± 0.005	0.573 ± 0.001	**68.817** ± 1.521
	SVMD-PMB-CMHA-TCN	4.263 ± 0.012	3.281 ± 0.006	2.177 ± 0.004	0.573 ± 0.002	56.989 ± 3.566
November 2024	Diff-TCN [27]	3.595 ± 0.000	2.840 ± 0.000	1.824 ± 0.000	0.517 ± 0.000	50.000 ± 0.000
	TCN	3.610 ± 0.031	2.851 ± 0.028	1.832 ± 0.018	0.513 ± 0.008	50.556 ± 1.242
	Diff-TCN	3.607 ± 0.003	2.808 ± 0.005	1.806 ± 0.004	0.514 ± 0.001	54.444 ± 1.571
	CMHA-TCN	3.618 ± 0.018	2.860 ± 0.024	1.837 ± 0.015	0.511 ± 0.005	47.778 ± 3.143
	Diff-CMHA-TCN	3.565 ± 0.010	2.776 ± 0.011	1.784 ± 0.007	0.525 ± 0.003	56.667 ± 3.849
	EVMD-TCN	**3.412** ± 0.017	**2.656** ± 0.017	**1.706** ± 0.010	**0.565** ± 0.004	65.000 ± 1.667
	EVMD-CMHA-TCN	3.468 ± 0.038	2.732 ± 0.028	1.756 ± 0.018	0.550 ± 0.010	63.333 ± 1.925
	EVMD-PMB-TCN	3.479 ± 0.023	2.713 ± 0.020	1.742 ± 0.013	0.548 ± 0.006	**65.556** ± 2.485
	EVMD-PMB-CMHA-TCN	3.500 ± 0.037	2.814 ± 0.036	1.807 ± 0.022	0.542 ± 0.010	60.556 ± 3.557
	SVMD-TCN	3.614 ± 0.032	2.831 ± 0.029	1.817 ± 0.018	0.512 ± 0.009	53.889 ± 3.557
	SVMD-CMHA-TCN	3.584 ± 0.027	2.803 ± 0.021	1.799 ± 0.014	0.520 ± 0.007	52.778 ± 2.992
	SVMD-PMB-TCN	3.631 ± 0.019	2.847 ± 0.015	1.828 ± 0.010	0.507 ± 0.005	49.444 ± 2.291
	SVMD-PMB-CMHA-TCN	3.599 ± 0.033	2.802 ± 0.039	1.799 ± 0.025	0.516 ± 0.009	57.222 ± 2.992
December 2024	**Diff-TCN** [27]	13.044 ± 0.000	7.974 ± 0.001	4.101 ± 0.001	0.026 ± 0.000	**64.516** ± 0.000
	TCN	13.024 ± 0.036	7.956 ± 0.058	4.088 ± 0.031	0.029 ± 0.005	53.763 ± 4.809
	Diff-TCN	12.781 ± 0.032	**7.723** ± 0.020	**3.967** ± 0.010	0.065 ± 0.005	55.376 ± 9.928
	CMHA-TCN	12.873 ± 0.077	7.757 ± 0.115	3.984 ± 0.062	0.051 ± 0.011	57.527 ± 7.313
	Diff-CMHA-TCN	13.047 ± 0.063	7.944 ± 0.062	4.085 ± 0.035	0.026 ± 0.009	59.677 ± 3.088
	EVMD-TCN	12.396 ± 0.022	7.880 ± 0.034	4.045 ± 0.016	0.121 ± 0.003	54.301 ± 2.217
	EVMD-CMHA-TCN	**12.334** ± 0.018	7.902 ± 0.029	4.056 ± 0.015	**0.129** ± 0.003	55.376 ± 1.202
	EVMD-PMB-TCN	12.506 ± 0.033	7.928 ± 0.024	4.075 ± 0.012	0.105 ± 0.005	55.376 ± 1.202
	EVMD-PMB-CMHA-TCN	12.410 ± 0.088	8.121 ± 0.083	4.167 ± 0.043	0.119 ± 0.013	56.452 ± 4.059
	SVMD-TCN	12.943 ± 0.065	8.001 ± 0.040	4.082 ± 0.022	0.041 ± 0.010	53.763 ± 2.404
	SVMD-CMHA-TCN	12.898 ± 0.014	7.963 ± 0.005	4.063 ± 0.003	0.048 ± 0.002	55.376 ± 1.202
	SVMD-PMB-TCN	12.978 ± 0.022	8.076 ± 0.027	4.125 ± 0.014	0.036 ± 0.003	49.462 ± 1.521
	SVMD-PMB-CMHA-TCN	12.702 ± 0.045	7.906 ± 0.013	4.037 ± 0.007	0.077 ± 0.007	56.452 ± 2.464
January 2025	**Diff-TCN** [27]	7.064 ± 0.001	6.011 ± 0.002	2.862 ± 0.001	0.682 ± 0.000	**64.516** ± 0.000
	TCN	**6.974** ± 0.113	**5.867** ± 0.158	**2.790** ± 0.071	**0.690** ± 0.010	63.441 ± 5.790
	Diff-TCN	7.092 ± 0.016	5.972 ± 0.023	2.835 ± 0.010	0.680 ± 0.002	54.839 ± 3.725
	CMHA-TCN	6.997 ± 0.103	5.870 ± 0.166	2.791 ± 0.075	0.688 ± 0.009	61.290 ± 6.177
	Diff-CMHA-TCN	7.169 ± 0.051	6.091 ± 0.061	2.897 ± 0.029	0.673 ± 0.005	52.688 ± 5.790
	EVMD-TCN	7.658 ± 0.058	6.497 ± 0.078	3.069 ± 0.035	0.627 ± 0.006	50.538 ± 1.521
	EVMD-CMHA-TCN	7.574 ± 0.050	6.373 ± 0.100	3.009 ± 0.048	0.635 ± 0.005	53.763 ± 2.404
	EVMD-PMB-TCN	7.662 ± 0.064	6.489 ± 0.083	3.065 ± 0.038	0.626 ± 0.006	54.301 ± 2.217
	EVMD-PMB-CMHA-TCN	7.658 ± 0.143	6.422 ± 0.171	3.028 ± 0.077	0.626 ± 0.014	52.151 ± 2.217
	SVMD-TCN	7.452 ± 0.066	6.418 ± 0.085	3.036 ± 0.040	0.646 ± 0.006	54.301 ± 2.217
	SVMD-CMHA-TCN	7.446 ± 0.082	6.394 ± 0.124	3.025 ± 0.058	0.647 ± 0.008	54.301 ± 3.442
	SVMD-PMB-TCN	7.407 ± 0.028	6.369 ± 0.042	3.013 ± 0.019	0.651 ± 0.003	53.763 ± 2.404
	SVMD-PMB-CMHA-TCN	7.418 ± 0.046	6.347 ± 0.071	3.001 ± 0.033	0.650 ± 0.004	52.688 ± 1.521
February 2025	Diff-TCN [27]	6.575 ± 0.001	5.032 ± 0.001	2.272 ± 0.000	0.446 ± 0.000	53.571 ± 0.000
	TCN	6.641 ± 0.125	5.000 ± 0.051	2.261 ± 0.023	0.434 ± 0.021	56.548 ± 5.223
	Diff-TCN	6.583 ± 0.016	4.916 ± 0.008	2.226 ± 0.004	0.444 ± 0.003	54.762 ± 4.454
	CMHA-TCN	**6.575** ± 0.086	4.978 ± 0.045	2.252 ± 0.019	**0.446** ± 0.015	**57.738** ± 5.223
	Diff-CMHA-TCN	6.636 ± 0.023	5.012 ± 0.035	2.265 ± 0.014	0.435 ± 0.004	53.571 ± 3.571
	EVMD-TCN	6.620 ± 0.050	**4.741** ± 0.028	**2.145** ± 0.013	0.438 ± 0.009	49.405 ± 3.205
	EVMD-CMHA-TCN	6.649 ± 0.064	4.810 ± 0.050	2.178 ± 0.021	0.433 ± 0.011	55.952 ± 2.662
	EVMD-PMB-TCN	6.585 ± 0.068	4.817 ± 0.047	2.175 ± 0.019	0.444 ± 0.011	50.000 ± 4.124
	EVMD-PMB-CMHA-TCN	6.659 ± 0.085	4.880 ± 0.111	2.207 ± 0.047	0.431 ± 0.015	51.786 ± 4.494
	SVMD-TCN	6.917 ± 0.088	5.182 ± 0.032	2.345 ± 0.015	0.386 ± 0.016	56.548 ± 3.205
	SVMD-CMHA-TCN	6.851 ± 0.081	5.149 ± 0.010	2.330 ± 0.005	0.398 ± 0.014	54.167 ± 3.205
	SVMD-PMB-TCN	6.904 ± 0.048	5.168 ± 0.016	2.341 ± 0.008	0.389 ± 0.009	55.357 ± 2.728
	SVMD-PMB-CMHA-TCN	7.012 ± 0.094	5.196 ± 0.041	2.355 ± 0.019	0.369 ± 0.017	56.548 ± 2.454
March 2025	Diff-TCN [27]	5.536 ± 0.003	4.404 ± 0.002	2.048 ± 0.001	0.331 ± 0.001	61.290 ± 0.000
	TCN	5.499 ± 0.070	4.296 ± 0.085	2.001 ± 0.037	0.340 ± 0.017	58.602 ± 4.718
	Diff-TCN	5.457 ± 0.004	4.360 ± 0.013	2.027 ± 0.005	0.350 ± 0.001	55.376 ± 3.914
	CMHA-TCN	5.449 ± 0.053	4.368 ± 0.044	2.031 ± 0.018	0.352 ± 0.013	57.527 ± 6.822
	Diff-CMHA-TCN	5.520 ± 0.024	4.350 ± 0.052	2.023 ± 0.023	0.335 ± 0.006	59.677 ± 3.088
	EVMD-TCN	5.326 ± 0.013	**4.159** ± 0.043	**1.935** ± 0.019	0.381 ± 0.003	**61.290** ± 1.862
	EVMD-CMHA-TCN	**5.279** ± 0.018	4.191 ± 0.061	1.948 ± 0.026	**0.392** ± 0.004	56.989 ± 3.566
	EVMD-PMB-TCN	5.372 ± 0.027	4.292 ± 0.093	1.993 ± 0.041	0.370 ± 0.006	54.839 ± 8.118
	EVMD-PMB-CMHA-TCN	5.318 ± 0.094	4.296 ± 0.247	1.993 ± 0.108	0.383 ± 0.022	49.462 ± 12.992
	SVMD-TCN	5.741 ± 0.016	4.394 ± 0.045	2.042 ± 0.020	0.281 ± 0.004	45.699 ± 2.895
	SVMD-CMHA-TCN	5.819 ± 0.057	4.364 ± 0.039	2.030 ± 0.016	0.261 ± 0.015	48.925 ± 5.403
	SVMD-PMB-TCN	5.734 ± 0.066	4.414 ± 0.039	2.050 ± 0.016	0.282 ± 0.017	46.774 ± 1.613
	SVMD-PMB-CMHA-TCN	5.727 ± 0.040	4.383 ± 0.015	2.036 ± 0.006	0.284 ± 0.010	46.237 ± 4.023
April 2025	**Diff-TCN** [27]	7.042 ± 0.004	4.718 ± 0.002	2.098 ± 0.001	0.864 ± 0.000	**60.000** ± 0.000
	TCN	**6.961** ± 0.082	**4.690** ± 0.036	**2.089** ± 0.011	**0.867** ±0.003	57.778 ± 2.485
	Diff-TCN	7.200 ± 0.061	4.794 ± 0.021	2.116 ± 0.005	0.858 ± 0.002	49.444 ± 2.291
	CMHA-TCN	7.247 ± 0.238	4.837 ± 0.119	2.140 ± 0.042	0.856 ± 0.010	52.778 ± 4.045

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	7.015 ± 0.059	4.725 ± 0.037	2.097 ± 0.014	0.865 ± 0.002	57.222 ± 4.479
	EVMD-TCN	7.518 ± 0.085	4.872 ± 0.057	2.132 ± 0.022	0.845 ± 0.004	49.444 ± 1.242
	EVMD-CMHA-TCN	7.632 ± 0.092	4.926 ± 0.052	2.152 ± 0.020	0.840 ± 0.004	48.889 ± 2.485
	EVMD-PMB-TCN	7.550 ± 0.124	4.907 ± 0.073	2.146 ± 0.029	0.843 ± 0.005	48.333 ± 1.667
	EVMD-PMB-CMHA-TCN	8.098 ± 0.179	5.224 ± 0.118	2.270 ± 0.049	0.820 ± 0.008	47.222 ± 2.291
	SVMD-TCN	7.753 ± 0.073	5.215 ± 0.038	2.282 ± 0.014	0.835 ± 0.003	50.000 ± 1.925
	SVMD-CMHA-TCN	7.683 ± 0.050	5.165 ± 0.028	2.264 ± 0.012	0.838 ± 0.002	53.889 ± 3.557
	SVMD-PMB-TCN	7.710 ± 0.060	5.175 ± 0.026	2.266 ± 0.009	0.837 ± 0.003	48.333 ± 3.191
	SVMD-PMB-CMHA-TCN	7.866 ± 0.099	5.249 ± 0.049	2.293 ± 0.018	0.830 ± 0.004	48.889 ± 2.485
May 2025	**Diff-TCN** [27]	**13.419** ± 0.002	9.632 ± 0.001	2.774 ± 0.000	**0.889** ± 0.000	58.065 ± 0.000
	TCN	14.111 ± 0.420	10.068 ± 0.270	2.902 ± 0.082	0.877 ± 0.007	55.914 ± 8.669
	Diff-TCN	13.980 ± 0.139	9.879 ± 0.116	2.844 ± 0.033	0.880 ± 0.002	47.849 ± 3.914
	CMHA-TCN	13.905 ± 0.094	10.024 ± 0.080	2.888 ± 0.022	0.881 ± 0.002	52.688 ± 11.730
	Diff-CMHA-TCN	13.618 ± 0.133	9.545 ± 0.130	2.747 ± 0.037	0.886 ± 0.002	**59.677** ± 7.153
	EVMD-TCN	13.741 ± 0.073	**9.514** ± 0.068	**2.743** ± 0.019	0.884 ± 0.001	54.839 ± 1.862
	EVMD-CMHA-TCN	14.253 ± 0.075	9.843 ± 0.086	2.838 ± 0.025	0.875 ± 0.001	50.538 ± 6.628
	EVMD-PMB-TCN	14.185 ± 0.088	9.705 ± 0.079	2.794 ± 0.023	0.876 ± 0.002	53.226 ± 6.906
	EVMD-PMB-CMHA-TCN	15.074 ± 0.360	10.311 ± 0.248	2.979 ± 0.074	0.860 ± 0.007	52.688 ± 6.361
	SVMD-TCN	14.760 ± 0.147	10.474 ± 0.124	3.010 ± 0.034	0.866 ± 0.003	54.301 ± 1.202
	SVMD-CMHA-TCN	14.789 ± 0.102	10.525 ± 0.068	3.025 ± 0.020	0.866 ± 0.002	54.301 ± 1.202
	SVMD-PMB-TCN	14.919 ± 0.091	10.657 ± 0.046	3.068 ± 0.015	0.863 ± 0.002	51.613 ± 0.000
	SVMD-PMB-CMHA-TCN	15.155 ± 0.085	10.772 ± 0.070	3.098 ± 0.022	0.859 ± 0.002	52.151 ± 1.202

Table 65: Average results of the *extended experiments* across 6 repetitions per split $M_1, \ldots, M_{36}$ corresponding to months June 2022 to May 2025 in relation to forecasting $\mathbf{S}_{\text{Close}}$ with respect to XMR/USD using the novel framework.

F.2.5 *XRP/USD*

Month	Model	RMSE	MAE	MAPE	R2	DA
June 2021	TCN [27]	0.0608 ± 0.0067	0.0477 ± 0.0054	6.263 ± 0.605	0.797 ± 0.045	53.889 ± 3.557
	Diff-TCN [27]	0.0523 ± 0.0000	0.0397 ± 0.0000	5.318 ± 0.002	0.852 ± 0.000	46.667 ± 0.000
	TCN	0.0506 ± 0.0003	0.0392 ± 0.0001	5.258 ± 0.012	0.861 ± 0.002	48.333 ± 3.727
	Diff-TCN	0.0523 ± 0.0001	0.0395 ± 0.0000	5.312 ± 0.006	0.852 ± 0.000	**61.667** ± 2.546
	CMHA-TCN	**0.0506** ± 0.0002	0.0390 ± 0.0001	5.234 ± 0.015	**0.861** ± 0.001	51.111 ± 1.571
	Diff-CMHA-TCN	0.0523 ± 0.0000	0.0397 ± 0.0001	5.324 ± 0.015	0.852 ± 0.000	51.111 ± 3.143
	EVMD-TCN	0.0517 ± 0.0008	**0.0384** ± 0.0006	**5.122** ± 0.086	0.855 ± 0.005	57.778 ± 1.571
	EVMD-CMHA-TCN	0.0521 ± 0.0021	0.0389 ± 0.0013	5.232 ± 0.187	0.853 ± 0.012	54.444 ± 3.685
	EVMD-PMB-TCN	0.0560 ± 0.0018	0.0420 ± 0.0020	5.537 ± 0.237	0.830 ± 0.011	53.889 ± 2.291
	EVMD-PMB-CMHA-TCN	0.0527 ± 0.0058	0.0389 ± 0.0050	5.177 ± 0.682	0.848 ± 0.036	52.222 ± 3.685
	SVMD-TCN	0.0516 ± 0.0005	0.0404 ± 0.0001	5.423 ± 0.022	0.856 ± 0.003	43.333 ± 1.925
	SVMD-CMHA-TCN	0.0512 ± 0.0007	0.0401 ± 0.0004	5.381 ± 0.059	0.858 ± 0.004	45.000 ± 4.194
	SVMD-PMB-TCN	0.0515 ± 0.0006	0.0402 ± 0.0002	5.387 ± 0.031	0.856 ± 0.004	48.333 ± 3.727
	SVMD-PMB-CMHA-TCN	0.0524 ± 0.0008	0.0409 ± 0.0007	5.512 ± 0.111	0.851 ± 0.004	45.556 ± 3.685
July 2021	TCN [27]	0.0312 ± 0.0018	0.0242 ± 0.0015	3.786 ± 0.211	0.669 ± 0.038	49.462 ± 2.404
	Diff-TCN [27]	0.0257 ± 0.0000	**0.0188** ± 0.0000	**2.955** ± 0.001	0.776 ± 0.000	48.387 ± 0.000
	TCN	0.0258 ± 0.0001	0.0193 ± 0.0002	3.022 ± 0.040	0.773 ± 0.003	49.462 ± 3.566
	Diff-TCN	0.0260 ± 0.0000	0.0191 ± 0.0000	3.004 ± 0.005	0.771 ± 0.001	38.172 ± 2.895
	CMHA-TCN	0.0260 ± 0.0001	0.0191 ± 0.0001	2.997 ± 0.017	0.770 ± 0.002	53.226 ± 1.613
	Diff-CMHA-TCN	0.0258 ± 0.0001	0.0189 ± 0.0001	2.964 ± 0.015	0.775 ± 0.002	48.387 ± 1.862
	EVMD-TCN	0.0265 ± 0.0008	0.0203 ± 0.0007	3.176 ± 0.118	0.762 ± 0.015	50.000 ± 4.059
	EVMD-CMHA-TCN	0.0277 ± 0.0004	0.0208 ± 0.0003	3.246 ± 0.053	0.739 ± 0.008	47.849 ± 5.715
	EVMD-PMB-TCN	0.0274 ± 0.0006	0.0208 ± 0.0004	3.270 ± 0.065	0.745 ± 0.011	52.688 ± 3.041
	EVMD-PMB-CMHA-TCN	0.0278 ± 0.0007	0.0217 ± 0.0007	3.401 ± 0.113	0.737 ± 0.014	42.473 ± 1.202
	SVMD-TCN	**0.0256** ± 0.0001	0.0190 ± 0.0001	2.973 ± 0.011	**0.777** ± 0.002	53.226 ± 6.106
	SVMD-CMHA-TCN	0.0261 ± 0.0001	0.0195 ± 0.0001	3.059 ± 0.016	0.768 ± 0.002	**53.763** ± 3.041
	SVMD-PMB-TCN	0.0259 ± 0.0002	0.0190 ± 0.0001	2.969 ± 0.012	0.772 ± 0.004	52.688 ± 3.041
	SVMD-PMB-CMHA-TCN	0.0262 ± 0.0003	0.0190 ± 0.0001	2.969 ± 0.020	0.767 ± 0.005	51.075 ± 1.202
August 2021	TCN [27]	0.0776 ± 0.0017	0.0570 ± 0.0016	5.295 ± 0.152	0.848 ± 0.007	51.613 ± 4.165
	Diff-TCN [27]	0.0740 ± 0.0000	0.0570 ± 0.0000	5.338 ± 0.001	0.862 ± 0.000	**61.290** ± 0.000
	TCN	0.0747 ± 0.0006	0.0578 ± 0.0007	5.406 ± 0.072	0.859 ± 0.002	42.473 ± 5.403
	Diff-TCN	0.0739 ± 0.0000	0.0565 ± 0.0001	5.275 ± 0.012	0.862 ± 0.000	58.065 ± 1.862
	CMHA-TCN	0.0751 ± 0.0003	0.0578 ± 0.0004	5.402 ± 0.034	0.858 ± 0.001	43.011 ± 5.483
	Diff-CMHA-TCN	0.0743 ± 0.0005	0.0570 ± 0.0004	5.332 ± 0.034	0.861 ± 0.002	54.839 ± 3.725
	EVMD-TCN	**0.0736** ± 0.0005	**0.0548** ± 0.0005	5.161 ± 0.049	**0.863** ± 0.002	59.677 ± 5.509
	EVMD-CMHA-TCN	0.0760 ± 0.0012	0.0551 ± 0.0009	**5.135** ± 0.077	0.854 ± 0.005	51.075 ± 1.202
	EVMD-PMB-TCN	0.0746 ± 0.0013	0.0577 ± 0.0014	5.467 ± 0.138	0.860 ± 0.005	59.140 ± 3.041
	EVMD-PMB-CMHA-TCN	0.0753 ± 0.0015	0.0554 ± 0.0016	5.185 ± 0.147	0.857 ± 0.006	47.849 ± 8.207
	SVMD-TCN	0.0765 ± 0.0005	0.0577 ± 0.0004	5.364 ± 0.036	0.852 ± 0.002	46.774 ± 2.464
	SVMD-CMHA-TCN	0.0757 ± 0.0003	0.0569 ± 0.0003	5.294 ± 0.028	0.856 ± 0.001	46.774 ± 3.088
	SVMD-PMB-TCN	0.0777 ± 0.0006	0.0580 ± 0.0005	5.405 ± 0.043	0.848 ± 0.002	48.387 ± 1.862
	SVMD-PMB-CMHA-TCN	0.0777 ± 0.0004	0.0576 ± 0.0006	5.349 ± 0.050	0.848 ± 0.002	53.763 ± 6.628
September 2021	TCN [27]	0.0720 ± 0.0033	0.0560 ± 0.0025	5.177 ± 0.159	0.700 ± 0.028	43.889 ± 4.479
	Diff-TCN [27]	0.0673 ± 0.0000	**0.0452** ± 0.0000	**4.231** ± 0.001	0.739 ± 0.000	46.667 ± 0.000
	TCN	0.0668 ± 0.0006	0.0462 ± 0.0008	4.306 ± 0.092	0.742 ± 0.005	51.667 ± 1.667
	Diff-TCN	0.0674 ± 0.0001	0.0464 ± 0.0001	4.345 ± 0.012	0.738 ± 0.000	43.889 ± 1.242
	CMHA-TCN	0.0659 ± 0.0003	0.0465 ± 0.0002	4.321 ± 0.019	0.749 ± 0.002	44.444 ± 3.685
	Diff-CMHA-TCN	0.0674 ± 0.0002	0.0455 ± 0.0004	4.263 ± 0.043	0.738 ± 0.002	51.667 ± 5.693
	EVMD-TCN	0.0682 ± 0.0004	0.0496 ± 0.0003	4.602 ± 0.030	0.731 ± 0.003	**59.444** ± 2.291
	EVMD-CMHA-TCN	**0.0656** ± 0.0003	0.0491 ± 0.0006	4.567 ± 0.060	**0.752** ± 0.003	53.333 ± 1.925
	EVMD-PMB-TCN	0.0727 ± 0.0019	0.0521 ± 0.0006	4.860 ± 0.063	0.694 ± 0.016	52.222 ± 3.685
	EVMD-PMB-CMHA-TCN	0.0661 ± 0.0011	0.0482 ± 0.0009	4.449 ± 0.101	0.747 ± 0.008	55.000 ± 4.194
	SVMD-TCN	0.0676 ± 0.0005	0.0479 ± 0.0003	4.488 ± 0.035	0.736 ± 0.004	45.000 ± 1.667
	SVMD-CMHA-TCN	0.0676 ± 0.0000	0.0482 ± 0.0002	4.523 ± 0.012	0.736 ± 0.000	43.333 ± 3.333
	SVMD-PMB-TCN	0.0669 ± 0.0004	0.0471 ± 0.0004	4.395 ± 0.042	0.742 ± 0.003	48.889 ± 2.485
	SVMD-PMB-CMHA-TCN	0.0669 ± 0.0006	0.0479 ± 0.0008	4.450 ± 0.067	0.741 ± 0.005	43.889 ± 2.291
October 2021	TCN [27]	0.0480 ± 0.0040	0.0391 ± 0.0041	3.585 ± 0.371	−0.736 ± 0.282	45.161 ± 2.634
	Diff-TCN [27]	0.0397 ± 0.0000	0.0270 ± 0.0000	2.494 ± 0.001	−0.178 ± 0.001	**57.527** ± 3.914
	TCN	0.0398 ± 0.0009	0.0274 ± 0.0009	2.530 ± 0.081	−0.183 ± 0.053	50.000 ± 5.509
	Diff-TCN	**0.0390** ± 0.0001	**0.0265** ± 0.0000	**2.447** ± 0.004	**-0.139** ± 0.003	55.914 ± 1.521
	CMHA-TCN	0.0399 ± 0.0004	0.0274 ± 0.0005	2.533 ± 0.046	−0.192 ± 0.027	47.849 ± 1.202
	Diff-CMHA-TCN	0.0396 ± 0.0003	0.0270 ± 0.0003	2.494 ± 0.028	−0.175 ± 0.020	52.688 ± 3.566
	EVMD-TCN	0.0406 ± 0.0003	0.0285 ± 0.0004	2.632 ± 0.035	−0.235 ± 0.019	55.376 ± 4.335
	EVMD-CMHA-TCN	0.0417 ± 0.0004	0.0298 ± 0.0006	2.745 ± 0.051	−0.302 ± 0.024	53.763 ± 1.521
	EVMD-PMB-TCN	0.0410 ± 0.0011	0.0295 ± 0.0014	2.724 ± 0.128	−0.259 ± 0.069	44.086 ± 2.404
	EVMD-PMB-CMHA-TCN	0.0428 ± 0.0012	0.0308 ± 0.0014	2.842 ± 0.124	−0.369 ± 0.076	54.839 ± 3.226
	SVMD-TCN	0.0406 ± 0.0005	0.0275 ± 0.0006	2.541 ± 0.052	−0.236 ± 0.032	52.151 ± 1.202
	SVMD-CMHA-TCN	0.0407 ± 0.0003	0.0273 ± 0.0003	2.521 ± 0.025	−0.239 ± 0.020	52.151 ± 7.992
	SVMD-PMB-TCN	0.0408 ± 0.0004	0.0281 ± 0.0004	2.595 ± 0.038	−0.249 ± 0.025	52.688 ± 3.566
	SVMD-PMB-CMHA-TCN	0.0421 ± 0.0012	0.0291 ± 0.0015	2.682 ± 0.134	−0.329 ± 0.078	48.925 ± 2.895
November 2021	TCN [27]	0.0450 ± 0.0016	0.0338 ± 0.0018	3.058 ± 0.182	0.762 ± 0.017	60.556 ± 5.583
	Diff-TCN [27]	0.0424 ± 0.0000	0.0330 ± 0.0000	2.991 ± 0.001	0.789 ± 0.000	50.000 ± 0.000
	TCN	0.0414 ± 0.0001	0.0320 ± 0.0003	2.897 ± 0.031	0.799 ± 0.001	64.444 ± 6.849
	Diff-TCN	0.0426 ± 0.0001	0.0327 ± 0.0001	2.959 ± 0.010	0.787 ± 0.001	52.778 ± 2.992
	CMHA-TCN	0.0415 ± 0.0002	0.0317 ± 0.0001	2.872 ± 0.009	0.798 ± 0.002	57.778 ± 3.143

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	0.0426 ± 0.0001	0.0330 ± 0.0001	2.983 ± 0.011	0.787 ± 0.001	50.556 ± 4.479
	EVMD-TCN	0.0428 ± 0.0001	0.0331 ± 0.0002	3.019 ± 0.016	0.785 ± 0.001	50.000 ± 3.333
	EVMD-CMHA-TCN	0.0437 ± 0.0001	0.0334 ± 0.0001	3.044 ± 0.009	0.776 ± 0.001	50.000 ± 4.303
	EVMD-PMB-TCN	0.0426 ± 0.0004	0.0338 ± 0.0006	3.078 ± 0.052	0.787 ± 0.004	56.111 ± 5.906
	EVMD-PMB-CMHA-TCN	0.0431 ± 0.0004	0.0337 ± 0.0003	3.066 ± 0.019	0.782 ± 0.004	60.000 ± 3.849
	SVMD-TCN	**0.0411** ± 0.0003	**0.0313** ± 0.0004	**2.829** ± 0.041	**0.802** ± 0.003	**69.444** ± 6.503
	SVMD-CMHA-TCN	0.0414 ± 0.0003	0.0317 ± 0.0003	2.872 ± 0.024	0.799 ± 0.003	60.556 ± 5.583
	SVMD-PMB-TCN	0.0411 ± 0.0003	0.0313 ± 0.0004	2.834 ± 0.033	0.802 ± 0.003	67.222 ± 8.032
	SVMD-PMB-CMHA-TCN	0.0419 ± 0.0002	0.0313 ± 0.0003	2.832 ± 0.031	0.794 ± 0.002	62.778 ± 2.992
December 2021	TCN [27]	0.0457 ± 0.0026	0.0354 ± 0.0025	4.124 ± 0.276	0.434 ± 0.065	48.925 ± 3.442
	Diff-TCN [27]	**0.0390** ± 0.0000	0.0308 ± 0.0000	3.588 ± 0.001	**0.587** ± 0.000	48.387 ± 0.000
	TCN	0.0391 ± 0.0004	**0.0306** ± 0.0001	**3.554** ± 0.011	0.585 ± 0.009	54.301 ± 4.335
	Diff-TCN	0.0394 ± 0.0000	0.0308 ± 0.0000	3.582 ± 0.001	0.580 ± 0.001	43.011 ± 2.404
	CMHA-TCN	0.0392 ± 0.0002	0.0307 ± 0.0001	3.565 ± 0.012	0.584 ± 0.004	47.849 ± 2.895
	Diff-CMHA-TCN	0.0391 ± 0.0001	0.0308 ± 0.0000	3.584 ± 0.003	0.587 ± 0.002	46.774 ± 3.607
	EVMD-TCN	0.0409 ± 0.0002	0.0309 ± 0.0002	3.570 ± 0.018	0.546 ± 0.005	58.065 ± 0.000
	EVMD-CMHA-TCN	0.0410 ± 0.0005	0.0309 ± 0.0003	3.569 ± 0.040	0.545 ± 0.011	**58.602** ± 1.202
	EVMD-PMB-TCN	0.0419 ± 0.0005	0.0324 ± 0.0004	3.744 ± 0.042	0.524 ± 0.011	58.065 ± 2.634
	EVMD-PMB-CMHA-TCN	0.0412 ± 0.0006	0.0312 ± 0.0006	3.602 ± 0.064	0.540 ± 0.013	58.602 ± 4.335
	SVMD-TCN	0.0414 ± 0.0005	0.0323 ± 0.0005	3.753 ± 0.064	0.537 ± 0.012	44.624 ± 2.895
	SVMD-CMHA-TCN	0.0413 ± 0.0003	0.0325 ± 0.0002	3.776 ± 0.030	0.538 ± 0.006	44.086 ± 1.521
	SVMD-PMB-TCN	0.0415 ± 0.0003	0.0327 ± 0.0003	3.809 ± 0.033	0.533 ± 0.007	40.323 ± 4.059
	SVMD-PMB-CMHA-TCN	0.0409 ± 0.0004	0.0327 ± 0.0002	3.799 ± 0.028	0.546 ± 0.008	39.247 ± 4.718
January 2022	TCN [27]	0.0275 ± 0.0011	0.0193 ± 0.0011	2.743 ± 0.166	0.891 ± 0.009	51.075 ± 6.293
	Diff-TCN [27]	**0.0248** ± 0.0000	**0.0183** ± 0.0000	**2.601** ± 0.002	**0.912** ± 0.000	45.161 ± 0.000
	TCN	0.0261 ± 0.0006	0.0189 ± 0.0004	2.688 ± 0.054	0.902 ± 0.005	46.237 ± 1.521
	Diff-TCN	0.0251 ± 0.0001	0.0183 ± 0.0000	2.603 ± 0.004	0.909 ± 0.001	45.161 ± 1.862
	CMHA-TCN	0.0262 ± 0.0004	0.0189 ± 0.0003	2.677 ± 0.036	0.901 ± 0.003	45.699 ± 2.217
	Diff-CMHA-TCN	0.0250 ± 0.0002	0.0183 ± 0.0001	2.602 ± 0.013	0.910 ± 0.001	47.312 ± 2.404
	EVMD-TCN	0.0282 ± 0.0004	0.0210 ± 0.0003	2.966 ± 0.051	0.886 ± 0.004	37.097 ± 1.613
	EVMD-CMHA-TCN	0.0293 ± 0.0005	0.0211 ± 0.0005	3.003 ± 0.066	0.877 ± 0.004	46.774 ± 3.088
	EVMD-PMB-TCN	0.0302 ± 0.0007	0.0236 ± 0.0006	3.308 ± 0.082	0.869 ± 0.006	43.011 ± 3.566
	EVMD-PMB-CMHA-TCN	0.0299 ± 0.0009	0.0221 ± 0.0009	3.139 ± 0.136	0.872 ± 0.008	43.011 ± 2.404
	SVMD-TCN	0.0263 ± 0.0005	0.0190 ± 0.0003	2.721 ± 0.049	0.901 ± 0.004	50.000 ± 2.464
	SVMD-CMHA-TCN	0.0261 ± 0.0004	0.0186 ± 0.0004	2.656 ± 0.053	0.902 ± 0.003	50.000 ± 4.059
	SVMD-PMB-TCN	0.0261 ± 0.0007	0.0187 ± 0.0004	2.663 ± 0.057	0.902 ± 0.005	48.925 ± 2.217
	SVMD-PMB-CMHA-TCN	0.0259 ± 0.0003	0.0185 ± 0.0002	2.659 ± 0.024	0.904 ± 0.002	**52.688** ± 1.521
February 2022	TCN [27]	0.0535 ± 0.0006	0.0402 ± 0.0009	5.239 ± 0.128	0.520 ± 0.011	48.214 ± 5.740
	Diff-TCN [27]	0.0485 ± 0.0000	0.0374 ± 0.0000	4.871 ± 0.000	0.604 ± 0.000	51.786 ± 2.728
	TCN	0.0487 ± 0.0003	0.0367 ± 0.0001	4.784 ± 0.017	0.601 ± 0.005	54.167 ± 3.811
	Diff-TCN	0.0486 ± 0.0002	0.0373 ± 0.0001	4.867 ± 0.018	0.602 ± 0.003	55.357 ± 3.419
	CMHA-TCN	**0.0480** ± 0.0001	**0.0361** ± 0.0001	**4.705** ± 0.019	**0.613** ± 0.002	64.286 ± 2.062
	Diff-CMHA-TCN	0.0486 ± 0.0002	0.0374 ± 0.0000	4.875 ± 0.004	0.604 ± 0.003	45.833 ± 5.223
	EVMD-TCN	0.0486 ± 0.0002	0.0365 ± 0.0001	4.754 ± 0.019	0.604 ± 0.003	62.500 ± 2.728
	EVMD-CMHA-TCN	0.0495 ± 0.0004	0.0374 ± 0.0006	4.871 ± 0.087	0.588 ± 0.006	**67.262** ± 1.331
	EVMD-PMB-TCN	0.0496 ± 0.0007	0.0363 ± 0.0003	4.727 ± 0.033	0.586 ± 0.012	64.881 ± 3.205
	EVMD-PMB-CMHA-TCN	0.0493 ± 0.0004	0.0370 ± 0.0006	4.818 ± 0.086	0.592 ± 0.007	66.667 ± 3.948
	SVMD-TCN	0.0490 ± 0.0002	0.0384 ± 0.0001	4.995 ± 0.013	0.596 ± 0.003	54.762 ± 2.662
	SVMD-CMHA-TCN	0.0491 ± 0.0003	0.0383 ± 0.0002	4.974 ± 0.029	0.595 ± 0.005	55.357 ± 5.357
	SVMD-PMB-TCN	0.0483 ± 0.0002	0.0376 ± 0.0003	4.885 ± 0.043	0.607 ± 0.003	52.976 ± 3.811
	SVMD-PMB-CMHA-TCN	0.0490 ± 0.0004	0.0386 ± 0.0004	5.016 ± 0.045	0.597 ± 0.006	52.381 ± 4.454
March 2022	TCN [27]	0.0286 ± 0.0030	0.0232 ± 0.0026	2.913 ± 0.324	0.587 ± 0.091	46.237 ± 1.521
	Diff-TCN [27]	0.0248 ± 0.0000	0.0187 ± 0.0000	2.393 ± 0.001	0.694 ± 0.000	47.849 ± 6.011
	TCN	0.0244 ± 0.0002	0.0183 ± 0.0002	2.348 ± 0.030	0.703 ± 0.005	55.914 ± 4.433
	Diff-TCN	0.0243 ± 0.0001	0.0184 ± 0.0001	2.358 ± 0.006	0.705 ± 0.002	63.441 ± 2.404
	CMHA-TCN	0.0242 ± 0.0002	0.0184 ± 0.0001	2.360 ± 0.018	0.707 ± 0.004	54.301 ± 5.072
	Diff-CMHA-TCN	0.0247 ± 0.0003	0.0187 ± 0.0002	2.385 ± 0.027	0.697 ± 0.007	47.849 ± 11.840
	EVMD-TCN	0.0260 ± 0.0002	0.0193 ± 0.0002	2.481 ± 0.032	0.663 ± 0.005	59.140 ± 2.404
	EVMD-CMHA-TCN	0.0245 ± 0.0002	**0.0181** ± 0.0001	**2.318** ± 0.021	0.700 ± 0.004	**65.054** ± 4.335
	EVMD-PMB-TCN	0.0276 ± 0.0003	0.0203 ± 0.0002	2.615 ± 0.025	0.620 ± 0.008	53.226 ± 6.106
	EVMD-PMB-CMHA-TCN	0.0253 ± 0.0002	0.0185 ± 0.0002	2.370 ± 0.018	0.681 ± 0.005	61.290 ± 7.213
	SVMD-TCN	0.0242 ± 0.0001	0.0189 ± 0.0001	2.431 ± 0.017	0.708 ± 0.002	52.688 ± 3.041
	SVMD-CMHA-TCN	**0.0239** ± 0.0002	0.0182 ± 0.0002	2.337 ± 0.021	**0.714** ± 0.004	58.602 ± 2.217
	SVMD-PMB-TCN	0.0242 ± 0.0001	0.0189 ± 0.0001	2.422 ± 0.016	0.709 ± 0.003	51.075 ± 3.442
	SVMD-PMB-CMHA-TCN	0.0240 ± 0.0002	0.0188 ± 0.0001	2.412 ± 0.018	0.713 ± 0.004	54.301 ± 5.715
April 2022	TCN [27]	0.0273 ± 0.0008	0.0209 ± 0.0009	2.909 ± 0.151	0.820 ± 0.011	56.111 ± 6.781
	Diff-TCN [27]	**0.0263** ± 0.0000	0.0204 ± 0.0000	2.829 ± 0.003	**0.833** ± 0.000	45.000 ± 11.824
	TCN	0.0273 ± 0.0003	0.0209 ± 0.0002	2.909 ± 0.034	0.820 ± 0.004	40.000 ± 3.333
	Diff-TCN	0.0264 ± 0.0001	0.0203 ± 0.0001	2.810 ± 0.008	0.832 ± 0.001	42.778 ± 2.992
	CMHA-TCN	0.0276 ± 0.0004	0.0208 ± 0.0003	2.909 ± 0.046	0.816 ± 0.005	42.222 ± 2.485
	Diff-CMHA-TCN	0.0264 ± 0.0005	0.0205 ± 0.0003	2.836 ± 0.048	0.831 ± 0.007	45.556 ± 13.833
	EVMD-TCN	0.0274 ± 0.0002	0.0205 ± 0.0002	2.846 ± 0.023	0.819 ± 0.003	53.333 ± 1.925
	EVMD-CMHA-TCN	0.0276 ± 0.0004	0.0203 ± 0.0004	2.826 ± 0.054	0.816 ± 0.006	46.111 ± 6.781
	EVMD-PMB-TCN	0.0267 ± 0.0007	**0.0196** ± 0.0005	**2.707** ± 0.072	0.827 ± 0.009	**58.889** ± 6.573
	EVMD-PMB-CMHA-TCN	0.0269 ± 0.0005	0.0197 ± 0.0004	2.737 ± 0.062	0.825 ± 0.006	52.778 ± 5.906
	SVMD-TCN	0.0280 ± 0.0004	0.0214 ± 0.0004	2.983 ± 0.062	0.811 ± 0.006	39.444 ± 2.992
	SVMD-CMHA-TCN	0.0273 ± 0.0002	0.0205 ± 0.0002	2.859 ± 0.033	0.821 ± 0.003	47.222 ± 4.479
	SVMD-PMB-TCN	0.0275 ± 0.0007	0.0210 ± 0.0007	2.921 ± 0.106	0.817 ± 0.009	42.778 ± 9.510
	SVMD-PMB-CMHA-TCN	0.0273 ± 0.0009	0.0206 ± 0.0008	2.857 ± 0.118	0.820 ± 0.011	46.667 ± 7.201

Month	Model	RMSE	MAE	MAPE	R2	DA
May 2022	TCN [27]	0.0317 ± 0.0011	0.0217 ± 0.0009	4.755 ± 0.180	0.861 ± 0.010	54.301 ± 1.202
	Diff-TCN [27]	0.0300 ± 0.0000	0.0212 ± 0.0001	4.584 ± 0.013	0.875 ± 0.000	46.774 ± 2.464
	TCN	0.0305 ± 0.0005	0.0211 ± 0.0003	4.572 ± 0.068	0.871 ± 0.004	54.839 ± 0.000
	Diff-TCN	**0.0298** ± 0.0000	**0.0210** ± 0.0001	**4.540** ± 0.020	**0.877** ± 0.000	**62.366** ± 1.521
	CMHA-TCN	0.0312 ± 0.0007	0.0217 ± 0.0003	4.723 ± 0.078	0.865 ± 0.006	51.613 ± 6.452
	Diff-CMHA-TCN	0.0298 ± 0.0004	0.0213 ± 0.0001	4.600 ± 0.017	0.877 ± 0.004	48.387 ± 5.889
	EVMD-TCN	0.0327 ± 0.0004	0.0237 ± 0.0004	5.179 ± 0.089	0.852 ± 0.003	49.462 ± 2.404
	EVMD-CMHA-TCN	0.0319 ± 0.0002	0.0223 ± 0.0002	4.888 ± 0.039	0.859 ± 0.002	51.075 ± 1.202
	EVMD-PMB-TCN	0.0341 ± 0.0005	0.0254 ± 0.0005	5.547 ± 0.131	0.839 ± 0.005	44.624 ± 3.914
	EVMD-PMB-CMHA-TCN	0.0322 ± 0.0002	0.0230 ± 0.0004	5.033 ± 0.074	0.856 ± 0.002	52.151 ± 3.442
	SVMD-TCN	0.0316 ± 0.0008	0.0224 ± 0.0006	4.857 ± 0.139	0.861 ± 0.007	50.000 ± 4.059
	SVMD-CMHA-TCN	0.0319 ± 0.0003	0.0226 ± 0.0002	4.889 ± 0.057	0.859 ± 0.003	45.161 ± 4.165
	SVMD-PMB-TCN	0.0320 ± 0.0006	0.0228 ± 0.0003	4.934 ± 0.071	0.858 ± 0.005	46.774 ± 4.466
	SVMD-PMB-CMHA-TCN	0.0312 ± 0.0014	0.0221 ± 0.0011	4.805 ± 0.283	0.865 ± 0.012	54.839 ± 1.862

Table 66: Average results of the *benchmark experiments* across 6 repetitions per split $M_1, \ldots, M_{12}$ corresponding to months June 2021 to May 2022 in relation to forecasting $\mathbf{S}_{\text{Close}}$ with respect to XRP/USD using the novel framework.

Month	Model	RMSE	MAE	MAPE	R2	DA
June 2022	Diff-TCN [27]	0.0152 ± 0.0001	0.0122 ± 0.0001	3.509 ± 0.014	0.787 ± 0.003	47.222 ± 7.049
	TCN	0.0168 ± 0.0005	0.0133 ± 0.0004	3.834 ± 0.112	0.740 ± 0.015	46.667 ± 0.000
	Diff-TCN	**0.0152** ± 0.0001	**0.0121** ± 0.0001	**3.488** ± 0.025	0.787 ± 0.004	**54.444** ± 3.685
	CMHA-TCN	0.0164 ± 0.0003	0.0128 ± 0.0002	3.701 ± 0.067	0.754 ± 0.009	46.667 ± 1.925
	Diff-CMHA-TCN	**0.0152** ± 0.0000	0.0122 ± 0.0000	3.515 ± 0.002	**0.788** ± 0.001	46.111 ± 1.242
	EVMD-TCN	0.0192 ± 0.0013	0.0155 ± 0.0012	4.464 ± 0.340	0.662 ± 0.047	48.333 ± 1.667
	EVMD-CMHA-TCN	0.0180 ± 0.0006	0.0143 ± 0.0005	4.122 ± 0.135	0.701 ± 0.018	46.667 ± 2.722
	EVMD-PMB-TCN	0.0177 ± 0.0003	0.0144 ± 0.0003	4.146 ± 0.093	0.712 ± 0.010	45.556 ± 1.571
	EVMD-PMB-CMHA-TCN	0.0169 ± 0.0010	0.0133 ± 0.0010	3.830 ± 0.272	0.738 ± 0.033	46.111 ± 2.291
	SVMD-TCN	0.0164 ± 0.0006	0.0127 ± 0.0004	3.663 ± 0.109	0.754 ± 0.018	47.222 ± 2.992
	SVMD-CMHA-TCN	0.0167 ± 0.0004	0.0128 ± 0.0004	3.699 ± 0.104	0.745 ± 0.013	44.444 ± 1.571
	SVMD-PMB-TCN	0.0161 ± 0.0006	0.0124 ± 0.0004	3.569 ± 0.130	0.762 ± 0.017	45.556 ± 3.143
	SVMD-PMB-CMHA-TCN	0.0158 ± 0.0005	0.0123 ± 0.0003	3.537 ± 0.078	0.772 ± 0.013	47.222 ± 8.696
July 2022	Diff-TCN [27]	0.0115 ± 0.0000	0.0093 ± 0.0001	2.682 ± 0.015	0.698 ± 0.002	44.624 ± 6.011
	TCN	0.0116 ± 0.0002	0.0093 ± 0.0002	2.694 ± 0.044	0.696 ± 0.010	57.527 ± 1.202
	Diff-TCN	0.0116 ± 0.0000	**0.0092** ± 0.0000	**2.666** ± 0.006	0.696 ± 0.002	56.989 ± 6.083
	CMHA-TCN	0.0116 ± 0.0001	0.0093 ± 0.0001	2.697 ± 0.030	0.695 ± 0.003	58.602 ± 5.072
	Diff-CMHA-TCN	0.0115 ± 0.0001	0.0093 ± 0.0001	2.681 ± 0.024	0.697 ± 0.004	49.462 ± 8.467
	EVMD-TCN	0.0126 ± 0.0002	0.0103 ± 0.0002	3.001 ± 0.049	0.637 ± 0.010	54.839 ± 2.634
	EVMD-CMHA-TCN	0.0121 ± 0.0001	0.0098 ± 0.0001	2.852 ± 0.025	0.666 ± 0.003	56.989 ± 4.023
	EVMD-PMB-TCN	0.0138 ± 0.0009	0.0113 ± 0.0006	3.297 ± 0.186	0.563 ± 0.057	48.925 ± 5.403
	EVMD-PMB-CMHA-TCN	0.0126 ± 0.0006	0.0102 ± 0.0006	2.967 ± 0.156	0.638 ± 0.034	53.763 ± 6.628
	SVMD-TCN	0.0115 ± 0.0001	0.0095 ± 0.0001	2.757 ± 0.026	0.697 ± 0.003	54.839 ± 2.634
	SVMD-CMHA-TCN	**0.0114** ± 0.0000	0.0094 ± 0.0000	2.741 ± 0.014	**0.704** ± 0.002	**58.602** ± 3.442
	SVMD-PMB-TCN	0.0117 ± 0.0003	0.0096 ± 0.0002	2.782 ± 0.058	0.689 ± 0.016	47.849 ± 5.072
	SVMD-PMB-CMHA-TCN	0.0115 ± 0.0002	0.0093 ± 0.0002	2.680 ± 0.045	0.699 ± 0.011	54.301 ± 5.072
August 2022	Diff-TCN [27]	0.0091 ± 0.0001	0.0059 ± 0.0001	1.677 ± 0.018	0.784 ± 0.003	41.935 ± 0.000
	TCN	0.0096 ± 0.0003	0.0063 ± 0.0003	1.804 ± 0.097	0.763 ± 0.016	41.935 ± 0.000
	Diff-TCN	**0.0090** ± 0.0000	**0.0057** ± 0.0001	**1.624** ± 0.015	**0.790** ± 0.002	48.387 ± 4.562
	CMHA-TCN	0.0096 ± 0.0006	0.0064 ± 0.0006	1.824 ± 0.175	0.759 ± 0.028	45.161 ± 4.928
	Diff-CMHA-TCN	0.0091 ± 0.0002	0.0058 ± 0.0002	1.663 ± 0.060	0.785 ± 0.009	46.237 ± 5.790
	EVMD-TCN	0.0112 ± 0.0013	0.0079 ± 0.0013	2.256 ± 0.358	0.672 ± 0.081	47.312 ± 5.157
	EVMD-CMHA-TCN	0.0100 ± 0.0004	0.0067 ± 0.0003	1.913 ± 0.095	0.743 ± 0.019	51.075 ± 6.011
	EVMD-PMB-TCN	0.0103 ± 0.0005	0.0071 ± 0.0004	2.018 ± 0.122	0.727 ± 0.025	51.613 ± 4.165
	EVMD-PMB-CMHA-TCN	0.0099 ± 0.0004	0.0067 ± 0.0004	1.913 ± 0.098	0.745 ± 0.022	52.151 ± 5.072
	SVMD-TCN	0.0098 ± 0.0004	0.0065 ± 0.0004	1.863 ± 0.108	0.753 ± 0.019	46.237 ± 3.566
	SVMD-CMHA-TCN	0.0099 ± 0.0003	0.0066 ± 0.0003	1.878 ± 0.091	0.748 ± 0.015	46.237 ± 1.521
	SVMD-PMB-TCN	0.0093 ± 0.0002	0.0060 ± 0.0002	1.723 ± 0.055	0.775 ± 0.009	46.237 ± 4.433
	SVMD-PMB-CMHA-TCN	0.0091 ± 0.0003	0.0059 ± 0.0003	1.679 ± 0.087	0.783 ± 0.016	**55.376** ± 8.207
September 2022	Diff-TCN [27]	0.0242 ± 0.0001	0.0165 ± 0.0001	4.055 ± 0.024	0.851 ± 0.001	47.778 ± 11.166
	TCN	0.0240 ± 0.0001	0.0163 ± 0.0001	3.999 ± 0.027	0.853 ± 0.002	**62.222**± 6.849
	Diff-TCN	0.0241 ± 0.0001	0.0164 ± 0.0001	4.023 ± 0.020	0.851 ± 0.001	61.667 ± 2.546
	CMHA-TCN	0.0240 ± 0.0002	**0.0162** ± 0.0001	**3.972** ± 0.023	0.852 ± 0.002	57.222 ± 5.583
	Diff-CMHA-TCN	0.0239 ± 0.0002	0.0163 ± 0.0002	3.994 ± 0.044	0.853 ± 0.002	56.111 ± 8.032
	EVMD-TCN	**0.0239** ± 0.0001	0.0166 ± 0.0000	4.030 ± 0.008	**0.854** ± 0.001	60.556 ± 2.992
	EVMD-CMHA-TCN	0.0240 ± 0.0002	0.0163 ± 0.0002	3.973 ± 0.042	0.853 ± 0.003	60.000 ± 2.722
	EVMD-PMB-TCN	0.0246 ± 0.0003	0.0176 ± 0.0002	4.276 ± 0.057	0.845 ± 0.004	51.667 ± 1.667
	EVMD-PMB-CMHA-TCN	0.0241 ± 0.0002	0.0166 ± 0.0003	4.027 ± 0.060	0.852 ± 0.003	59.444 ± 2.992
	SVMD-TCN	0.0246 ± 0.0004	0.0169 ± 0.0003	4.106 ± 0.087	0.846 ± 0.005	51.667 ± 4.194
	SVMD-CMHA-TCN	0.0244 ± 0.0002	0.0165 ± 0.0001	4.022 ± 0.034	0.848 ± 0.002	52.222 ± 2.485
	SVMD-PMB-TCN	0.0244 ± 0.0002	0.0166 ± 0.0002	4.056 ± 0.039	0.848 ± 0.003	52.222 ± 2.485
	SVMD-PMB-CMHA-TCN	0.0244 ± 0.0002	0.0167 ± 0.0001	4.064 ± 0.027	0.848 ± 0.002	55.000 ± 3.727
October 2022	**Diff-TCN** [27]	**0.0132** ± 0.0001	0.0106 ± 0.0001	2.220 ± 0.029	**0.560** ± 0.008	48.925 ± 1.202
	TCN	0.0133 ± 0.0000	0.0105 ± 0.0000	2.212 ± 0.010	0.559 ± 0.001	52.688 ± 1.521
	Diff-TCN	0.0133 ± 0.0000	0.0107 ± 0.0000	2.246 ± 0.003	0.557 ± 0.001	52.151 ± 2.217
	CMHA-TCN	0.0133 ± 0.0001	0.0106 ± 0.0001	2.220 ± 0.011	0.560 ± 0.005	54.301 ± 2.895

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	0.0134 ± 0.0001	0.0106 ± 0.0000	2.236 ± 0.006	0.551 ± 0.006	49.462 ± 4.433
	EVMD-TCN	0.0136 ± 0.0001	0.0111 ± 0.0001	2.333 ± 0.015	0.533 ± 0.005	55.376 ± 5.072
	EVMD-CMHA-TCN	0.0136 ± 0.0001	0.0109 ± 0.0000	2.293 ± 0.004	0.533 ± 0.004	55.914 ± 5.157
	EVMD-PMB-TCN	0.0136 ± 0.0001	0.0113 ± 0.0001	2.369 ± 0.029	0.534 ± 0.009	59.140 ± 3.041
	EVMD-PMB-CMHA-TCN	0.0136 ± 0.0001	0.0110 ± 0.0001	2.309 ± 0.023	0.536 ± 0.006	59.140 ± 3.041
	SVMD-TCN	0.0136 ± 0.0001	**0.0104** ± 0.0002	**2.185** ± 0.028	0.535 ± 0.006	**62.366** ± 5.790
	SVMD-CMHA-TCN	0.0139 ± 0.0001	0.0108 ± 0.0001	2.260 ± 0.020	0.517 ± 0.005	53.763 ± 4.809
	SVMD-PMB-TCN	0.0140 ± 0.0000	0.0109 ± 0.0002	2.277 ± 0.034	0.508 ± 0.003	53.226 ± 9.986
	SVMD-PMB-CMHA-TCN	0.0137 ± 0.0001	0.0107 ± 0.0002	2.251 ± 0.032	0.529 ± 0.008	58.065 ± 4.165
November 2022	Diff-TCN [27]	0.0261 ± 0.0000	0.0179 ± 0.0000	4.556 ± 0.002	0.623 ± 0.000	53.333 ± 0.000
	TCN	0.0260 ± 0.0001	0.0177 ± 0.0001	4.519 ± 0.034	0.626 ± 0.004	54.444 ± 4.969
	Diff-TCN	0.0260 ± 0.0001	0.0179 ± 0.0000	4.543 ± 0.008	0.624 ± 0.002	50.556 ± 5.583
	CMHA-TCN	0.0260 ± 0.0001	0.0175 ± 0.0003	4.473 ± 0.062	0.626 ± 0.002	57.222 ± 9.313
	Diff-CMHA-TCN	0.0260 ± 0.0001	0.0178 ± 0.0001	4.533 ± 0.028	0.626 ± 0.004	52.778 ± 6.503
	EVMD-TCN	0.0268 ± 0.0001	0.0187 ± 0.0001	4.795 ± 0.024	0.602 ± 0.003	42.222 ± 2.485
	EVMD-CMHA-TCN	0.0268 ± 0.0000	0.0184 ± 0.0001	4.717 ± 0.024	0.604 ± 0.001	47.778 ± 5.666
	EVMD-PMB-TCN	0.0267 ± 0.0002	0.0186 ± 0.0002	4.768 ± 0.058	0.606 ± 0.007	43.333 ± 3.333
	EVMD-PMB-CMHA-TCN	0.0265 ± 0.0001	0.0180 ± 0.0002	4.600 ± 0.052	0.610 ± 0.003	52.778 ± 3.557
	SVMD-TCN	0.0263 ± 0.0003	0.0179 ± 0.0003	4.572 ± 0.083	0.618 ± 0.010	49.444 ± 4.045
	SVMD-CMHA-TCN	0.0258 ± 0.0001	**0.0175** ± 0.0001	**4.461** ± 0.017	0.632 ± 0.004	56.111 ± 3.557
	SVMD-PMB-TCN	**0.0257** ± 0.0001	0.0176 ± 0.0001	4.486 ± 0.020	**0.634** ± 0.003	**57.222** ± 3.557
	SVMD-PMB-CMHA-TCN	0.0262 ± 0.0001	0.0179 ± 0.0001	4.588 ± 0.018	0.619 ± 0.002	51.111 ± 3.143
December 2022	Diff-TCN [27]	0.0091 ± 0.0000	0.0072 ± 0.0000	1.963 ± 0.001	0.801 ± 0.001	39.785 ± 2.404
	TCN	0.0094 ± 0.0001	0.0073 ± 0.0001	2.010 ± 0.017	0.789 ± 0.004	38.710 ± 0.000
	Diff-TCN	0.0091 ± 0.0002	0.0071 ± 0.0001	1.955 ± 0.034	0.799 ± 0.007	51.075 ± 12.959
	CMHA-TCN	0.0092 ± 0.0002	0.0072 ± 0.0002	1.980 ± 0.045	0.794 ± 0.009	45.161 ± 9.855
	Diff-CMHA-TCN	0.0091 ± 0.0001	0.0071 ± 0.0000	1.957 ± 0.013	0.800 ± 0.003	46.237 ± 4.809
	EVMD-TCN	0.0095 ± 0.0002	0.0075 ± 0.0002	2.050 ± 0.052	0.781 ± 0.009	45.161 ± 1.862
	EVMD-CMHA-TCN	0.0093 ± 0.0001	0.0073 ± 0.0001	1.992 ± 0.019	0.793 ± 0.003	51.075 ± 1.202
	EVMD-PMB-TCN	0.0094 ± 0.0002	0.0073 ± 0.0002	2.014 ± 0.056	0.787 ± 0.009	48.387 ± 6.177
	EVMD-PMB-CMHA-TCN	0.0096 ± 0.0004	0.0075 ± 0.0004	2.071 ± 0.109	0.778 ± 0.019	51.075 ± 2.217
	SVMD-TCN	**0.0087** ± 0.0002	**0.0067** ± 0.0002	**1.847** ± 0.047	**0.817** ± 0.009	**62.903**± 8.277
	SVMD-CMHA-TCN	0.0089 ± 0.0003	0.0069 ± 0.0003	1.895 ± 0.079	0.809 ± 0.011	53.763 ± 10.144
	SVMD-PMB-TCN	0.0088 ± 0.0001	0.0068 ± 0.0002	1.854 ± 0.043	0.815 ± 0.006	60.753 ± 8.619
	SVMD-PMB-CMHA-TCN	0.0090 ± 0.0002	0.0069 ± 0.0001	1.879 ± 0.040	0.807 ± 0.007	60.215 ± 6.083
January 2023	Diff-TCN [27]	0.0105 ± 0.0001	0.0083 ± 0.0001	2.124 ± 0.019	0.856 ± 0.002	43.548 ± 10.820
	TCN	0.0103 ± 0.0000	0.0081 ± 0.0000	2.070 ± 0.010	0.860 ± 0.001	63.441 ± 3.566
	Diff-TCN	0.0102 ± 0.0001	0.0080 ± 0.0001	2.060 ± 0.037	0.863 ± 0.004	62.903 ± 6.906
	CMHA-TCN	0.0102 ± 0.0003	0.0080 ± 0.0002	2.055 ± 0.059	0.863 ± 0.007	59.677 ± 8.277
	Diff-CMHA-TCN	0.0103 ± 0.0002	0.0081 ± 0.0002	2.070 ± 0.050	0.862 ± 0.005	60.753 ± 8.619
	EVMD-TCN	**0.0098** ± 0.0001	**0.0076** ± 0.0001	1.961 ± 0.034	**0.874** ± 0.003	**74.194**± 6.715
	EVMD-CMHA-TCN	0.0100 ± 0.0001	**0.0076** ± 0.0001	**1.952** ± 0.022	0.871 ± 0.003	69.355 ± 5.185
	EVMD-PMB-TCN	0.0099 ± 0.0001	0.0077 ± 0.0001	1.975 ± 0.028	0.873 ± 0.003	71.505 ± 7.772
	EVMD-PMB-CMHA-TCN	0.0102 ± 0.0002	0.0076 ± 0.0001	1.963 ± 0.024	0.866 ± 0.004	66.667 ± 2.404
	SVMD-TCN	0.0101 ± 0.0002	0.0078 ± 0.0001	2.010 ± 0.031	0.867 ± 0.005	61.290 ± 4.165
	SVMD-CMHA-TCN	0.0105 ± 0.0001	0.0082 ± 0.0001	2.099 ± 0.019	0.857 ± 0.002	55.376 ± 5.403
	SVMD-PMB-TCN	0.0104 ± 0.0002	0.0080 ± 0.0002	2.069 ± 0.059	0.860 ± 0.007	58.602 ± 9.203
	SVMD-PMB-CMHA-TCN	0.0102 ± 0.0002	0.0078 ± 0.0001	2.015 ± 0.035	0.864 ± 0.004	61.290 ± 4.928
February 2023	Diff-TCN [27]	0.0087 ± 0.0000	0.0069 ± 0.0000	1.766 ± 0.001	0.477 ± 0.000	39.286 ± 0.000
	TCN	0.0086 ± 0.0001	0.0069 ± 0.0001	1.763 ± 0.035	0.486 ± 0.012	45.833 ± 9.763
	Diff-TCN	0.0086 ± 0.0001	0.0068 ± 0.0001	1.740 ± 0.023	0.489 ± 0.008	50.595 ± 2.454
	CMHA-TCN	0.0087 ± 0.0002	0.0070 ± 0.0003	1.795 ± 0.070	0.476 ± 0.020	44.048 ± 7.623
	Diff-CMHA-TCN	0.0086 ± 0.0001	0.0068 ± 0.0002	1.746 ± 0.043	0.492 ± 0.012	50.000 ± 5.051
	EVMD-TCN	0.0087 ± 0.0000	0.0068 ± 0.0000	1.748 ± 0.009	0.479 ± 0.003	54.167 ± 1.331
	EVMD-CMHA-TCN	0.0085 ± 0.0001	0.0067 ± 0.0001	1.715 ± 0.027	0.501 ± 0.008	59.524 ± 5.709
	EVMD-PMB-TCN	0.0087 ± 0.0001	0.0068 ± 0.0001	1.738 ± 0.026	0.480 ± 0.011	52.976 ± 3.811
	EVMD-PMB-CMHA-TCN	**0.0084** ± 0.0000	**0.0066** ± 0.0001	**1.685** ± 0.018	**0.512** ± 0.004	**61.309** ± 2.454
	SVMD-TCN	0.0089 ± 0.0001	0.0073 ± 0.0002	1.859 ± 0.052	0.455 ± 0.018	44.048 ± 6.070
	SVMD-CMHA-TCN	0.0088 ± 0.0001	0.0071 ± 0.0001	1.818 ± 0.023	0.468 ± 0.009	45.833 ± 5.615
	SVMD-PMB-TCN	0.0089 ± 0.0001	0.0072 ± 0.0001	1.847 ± 0.030	0.458 ± 0.011	43.452 ± 5.223
	SVMD-PMB-CMHA-TCN	0.0086 ± 0.0001	0.0070 ± 0.0001	1.787 ± 0.032	0.487 ± 0.013	48.214 ± 5.740
March 2023	Diff-TCN [27]	0.0237 ± 0.0000	0.0149 ± 0.0000	3.438 ± 0.001	0.824 ± 0.000	43.011 ± 9.617
	TCN	0.0237 ± 0.0001	0.0149 ± 0.0001	3.409 ± 0.036	0.825 ± 0.002	53.226 ± 5.509
	Diff-TCN	0.0235 ± 0.0002	0.0148 ± 0.0002	3.397 ± 0.051	0.828 ± 0.003	52.688 ± 9.617
	CMHA-TCN	0.0239 ± 0.0003	0.0150 ± 0.0002	3.438 ± 0.021	0.822 ± 0.005	46.237 ± 4.023
	Diff-CMHA-TCN	0.0236 ± 0.0004	0.0149 ± 0.0003	3.428 ± 0.073	0.826 ± 0.006	43.548 ± 6.384
	EVMD-TCN	0.0229 ± 0.0001	0.0138 ± 0.0001	3.165 ± 0.020	0.837 ± 0.002	60.215 ± 3.041
	EVMD-CMHA-TCN	0.0230 ± 0.0001	0.0138 ± 0.0001	3.143 ± 0.018	0.835 ± 0.002	57.527 ± 1.202
	EVMD-PMB-TCN	0.0227 ± 0.0002	**0.0135** ± 0.0001	3.099 ± 0.018	0.839 ± 0.003	**65.054** ± 2.217
	EVMD-PMB-CMHA-TCN	0.0229 ± 0.0003	0.0136 ± 0.0002	**3.078** ± 0.047	0.836 ± 0.004	51.613 ± 3.226
	SVMD-TCN	0.0235 ± 0.0005	0.0143 ± 0.0002	3.291 ± 0.044	0.828 ± 0.007	59.140 ± 8.669
	SVMD-CMHA-TCN	0.0230 ± 0.0001	0.0140 ± 0.0001	3.222 ± 0.026	0.835 ± 0.002	62.366 ± 2.404
	SVMD-PMB-TCN	0.0230 ± 0.0001	0.0140 ± 0.0001	3.226 ± 0.018	0.835 ± 0.002	61.290 ± 4.165
	SVMD-PMB-CMHA-TCN	**0.0226** ± 0.0001	0.0138 ± 0.0001	3.181 ± 0.023	**0.840** ± 0.002	58.602 ± 2.217
April 2023	Diff-TCN [27]	0.0145 ± 0.0003	0.0110 ± 0.0002	2.245 ± 0.044	0.589 ± 0.015	48.889 ± 4.581
	TCN	0.0142 ± 0.0002	0.0107 ± 0.0001	2.178 ± 0.026	0.608 ± 0.012	54.444 ± 4.157
	Diff-TCN	0.0142 ± 0.0001	0.0107 ± 0.0001	2.169 ± 0.020	0.607 ± 0.008	66.111 ± 5.906
	CMHA-TCN	0.0141 ± 0.0001	0.0106 ± 0.0001	2.160 ± 0.020	0.610 ± 0.006	61.667 ± 5.693

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	0.0144 ± 0.0001	0.0107 ± 0.0002	2.179 ± 0.031	0.595 ± 0.006	61.667 ± 6.597
	EVMD-TCN	0.0139 ± 0.0001	0.0105 ± 0.0001	2.134 ± 0.009	0.622 ± 0.006	60.556 ± 1.242
	EVMD-CMHA-TCN	0.0140 ± 0.0001	0.0101 ± 0.0000	2.061 ± 0.008	0.619 ± 0.006	68.333 ± 1.667
	EVMD-PMB-TCN	0.0144 ± 0.0001	0.0106 ± 0.0000	2.162 ± 0.008	0.595 ± 0.005	56.667 ± 1.925
	EVMD-PMB-CMHA-TCN	0.0145 ± 0.0004	**0.0100** ± 0.0001	**2.036** ± 0.024	0.588 ± 0.021	**70.556** ± 2.992
	SVMD-TCN	0.0137 ± 0.0002	0.0106 ± 0.0002	2.163 ± 0.031	0.631 ± 0.012	59.444 ± 5.906
	SVMD-CMHA-TCN	0.0137 ± 0.0000	0.0105 ± 0.0001	2.135 ± 0.017	0.633 ± 0.003	62.778 ± 3.557
	SVMD-PMB-TCN	0.0136 ± 0.0001	0.0106 ± 0.0001	2.150 ± 0.023	0.638 ± 0.003	64.444 ± 3.143
	SVMD-PMB-CMHA-TCN	**0.0133** ± 0.0000	0.0104 ± 0.0001	2.112 ± 0.011	**0.653** ± 0.002	58.333 ± 4.194
May 2023	**Diff-TCN** [27]	**0.0096** ± 0.0000	**0.0074** ± 0.0000	**1.602** ± 0.002	**0.845** ± 0.000	**61.290** ± 0.000
	TCN	0.0101 ± 0.0002	0.0078 ± 0.0002	1.687 ± 0.038	0.827 ± 0.007	43.011 ± 5.157
	Diff-TCN	0.0097 ± 0.0001	0.0074 ± 0.0001	1.609 ± 0.017	0.841 ± 0.002	47.312 ± 6.628
	CMHA-TCN	0.0098 ± 0.0001	0.0075 ± 0.0001	1.623 ± 0.019	0.838 ± 0.004	47.849 ± 5.403
	Diff-CMHA-TCN	0.0097 ± 0.0001	0.0074 ± 0.0001	1.615 ± 0.017	0.842 ± 0.003	49.462 ± 7.828
	EVMD-TCN	0.0104 ± 0.0001	0.0081 ± 0.0001	1.763 ± 0.015	0.816 ± 0.003	43.011 ± 1.521
	EVMD-CMHA-TCN	0.0108 ± 0.0001	0.0085 ± 0.0001	1.832 ± 0.013	0.802 ± 0.003	44.086 ± 3.041
	EVMD-PMB-TCN	0.0104 ± 0.0001	0.0081 ± 0.0001	1.753 ± 0.020	0.817 ± 0.004	38.172 ± 2.217
	EVMD-PMB-CMHA-TCN	0.0117 ± 0.0003	0.0092 ± 0.0003	1.981 ± 0.059	0.767 ± 0.010	44.086 ± 3.566
	SVMD-TCN	0.0101 ± 0.0001	0.0079 ± 0.0000	1.710 ± 0.010	0.826 ± 0.003	48.387 ± 2.634
	SVMD-CMHA-TCN	0.0102 ± 0.0001	0.0080 ± 0.0001	1.723 ± 0.015	0.822 ± 0.004	50.538 ± 1.521
	SVMD-PMB-TCN	0.0103 ± 0.0001	0.0080 ± 0.0001	1.730 ± 0.011	0.821 ± 0.003	46.237 ± 2.404
	SVMD-PMB-CMHA-TCN	0.0106 ± 0.0002	0.0083 ± 0.0002	1.800 ± 0.039	0.811 ± 0.007	46.774 ± 3.088
June 2023	Diff-TCN [27]	0.0141 ± 0.0001	0.0108 ± 0.0000	2.142 ± 0.004	0.532 ± 0.005	50.556 ± 4.875
	TCN	0.0139 ± 0.0001	0.0108 ± 0.0001	2.145 ± 0.022	0.544 ± 0.003	52.222 ± 6.849
	Diff-TCN	0.0138 ± 0.0001	0.0104 ± 0.0001	2.073 ± 0.021	0.555 ± 0.005	72.222 ± 3.143
	CMHA-TCN	0.0139 ± 0.0001	0.0107 ± 0.0001	2.125 ± 0.022	0.549 ± 0.007	52.222 ± 7.857
	Diff-CMHA-TCN	0.0140 ± 0.0004	0.0106 ± 0.0003	2.113 ± 0.069	0.541 ± 0.024	53.333 ± 9.027
	EVMD-TCN	0.0131 ± 0.0000	0.0097 ± 0.0001	1.925 ± 0.015	0.600 ± 0.003	**73.889** ± 3.557
	EVMD-CMHA-TCN	0.0129 ± 0.0000	0.0096 ± 0.0001	1.917 ± 0.011	0.608 ± 0.002	72.778 ± 2.291
	EVMD-PMB-TCN	0.0131 ± 0.0000	0.0098 ± 0.0001	1.953 ± 0.010	0.598 ± 0.002	66.667 ± 1.925
	EVMD-PMB-CMHA-TCN	**0.0128** ± 0.0000	**0.0096** ± 0.0001	**1.911** ± 0.010	**0.615** ± 0.003	71.667 ± 1.667
	SVMD-TCN	0.0135 ± 0.0001	0.0106 ± 0.0001	2.111 ± 0.025	0.575 ± 0.004	54.444 ± 5.666
	SVMD-CMHA-TCN	0.0133 ± 0.0001	0.0102 ± 0.0001	2.039 ± 0.014	0.585 ± 0.005	69.444 ± 7.049
	SVMD-PMB-TCN	0.0134 ± 0.0000	0.0102 ± 0.0001	2.026 ± 0.018	0.582 ± 0.002	73.889 ± 2.291
	SVMD-PMB-CMHA-TCN	0.0130 ± 0.0002	0.0100 ± 0.0002	1.991 ± 0.041	0.605 ± 0.013	67.222 ± 5.241
July 2023	Diff-TCN [27]	0.0666 ± 0.0000	0.0259 ± 0.0000	3.522 ± 0.002	0.744 ± 0.000	45.161 ± 0.000
	TCN	0.0665 ± 0.0001	0.0260 ± 0.0003	3.540 ± 0.042	0.744 ± 0.001	54.839 ± 0.000
	Diff-TCN	0.0655 ± 0.0001	0.0251 ± 0.0001	3.414 ± 0.009	0.752 ± 0.001	54.301 ± 3.442
	CMHA-TCN	0.0662 ± 0.0006	0.0256 ± 0.0008	3.485 ± 0.107	0.747 ± 0.005	55.914 ± 2.404
	Diff-CMHA-TCN	0.0659 ± 0.0006	0.0253 ± 0.0005	3.447 ± 0.071	0.750 ± 0.005	51.613 ± 6.452
	EVMD-TCN	0.0658 ± 0.0001	0.0258 ± 0.0002	3.505 ± 0.025	0.750 ± 0.001	51.075 ± 2.217
	EVMD-CMHA-TCN	0.0656 ± 0.0001	0.0247 ± 0.0003	3.350 ± 0.031	0.751 ± 0.001	51.613 ± 4.562
	EVMD-PMB-TCN	0.0661 ± 0.0009	0.0265 ± 0.0005	3.618 ± 0.066	0.747 ± 0.007	56.452 ± 4.059
	EVMD-PMB-CMHA-TCN	0.0650 ± 0.0002	**0.0240** ± 0.0004	**3.273** ± 0.054	0.756 ± 0.001	53.226 ± 3.607
	SVMD-TCN	0.0652 ± 0.0002	0.0252 ± 0.0004	3.448 ± 0.062	0.754 ± 0.001	57.527 ± 2.217
	SVMD-CMHA-TCN	**0.0649** ± 0.0002	0.0246 ± 0.0002	3.365 ± 0.033	**0.757** ± 0.001	**59.677** ± 2.464
	SVMD-PMB-TCN	0.0653 ± 0.0003	0.0252 ± 0.0006	3.454 ± 0.083	0.754 ± 0.002	57.527 ± 3.914
	SVMD-PMB-CMHA-TCN	0.0652 ± 0.0001	0.0252 ± 0.0003	3.444 ± 0.039	0.755 ± 0.001	52.151 ± 1.202
August 2023	Diff-TCN [27]	0.0198 ± 0.0001	0.0128 ± 0.0001	2.257 ± 0.019	0.895 ± 0.001	39.247 ± 9.928
	TCN	**0.0196** ± 0.0007	**0.0127** ± 0.0005	2.233 ± 0.093	0.896 ± 0.007	**58.602**± 8.207
	Diff-TCN	0.0201 ± 0.0002	0.0132 ± 0.0002	2.327 ± 0.032	0.891 ± 0.002	45.699 ± 3.914
	CMHA-TCN	**0.0196** ± 0.0006	**0.0127** ± 0.0005	**2.232** ± 0.083	0.896 ± 0.006	54.839 ± 11.175
	Diff-CMHA-TCN	0.0201 ± 0.0003	0.0131 ± 0.0003	2.314 ± 0.055	0.892 ± 0.003	41.935 ± 8.736
	EVMD-TCN	0.0209 ± 0.0005	0.0136 ± 0.0003	2.386 ± 0.046	0.883 ± 0.005	45.161 ± 4.562
	EVMD-CMHA-TCN	0.0213 ± 0.0001	0.0137 ± 0.0001	2.399 ± 0.010	0.879 ± 0.001	40.860 ± 1.521
	EVMD-PMB-TCN	0.0214 ± 0.0002	0.0143 ± 0.0001	2.504 ± 0.025	0.877 ± 0.003	48.387 ± 1.862
	EVMD-PMB-CMHA-TCN	0.0217 ± 0.0004	0.0141 ± 0.0002	2.471 ± 0.033	0.873 ± 0.004	44.624 ± 4.335
	SVMD-TCN	**0.0196** ± 0.0007	0.0128 ± 0.0004	2.237 ± 0.068	**0.897** ± 0.007	56.989 ± 9.060
	SVMD-CMHA-TCN	0.0203 ± 0.0001	0.0134 ± 0.0001	2.343 ± 0.015	0.889 ± 0.001	54.301 ± 3.442
	SVMD-PMB-TCN	0.0200 ± 0.0003	0.0130 ± 0.0002	2.273 ± 0.035	0.893 ± 0.003	56.452 ± 5.509
	SVMD-PMB-CMHA-TCN	0.0202 ± 0.0004	0.0130 ± 0.0005	2.282 ± 0.086	0.890 ± 0.005	46.774 ± 5.509
September 2023	**Diff-TCN** [27]	**0.0080** ± 0.0000	**0.0064** ± 0.0000	1.278 ± 0.003	**0.410** ± 0.000	48.333 ± 2.546
	TCN	0.0082 ± 0.0002	**0.0064** ±0.0002	**1.270** ± 0.042	0.387 ± 0.023	53.889 ± 5.241
	Diff-TCN	0.0081 ± 0.0000	0.0064 ± 0.0000	1.277 ± 0.003	0.394 ± 0.004	49.444 ± 4.045
	CMHA-TCN	0.0084 ± 0.0003	0.0065 ± 0.0003	1.298 ± 0.054	0.355 ± 0.048	53.333 ± 1.925
	Diff-CMHA-TCN	0.0081 ± 0.0001	0.0064 ± 0.0000	1.287 ± 0.008	0.406 ± 0.008	47.222 ± 4.045
	EVMD-TCN	0.0088 ± 0.0001	0.0066 ± 0.0002	1.323 ± 0.030	0.300 ± 0.017	58.889 ± 1.571
	EVMD-CMHA-TCN	0.0088 ± 0.0001	0.0066 ± 0.0001	1.322 ± 0.028	0.295 ± 0.018	56.667 ± 2.722
	EVMD-PMB-TCN	0.0087 ± 0.0000	0.0066 ± 0.0001	1.318 ± 0.014	0.301 ± 0.007	54.444 ± 3.685
	EVMD-PMB-CMHA-TCN	0.0089 ± 0.0001	0.0067 ± 0.0001	1.332 ± 0.016	0.275 ± 0.016	57.222 ± 2.291
	SVMD-TCN	0.0085 ± 0.0001	0.0066 ± 0.0001	1.316 ± 0.024	0.342 ± 0.021	55.556 ± 2.485
	SVMD-CMHA-TCN	0.0085 ± 0.0000	0.0066 ± 0.0001	1.308 ± 0.011	0.342 ± 0.006	57.222 ± 5.583
	SVMD-PMB-TCN	0.0085 ± 0.0001	0.0066 ± 0.0002	1.311 ± 0.030	0.346 ± 0.015	57.222 ± 6.503
	SVMD-PMB-CMHA-TCN	0.0087 ± 0.0001	0.0067 ± 0.0001	1.344 ± 0.018	0.309 ± 0.012	**59.444** ± 1.242
October 2023	Diff-TCN [27]	0.0123 ± 0.0000	0.0093 ± 0.0000	1.740 ± 0.000	0.822 ± 0.000	51.613 ± 0.000
	TCN	0.0128 ± 0.0003	0.0094 ± 0.0001	1.758 ± 0.020	0.804 ± 0.009	48.925 ± 1.202
	Diff-TCN	0.0123 ± 0.0000	0.0092 ± 0.0000	1.732 ± 0.001	0.819 ± 0.001	44.086 ± 4.809
	CMHA-TCN	0.0129 ± 0.0002	0.0093 ± 0.0001	1.749 ± 0.009	0.803 ± 0.006	46.237 ± 2.404

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	**0.0122** ± 0.0001	**0.0092** ± 0.0000	**1.731** ± 0.003	**0.822** ± 0.002	**51.613** ± 2.634
	EVMD-TCN	0.0135 ± 0.0003	0.0101 ± 0.0001	1.882 ± 0.023	0.784 ± 0.009	48.387 ± 0.000
	EVMD-CMHA-TCN	0.0137 ± 0.0002	0.0102 ± 0.0001	1.897 ± 0.025	0.777 ± 0.008	48.925 ± 3.442
	EVMD-PMB-TCN	0.0131 ± 0.0001	0.0100 ± 0.0000	1.875 ± 0.004	0.796 ± 0.003	47.849 ± 2.895
	EVMD-PMB-CMHA-TCN	0.0135 ± 0.0001	0.0100 ± 0.0001	1.877 ± 0.011	0.784 ± 0.004	46.237 ± 3.566
	SVMD-TCN	0.0129 ± 0.0002	0.0094 ± 0.0001	1.759 ± 0.015	0.801 ± 0.007	50.538 ± 3.566
	SVMD-CMHA-TCN	0.0131 ± 0.0002	0.0095 ± 0.0001	1.772 ± 0.008	0.797 ± 0.005	47.312 ± 2.404
	SVMD-PMB-TCN	0.0129 ± 0.0002	0.0094 ± 0.0001	1.764 ± 0.012	0.802 ± 0.006	49.462 ± 3.041
	SVMD-PMB-CMHA-TCN	0.0130 ± 0.0001	0.0094 ± 0.0001	1.752 ± 0.022	0.798 ± 0.003	51.075 ± 2.895
November 2023	Diff-TCN [27]	0.0207 ± 0.0000	0.0143 ± 0.0000	2.240 ± 0.000	0.555 ± 0.000	51.111 ± 4.969
	TCN	0.0207 ± 0.0002	0.0146 ± 0.0004	2.281 ± 0.059	0.553 ± 0.008	47.778 ± 2.485
	Diff-TCN	0.0206 ± 0.0000	0.0141 ± 0.0000	2.212 ± 0.005	0.558 ± 0.002	58.889 ± 5.329
	CMHA-TCN	0.0207 ± 0.0001	0.0144 ± 0.0003	2.251 ± 0.043	0.554 ± 0.006	51.111 ± 3.685
	Diff-CMHA-TCN	0.0207 ± 0.0001	0.0143 ± 0.0001	2.239 ± 0.013	0.554 ± 0.003	52.222 ± 7.115
	EVMD-TCN	0.0214 ± 0.0001	0.0150 ± 0.0001	2.348 ± 0.016	0.526 ± 0.003	49.444 ± 1.242
	EVMD-CMHA-TCN	0.0214 ± 0.0001	0.0149 ± 0.0002	2.333 ± 0.024	0.525 ± 0.004	50.000 ± 1.925
	EVMD-PMB-TCN	0.0214 ± 0.0000	0.0149 ± 0.0000	2.328 ± 0.006	0.522 ± 0.001	48.889 ± 2.485
	EVMD-PMB-CMHA-TCN	0.0214 ± 0.0000	0.0146 ± 0.0002	2.277 ± 0.025	0.524 ± 0.002	48.889 ± 3.143
	SVMD-TCN	0.0205 ± 0.0001	0.0138 ± 0.0001	2.165 ± 0.015	0.561 ± 0.005	63.889 ± 3.557
	SVMD-CMHA-TCN	**0.0203** ± 0.0001	**0.0137** ± 0.0001	**2.146** ± 0.012	0.570 ± 0.003	**63.889** ± 2.291
	SVMD-PMB-TCN	**0.0203** ± 0.0002	0.0139 ± 0.0003	2.182 ± 0.047	**0.572** ± 0.009	58.889 ± 7.857
	SVMD-PMB-CMHA-TCN	0.0219 ± 0.0002	0.0143 ± 0.0001	2.237 ± 0.020	0.503 ± 0.009	60.000 ± 3.333
December 2023	**Diff-TCN** [27]	0.0142 ± 0.0000	**0.0099** ± 0.0000	**1.575** ± 0.001	0.149 ± 0.000	**59.140** ± 4.809
	TCN	0.0142 ± 0.0001	0.0103 ± 0.0001	1.627 ± 0.018	0.149 ± 0.015	40.323 ± 2.464
	Diff-TCN	**0.0140** ± 0.0002	**0.0099** ± 0.0001	**1.575** ± 0.015	0.173 ± 0.019	56.989 ± 1.521
	CMHA-TCN	0.0140 ± 0.0002	0.0101 ± 0.0002	1.605 ± 0.029	0.178 ± 0.019	48.387 ± 3.725
	Diff-CMHA-TCN	0.0142 ± 0.0001	0.0100 ± 0.0001	1.593 ± 0.020	0.145 ± 0.016	47.849 ± 5.072
	EVMD-TCN	0.0144 ± 0.0000	0.0107 ± 0.0000	1.690 ± 0.006	0.127 ± 0.004	43.011 ± 1.521
	EVMD-CMHA-TCN	0.0142 ± 0.0002	0.0105 ± 0.0002	1.660 ± 0.031	0.144 ± 0.019	45.161 ± 3.725
	EVMD-PMB-TCN	0.0143 ± 0.0001	0.0104 ± 0.0002	1.649 ± 0.031	0.135 ± 0.010	43.011 ± 3.566
	EVMD-PMB-CMHA-TCN	0.0141 ± 0.0001	0.0104 ± 0.0001	1.651 ± 0.014	0.159 ± 0.011	50.538 ± 2.404
	SVMD-TCN	0.0141 ± 0.0002	0.0101 ± 0.0002	1.591 ± 0.035	0.166 ± 0.023	47.312 ± 2.404
	SVMD-CMHA-TCN	**0.0140** ± 0.0001	0.0100 ± 0.0001	1.589 ± 0.011	**0.178** ± 0.008	50.538 ± 1.521
	SVMD-PMB-TCN	0.0141 ± 0.0002	0.0101 ± 0.0001	1.605 ± 0.022	0.157 ± 0.019	46.774 ± 1.613
	SVMD-PMB-CMHA-TCN	0.0140 ± 0.0002	0.0101 ± 0.0002	1.592 ± 0.037	0.170 ± 0.030	48.925 ± 3.442
January 2024	Diff-TCN [27]	0.0157 ± 0.0000	0.0117 ± 0.0000	2.098 ± 0.006	0.760 ± 0.000	32.258 ± 0.000
	TCN	0.0154 ± 0.0003	0.0114 ± 0.0004	2.036 ± 0.073	0.770 ± 0.010	55.914 ± 11.730
	Diff-TCN	0.0156 ± 0.0001	0.0115 ± 0.0001	2.056 ± 0.022	0.764 ± 0.002	52.151 ± 6.563
	CMHA-TCN	**0.0152** ± 0.0002	**0.0113** ± 0.0002	**2.028** ± 0.030	**0.774** ± 0.006	58.065 ± 4.165
	Diff-CMHA-TCN	0.0156 ± 0.0001	0.0115 ± 0.0001	2.048 ± 0.020	0.763 ± 0.003	55.914 ± 6.885
	EVMD-TCN	0.0154 ± 0.0001	0.0117 ± 0.0001	2.090 ± 0.024	0.769 ± 0.004	**63.978** ± 4.335
	EVMD-CMHA-TCN	0.0154 ± 0.0001	0.0118 ± 0.0002	2.112 ± 0.029	0.770 ± 0.004	**63.978** ± 4.718
	EVMD-PMB-TCN	0.0157 ± 0.0001	0.0118 ± 0.0002	2.114 ± 0.037	0.760 ± 0.004	62.366 ± 1.521
	EVMD-PMB-CMHA-TCN	0.0154 ± 0.0001	0.0120 ± 0.0001	2.146 ± 0.025	0.768 ± 0.003	62.366 ± 3.041
	SVMD-TCN	0.0156 ± 0.0001	0.0114 ± 0.0001	2.042 ± 0.019	0.762 ± 0.002	51.613 ± 6.968
	SVMD-CMHA-TCN	0.0156 ± 0.0001	0.0114 ± 0.0001	2.030 ± 0.017	0.765 ± 0.002	53.226 ± 4.059
	SVMD-PMB-TCN	0.0157 ± 0.0001	0.0114 ± 0.0001	2.040 ± 0.014	0.759 ± 0.003	50.000 ± 4.466
	SVMD-PMB-CMHA-TCN	0.0157 ± 0.0001	0.0116 ± 0.0001	2.063 ± 0.022	0.759 ± 0.003	51.613 ± 4.928
February 2024	**Diff-TCN** [27]	**0.0113** ± 0.0000	**0.0086** ± 0.0000	1.579 ± 0.004	**0.776** ± 0.001	41.954 ± 8.996
	TCN	0.0116 ± 0.0003	0.0087 ± 0.0002	1.588 ± 0.043	0.767 ± 0.012	48.851 ± 9.426
	Diff-TCN	0.0114 ± 0.0000	**0.0086** ± 0.0000	**1.565** ± 0.004	0.775 ± 0.001	**52.299** ± 1.285
	CMHA-TCN	0.0118 ± 0.0002	0.0089 ± 0.0002	1.620 ± 0.040	0.756 ± 0.010	44.828 ± 3.982
	Diff-CMHA-TCN	0.0114 ± 0.0001	0.0087 ± 0.0001	1.587 ± 0.012	0.774 ± 0.004	44.828 ± 5.973
	EVMD-TCN	0.0120 ± 0.0002	0.0090 ± 0.0001	1.643 ± 0.025	0.749 ± 0.007	48.851 ± 1.285
	EVMD-CMHA-TCN	0.0119 ± 0.0001	0.0089 ± 0.0001	1.625 ± 0.024	0.752 ± 0.006	49.425 ± 1.625
	EVMD-PMB-TCN	0.0117 ± 0.0001	0.0088 ± 0.0001	1.611 ± 0.018	0.761 ± 0.003	51.724 ± 0.000
	EVMD-PMB-CMHA-TCN	0.0120 ± 0.0001	0.0089 ± 0.0001	1.623 ± 0.025	0.751 ± 0.006	48.276 ± 3.982
	SVMD-TCN	0.0116 ± 0.0001	0.0087 ± 0.0001	1.587 ± 0.022	0.765 ± 0.003	45.977 ± 4.739
	SVMD-CMHA-TCN	0.0118 ± 0.0001	0.0088 ± 0.0001	1.614 ± 0.013	0.759 ± 0.003	44.253 ± 3.095
	SVMD-PMB-TCN	0.0116 ± 0.0001	0.0086 ± 0.0001	1.581 ± 0.018	0.767 ± 0.004	52.299 ± 8.773
	SVMD-PMB-CMHA-TCN	0.0118 ± 0.0001	0.0088 ± 0.0002	1.612 ± 0.033	0.756 ± 0.006	41.954 ± 2.370
March 2024	Diff-TCN [27]	0.0321 ± 0.0000	0.0234 ± 0.0000	3.673 ± 0.002	−0.251 ± 0.001	48.387 ± 3.725
	TCN	0.0319 ± 0.0003	0.0230 ± 0.0007	3.613 ± 0.115	−0.232 ± 0.024	45.699 ± 4.335
	Diff-TCN	0.0316 ± 0.0001	0.0227 ± 0.0001	3.564 ± 0.014	−0.206 ± 0.005	58.602 ± 2.217
	CMHA-TCN	0.0313 ± 0.0003	0.0223 ± 0.0004	3.502 ± 0.070	−0.187 ± 0.019	61.290 ± 8.329
	Diff-CMHA-TCN	0.0319 ± 0.0003	0.0231 ± 0.0003	3.622 ± 0.049	−0.234 ± 0.021	56.989 ± 3.566
	EVMD-TCN	0.0306 ± 0.0000	0.0212 ± 0.0001	3.321 ± 0.016	−0.131 ± 0.003	55.914 ± 1.521
	EVMD-CMHA-TCN	0.0304 ± 0.0000	0.0208 ± 0.0002	3.258 ± 0.024	−0.117 ± 0.004	58.065 ± 0.000
	EVMD-PMB-TCN	0.0314 ± 0.0000	0.0216 ± 0.0001	3.387 ± 0.008	−0.193 ± 0.003	**61.828** ± 2.217
	EVMD-PMB-CMHA-TCN	**0.0304** ± 0.0001	**0.0203** ± 0.0001	**3.191** ± 0.013	**-0.117** ± 0.006	61.290 ± 2.634
	SVMD-TCN	0.0317 ± 0.0001	0.0232 ± 0.0001	3.651 ± 0.024	−0.216 ± 0.005	48.387 ± 0.000
	SVMD-CMHA-TCN	0.0314 ± 0.0000	0.0231 ± 0.0000	3.628 ± 0.006	−0.196 ± 0.003	53.226 ± 2.464
	SVMD-PMB-TCN	0.0317 ± 0.0001	0.0235 ± 0.0001	3.693 ± 0.016	−0.216 ± 0.009	47.849 ± 2.895
	SVMD-PMB-CMHA-TCN	0.0314 ± 0.0001	0.0231 ± 0.0001	3.631 ± 0.012	−0.194 ± 0.005	52.151 ± 2.895
April 2024	**Diff-TCN** [27]	**0.0214** ± 0.0000	0.0140 ± 0.0000	2.601 ± 0.003	**0.764** ± 0.000	41.667 ± 3.727
	TCN	0.0219 ± 0.0008	0.0142 ± 0.0004	2.644 ± 0.081	0.752 ± 0.018	52.778 ± 5.241
	Diff-TCN	0.0217 ± 0.0001	0.0138 ± 0.0001	2.566 ± 0.011	0.757 ± 0.002	56.667 ± 7.698
	CMHA-TCN	0.0218 ± 0.0003	0.0140 ± 0.0002	2.607 ± 0.032	0.753 ± 0.007	51.111 ± 5.984

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	0.0214 ± 0.0002	0.0139 ± 0.0001	2.591 ± 0.020	0.762 ± 0.004	45.556 ± 5.666
	EVMD-TCN	0.0228 ± 0.0001	0.0141 ± 0.0001	2.627 ± 0.022	0.731 ± 0.003	59.444 ± 1.242
	EVMD-CMHA-TCN	0.0230 ± 0.0002	0.0141 ± 0.0001	2.627 ± 0.023	0.725 ± 0.004	60.000 ± 0.000
	EVMD-PMB-TCN	0.0231 ± 0.0001	0.0146 ± 0.0001	2.725 ± 0.019	0.724 ± 0.002	55.000 ± 3.727
	EVMD-PMB-CMHA-TCN	0.0234 ± 0.0002	0.0142 ± 0.0003	2.644 ± 0.049	0.716 ± 0.006	**60.556** ± 2.291
	SVMD-TCN	**0.0214** ± 0.0001	**0.0137** ± 0.0001	**2.544** ± 0.015	0.762 ± 0.002	53.333 ± 1.925
	SVMD-CMHA-TCN	0.0214 ± 0.0002	0.0137 ± 0.0001	2.552 ± 0.017	0.762 ± 0.004	49.444 ± 2.291
	SVMD-PMB-TCN	0.0215 ± 0.0003	0.0138 ± 0.0002	2.575 ± 0.042	0.761 ± 0.007	53.889 ± 2.992
	SVMD-PMB-CMHA-TCN	0.0217 ± 0.0002	0.0137 ± 0.0003	2.549 ± 0.052	0.756 ± 0.004	51.111 ± 3.143
May 2024	Diff-TCN [27]	0.0102 ± 0.0000	0.0078 ± 0.0000	1.502 ± 0.001	0.225 ± 0.000	47.312 ± 2.404
	TCN	0.0102 ± 0.0001	0.0079 ± 0.0001	1.507 ± 0.022	0.216 ± 0.014	53.763 ± 9.796
	Diff-TCN	0.0100 ± 0.0000	0.0076 ± 0.0000	1.463 ± 0.003	0.256 ± 0.002	67.204 ± 2.217
	CMHA-TCN	0.0099 ± 0.0001	0.0076 ± 0.0001	1.453 ± 0.015	0.260 ± 0.013	62.903 ± 5.185
	Diff-CMHA-TCN	0.0100 ± 0.0000	0.0078 ± 0.0001	1.488 ± 0.010	0.244 ± 0.007	50.538 ± 4.433
	EVMD-TCN	0.0099 ± 0.0000	0.0076 ± 0.0000	1.446 ± 0.002	0.265 ± 0.003	57.527 ± 2.895
	EVMD-CMHA-TCN	0.0098 ± 0.0000	0.0076 ± 0.0000	1.445 ± 0.002	0.282 ± 0.005	66.667 ± 1.521
	EVMD-PMB-TCN	0.0103 ± 0.0001	0.0079 ± 0.0000	1.518 ± 0.008	0.207 ± 0.008	44.624 ± 1.202
	EVMD-PMB-CMHA-TCN	**0.0096** ± 0.0000	0.0075 ± 0.0000	1.435 ± 0.005	**0.309** ± 0.005	62.366 ± 3.566
	SVMD-TCN	0.0098 ± 0.0001	0.0075 ± 0.0000	1.434 ± 0.009	0.284 ± 0.008	67.742 ± 4.562
	SVMD-CMHA-TCN	0.0098 ± 0.0001	0.0075 ± 0.0001	1.427 ± 0.011	0.278 ± 0.011	67.742 ± 2.634
	SVMD-PMB-TCN	0.0098 ± 0.0000	0.0075 ± 0.0000	1.442 ± 0.008	0.273 ± 0.005	**69.892** ± 3.041
	SVMD-PMB-CMHA-TCN	**0.0096** ± 0.0001	**0.0074** ± 0.0001	**1.423** ± 0.010	0.304 ± 0.015	67.742 ± 2.634
June 2024	Diff-TCN [27]	0.0086 ± 0.0000	0.0065 ± 0.0000	1.322 ± 0.001	0.742 ± 0.000	53.333 ± 0.000
	TCN	0.0088 ± 0.0002	0.0066 ± 0.0002	1.340 ± 0.033	0.735 ± 0.010	50.556 ± 6.211
	Diff-TCN	0.0085 ± 0.0001	0.0064 ± 0.0000	1.295 ± 0.007	0.751 ± 0.003	60.556 ± 6.211
	CMHA-TCN	0.0085 ± 0.0001	0.0064 ± 0.0001	1.309 ± 0.016	0.747 ± 0.005	52.222 ± 3.143
	Diff-CMHA-TCN	0.0086 ± 0.0000	0.0064 ± 0.0000	1.309 ± 0.007	0.745 ± 0.003	48.333 ± 5.358
	EVMD-TCN	0.0088 ± 0.0001	0.0064 ± 0.0000	1.292 ± 0.008	0.730 ± 0.004	60.000 ± 3.333
	EVMD-CMHA-TCN	0.0087 ± 0.0000	**0.0063** ± 0.0000	**1.275** ± 0.005	0.738 ± 0.003	67.222 ± 2.291
	EVMD-PMB-TCN	0.0092 ± 0.0000	0.0066 ± 0.0001	1.349 ± 0.011	0.709 ± 0.003	51.111 ± 3.143
	EVMD-PMB-CMHA-TCN	0.0088 ± 0.0001	0.0064 ± 0.0001	1.298 ± 0.013	0.735 ± 0.004	**63.889** ± 5.906
	SVMD-TCN	0.0085 ± 0.0001	0.0065 ± 0.0000	1.317 ± 0.011	0.753 ± 0.003	55.556 ± 3.143
	SVMD-CMHA-TCN	0.0084 ± 0.0001	0.0065 ± 0.0000	1.314 ± 0.008	0.754 ± 0.004	55.556 ± 1.571
	SVMD-PMB-TCN	0.0085 ± 0.0001	0.0065 ± 0.0001	1.330 ± 0.018	0.748 ± 0.006	55.000 ± 5.358
	SVMD-PMB-CMHA-TCN	**0.0083** ± 0.0001	**0.0063** ± 0.0001	1.285 ± 0.014	**0.759** ± 0.004	61.111 ± 4.157
July 2024	Diff-TCN [27]	0.0229 ± 0.0000	0.0172 ± 0.0000	3.260 ± 0.005	0.904 ± 0.000	36.022 ± 8.415
	TCN	0.0230 ± 0.0001	0.0171 ± 0.0001	3.241 ± 0.024	0.903 ± 0.001	50.000 ± 7.622
	Diff-TCN	0.0230 ± 0.0000	**0.0169** ± 0.0001	**3.216** ± 0.014	0.903 ± 0.000	51.613 ± 4.928
	CMHA-TCN	0.0231 ± 0.0002	0.0172 ± 0.0002	3.257 ± 0.046	0.902 ± 0.001	47.849 ± 5.072
	Diff-CMHA-TCN	0.0228 ± 0.0002	0.0170 ± 0.0002	3.233 ± 0.034	0.904 ± 0.002	50.538 ± 10.144
	EVMD-TCN	0.0228 ± 0.0000	0.0171 ± 0.0001	3.237 ± 0.015	0.905 ± 0.000	52.688 ± 3.041
	EVMD-CMHA-TCN	0.0230 ± 0.0000	0.0172 ± 0.0001	3.264 ± 0.013	0.903 ± 0.000	**54.839** ± 1.862
	EVMD-PMB-TCN	**0.0225** ± 0.0001	0.0170 ± 0.0001	3.232 ± 0.015	**0.907** ± 0.001	54.301 ± 1.202
	EVMD-PMB-CMHA-TCN	0.0233 ± 0.0001	0.0175 ± 0.0001	3.326 ± 0.020	0.901 ± 0.001	46.237 ± 2.404
	SVMD-TCN	0.0234 ± 0.0001	0.0172 ± 0.0001	3.268 ± 0.024	0.900 ± 0.001	39.785 ± 2.404
	SVMD-CMHA-TCN	0.0235 ± 0.0001	0.0173 ± 0.0001	3.286 ± 0.017	0.899 ± 0.001	43.011 ± 3.041
	SVMD-PMB-TCN	0.0233 ± 0.0002	0.0172 ± 0.0002	3.269 ± 0.042	0.900 ± 0.002	41.935 ± 4.928
	SVMD-PMB-CMHA-TCN	0.0233 ± 0.0002	0.0172 ± 0.0002	3.271 ± 0.043	0.900 ± 0.001	51.075 ± 5.715
August 2024	**Diff-TCN** [27]	**0.0246** ± 0.0000	0.0164 ± 0.0000	2.880 ± 0.001	**0.259** ± 0.000	44.624 ± 1.202
	TCN	0.0247 ± 0.0002	**0.0163** ± 0.0001	**2.856** ± 0.021	0.254 ± 0.015	54.839 ± 7.450
	Diff-TCN	0.0251 ± 0.0001	0.0165 ± 0.0000	2.898 ± 0.004	0.232 ± 0.004	58.065 ± 0.000
	CMHA-TCN	0.0253 ± 0.0002	0.0167 ± 0.0001	2.933 ± 0.023	0.219 ± 0.011	52.688 ± 1.521
	Diff-CMHA-TCN	0.0247 ± 0.0002	0.0164 ± 0.0000	2.890 ± 0.007	0.251 ± 0.009	45.699 ± 6.011
	EVMD-TCN	0.0269 ± 0.0001	0.0177 ± 0.0001	3.100 ± 0.017	0.117 ± 0.006	55.376 ± 2.217
	EVMD-CMHA-TCN	0.0271 ± 0.0001	0.0178 ± 0.0000	3.123 ± 0.009	0.101 ± 0.004	54.301 ± 2.217
	EVMD-PMB-TCN	0.0273 ± 0.0001	0.0181 ± 0.0001	3.166 ± 0.020	0.090 ± 0.003	51.075 ± 2.217
	EVMD-PMB-CMHA-TCN	0.0276 ± 0.0003	0.0182 ± 0.0002	3.192 ± 0.043	0.065 ± 0.021	51.613 ± 2.634
	SVMD-TCN	0.0253 ± 0.0003	0.0166 ± 0.0002	2.909 ± 0.040	0.218 ± 0.020	53.226 ± 2.464
	SVMD-CMHA-TCN	0.0255 ± 0.0001	0.0167 ± 0.0001	2.931 ± 0.016	0.205 ± 0.008	55.376 ± 2.217
	SVMD-PMB-TCN	0.0253 ± 0.0002	0.0165 ± 0.0002	2.903 ± 0.028	0.215 ± 0.014	58.602 ± 2.217
	SVMD-PMB-CMHA-TCN	0.0258 ± 0.0004	0.0172 ± 0.0002	3.008 ± 0.036	0.183 ± 0.023	**61.828** ± 1.202
September 2024	Diff-TCN [27]	0.0150 ± 0.0000	0.0118 ± 0.0000	2.042 ± 0.001	0.713 ± 0.000	55.556 ± 4.969
	TCN	0.0151 ± 0.0001	0.0117 ± 0.0001	2.026 ± 0.016	0.712 ± 0.004	50.556 ± 6.211
	Diff-TCN	0.0148 ± 0.0000	0.0115 ± 0.0001	1.999 ± 0.009	0.720 ± 0.002	62.222 ± 3.685
	CMHA-TCN	0.0149 ± 0.0001	0.0114 ± 0.0001	1.971 ± 0.018	0.720 ± 0.004	61.111 ± 6.285
	Diff-CMHA-TCN	0.0150 ± 0.0001	0.0117 ± 0.0001	2.028 ± 0.018	0.716 ± 0.003	54.444 ± 4.581
	EVMD-TCN	0.0152 ± 0.0000	0.0119 ± 0.0000	2.067 ± 0.003	0.705 ± 0.001	52.778 ± 1.242
	EVMD-CMHA-TCN	0.0153 ± 0.0001	0.0118 ± 0.0000	2.054 ± 0.007	0.704 ± 0.003	56.111 ± 1.242
	EVMD-PMB-TCN	0.0155 ± 0.0001	0.0123 ± 0.0001	2.127 ± 0.012	0.696 ± 0.003	41.667 ± 1.667
	EVMD-PMB-CMHA-TCN	0.0152 ± 0.0002	0.0117 ± 0.0002	2.032 ± 0.025	0.707 ± 0.006	57.222 ± 2.291
	SVMD-TCN	**0.0148** ± 0.0001	**0.0113** ± 0.0000	1.958 ± 0.007	0.723 ± 0.002	**70.000** ± 1.925
	SVMD-CMHA-TCN	**0.0148** ± 0.0000	**0.0113** ± 0.0000	**1.953** ± 0.006	0.723 ± 0.001	67.222 ± 1.242
	SVMD-PMB-TCN	0.0149 ± 0.0001	0.0114 ± 0.0001	1.976 ± 0.010	0.720 ± 0.002	62.222 ± 3.685
	SVMD-PMB-CMHA-TCN	**0.0148** ± 0.0001	**0.0113** ± 0.0001	1.957 ± 0.012	**0.724** ± 0.004	62.222 ± 4.157
October 2024	Diff-TCN [27]	0.0142 ± 0.0000	0.0094 ± 0.0000	1.775 ± 0.001	0.235 ± 0.001	48.925 ± 1.202
	TCN	0.0143 ± 0.0003	0.0093 ± 0.0000	1.747 ± 0.008	0.230 ± 0.028	59.677 ± 5.815
	Diff-TCN	0.0144 ± 0.0001	0.0094 ± 0.0000	1.773 ± 0.003	0.214 ± 0.013	58.065 ± 4.928
	CMHA-TCN	0.0144 ± 0.0002	0.0092 ± 0.0001	1.731 ± 0.010	0.216 ± 0.026	60.753 ± 3.442

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	0.0144 ± 0.0001	0.0095 ± 0.0001	1.783 ± 0.011	0.221 ± 0.011	48.925 ± 6.822
	EVMD-TCN	0.0165 ± 0.0001	0.0097 ± 0.0000	1.830 ± 0.006	−0.027 ± 0.007	57.527 ± 2.217
	EVMD-CMHA-TCN	0.0164 ± 0.0002	0.0096 ± 0.0001	1.800 ± 0.012	−0.019 ± 0.020	58.602 ± 1.202
	EVMD-PMB-TCN	0.0170 ± 0.0001	0.0101 ± 0.0001	1.895 ± 0.014	−0.094 ± 0.018	58.602 ± 4.335
	EVMD-PMB-CMHA-TCN	0.0167 ± 0.0003	0.0098 ± 0.0001	1.833 ± 0.016	−0.049 ± 0.034	58.602 ± 5.072
	SVMD-TCN	0.0143 ± 0.0001	0.0091 ± 0.0001	1.710 ± 0.011	0.230 ± 0.015	56.452 ± 5.185
	SVMD-CMHA-TCN	0.0144 ± 0.0001	**0.0090** ± 0.0000	**1.686** ± 0.006	0.223 ± 0.009	59.140 ± 3.566
	SVMD-PMB-TCN	0.0145 ± 0.0003	0.0091 ± 0.0001	1.707 ± 0.018	0.211 ± 0.028	60.215 ± 2.404
	SVMD-PMB-CMHA-TCN	**0.0142** ± 0.0001	**0.0090** ± 0.0001	1.694 ± 0.021	**0.243** ± 0.014	**64.516** ± 1.862
November 2024	**Diff-TCN** [27]	**0.0939** ± 0.0000	**0.0600** ± 0.0000	**5.300** ± 0.002	**0.954** ± 0.000	**65.556** ± 2.485
	TCN	0.1029 ± 0.0021	0.0639 ± 0.0010	5.538 ± 0.069	0.944 ± 0.002	40.000 ± 3.849
	Diff-TCN	0.0967 ± 0.0006	0.0612 ± 0.0003	5.361 ± 0.022	0.951 ± 0.001	45.556 ± 3.143
	CMHA-TCN	0.1128 ± 0.0037	0.0710 ± 0.0034	6.034 ± 0.265	0.933 ± 0.004	41.667 ± 3.191
	Diff-CMHA-TCN	0.0942 ± 0.0009	0.0603 ± 0.0003	5.308 ± 0.018	0.953 ± 0.001	57.222 ± 8.480
	EVMD-TCN	0.1164 ± 0.0014	0.0737 ± 0.0006	6.311 ± 0.042	0.929 ± 0.002	37.222 ± 2.291
	EVMD-CMHA-TCN	0.1210 ± 0.0020	0.0769 ± 0.0013	6.570 ± 0.115	0.923 ± 0.003	37.222 ± 2.291
	EVMD-PMB-TCN	0.1096 ± 0.0009	0.0701 ± 0.0004	6.012 ± 0.035	0.937 ± 0.001	45.000 ± 1.667
	EVMD-PMB-CMHA-TCN	0.1177 ± 0.0013	0.0753 ± 0.0009	6.453 ± 0.084	0.927 ± 0.002	40.000 ± 1.925
	SVMD-TCN	0.1051 ± 0.0021	0.0650 ± 0.0014	5.612 ± 0.095	0.942 ± 0.002	43.889 ± 1.242
	SVMD-CMHA-TCN	0.1103 ± 0.0015	0.0672 ± 0.0010	5.773 ± 0.075	0.936 ± 0.002	40.000 ± 0.000
	SVMD-PMB-TCN	0.1015 ± 0.0084	0.0633 ± 0.0046	5.505 ± 0.283	0.945 ± 0.009	48.333 ± 4.194
	SVMD-PMB-CMHA-TCN	0.1188 ± 0.0046	0.0736 ± 0.0031	6.259 ± 0.241	0.926 ± 0.006	39.444 ± 1.242
December 2024	Diff-TCN [27]	0.1570 ± 0.0000	0.1115 ± 0.0000	4.712 ± 0.001	0.047 ± 0.000	49.462 ± 2.404
	TCN	**0.1569** ± 0.0004	0.1110 ± 0.0003	4.679 ± 0.011	**0.048** ± 0.005	51.613 ± 3.226
	Diff-TCN	0.1589 ± 0.0005	0.1122 ± 0.0003	4.745 ± 0.011	0.024 ± 0.006	51.613 ± 0.000
	CMHA-TCN	0.1571 ± 0.0002	**0.1107** ± 0.0001	**4.668** ± 0.004	0.046 ± 0.003	53.763 ± 2.404
	Diff-CMHA-TCN	0.1580 ± 0.0008	0.1119 ± 0.0004	4.733 ± 0.019	0.035 ± 0.010	49.462 ± 3.041
	EVMD-TCN	0.1693 ± 0.0001	0.1155 ± 0.0001	4.873 ± 0.009	−0.108 ± 0.001	55.376 ± 1.202
	EVMD-CMHA-TCN	0.1687 ± 0.0005	0.1155 ± 0.0004	4.872 ± 0.021	−0.100 ± 0.007	**60.215** ± 1.521
	EVMD-PMB-TCN	0.1709 ± 0.0007	0.1190 ± 0.0013	5.031 ± 0.057	−0.129 ± 0.009	53.226 ± 2.464
	EVMD-PMB-CMHA-TCN	0.1692 ± 0.0006	0.1163 ± 0.0012	4.895 ± 0.044	−0.107 ± 0.008	55.914 ± 3.041
	SVMD-TCN	0.1686 ± 0.0025	0.1243 ± 0.0048	5.221 ± 0.200	−0.100 ± 0.033	51.075 ± 2.217
	SVMD-CMHA-TCN	0.1692 ± 0.0009	0.1223 ± 0.0007	5.140 ± 0.034	−0.107 ± 0.011	51.613 ± 2.634
	SVMD-PMB-TCN	0.1691 ± 0.0009	0.1241 ± 0.0019	5.221 ± 0.071	−0.106 ± 0.012	48.387 ± 1.862
	SVMD-PMB-CMHA-TCN	0.1690 ± 0.0020	0.1199 ± 0.0027	5.039 ± 0.104	−0.104 ± 0.026	46.237 ± 3.041
January 2025	**Diff-TCN** [27]	0.1377 ± 0.0000	**0.0931** ± 0.0000	**3.394** ± 0.000	**0.854** ± 0.000	**58.602** ± 3.442
	TCN	0.1414 ± 0.0026	0.0968 ± 0.0029	3.519 ± 0.096	0.845 ± 0.006	40.860 ± 7.828
	Diff-TCN	0.1385 ± 0.0006	0.0935 ± 0.0005	3.401 ± 0.014	0.852 ± 0.001	48.387 ± 3.226
	CMHA-TCN	0.1407 ± 0.0017	0.0966 ± 0.0021	3.507 ± 0.070	0.847 ± 0.004	40.323 ± 4.059
	Diff-CMHA-TCN	**0.1376** ± 0.0001	**0.0931** ± 0.0001	**3.394** ± 0.002	**0.854** ± 0.000	48.925 ± 2.217
	EVMD-TCN	0.1480 ± 0.0011	0.1004 ± 0.0013	3.601 ± 0.045	0.831 ± 0.002	44.624 ± 1.202
	EVMD-CMHA-TCN	0.1490 ± 0.0013	0.1004 ± 0.0014	3.598 ± 0.048	0.828 ± 0.003	46.237 ± 2.404
	EVMD-PMB-TCN	0.1544 ± 0.0062	0.1073 ± 0.0077	3.861 ± 0.270	0.815 ± 0.015	41.935 ± 4.562
	EVMD-PMB-CMHA-TCN	0.1566 ± 0.0092	0.1091 ± 0.0111	3.902 ± 0.386	0.810 ± 0.022	44.086 ± 9.617
	SVMD-TCN	0.1417 ± 0.0033	0.0966 ± 0.0037	3.486 ± 0.123	0.845 ± 0.007	41.935 ± 6.452
	SVMD-CMHA-TCN	0.1409 ± 0.0018	0.0953 ± 0.0025	3.442 ± 0.082	0.847 ± 0.004	39.247 ± 2.895
	SVMD-PMB-TCN	0.1430 ± 0.0017	0.0978 ± 0.0023	3.527 ± 0.077	0.842 ± 0.004	35.484 ± 0.000
	SVMD-PMB-CMHA-TCN	0.1430 ± 0.0048	0.0989 ± 0.0046	3.552 ± 0.158	0.842 ± 0.011	39.785 ± 6.361
February 2025	Diff-TCN [27]	0.1203 ± 0.0000	0.0902 ± 0.0000	3.588 ± 0.001	0.588 ± 0.000	46.429 ± 0.000
	TCN	0.1238 ± 0.0025	0.0925 ± 0.0016	3.685 ± 0.068	0.563 ± 0.018	45.833 ± 1.331
	Diff-TCN	0.1207 ± 0.0001	0.0904 ± 0.0000	3.593 ± 0.001	0.585 ± 0.001	54.167 ± 1.331
	CMHA-TCN	0.1225 ± 0.0007	0.0919 ± 0.0005	3.661 ± 0.022	0.573 ± 0.005	43.452 ± 3.205
	Diff-CMHA-TCN	0.1205 ± 0.0003	0.0903 ± 0.0001	3.590 ± 0.005	0.587 ± 0.002	44.643 ± 1.786
	EVMD-TCN	0.1311 ± 0.0018	0.1016 ± 0.0011	4.065 ± 0.050	0.510 ± 0.013	33.929 ± 1.786
	EVMD-CMHA-TCN	0.1317 ± 0.0014	0.1022 ± 0.0009	4.091 ± 0.038	0.506 ± 0.010	32.738 ± 2.454
	EVMD-PMB-TCN	0.1330 ± 0.0023	0.1031 ± 0.0011	4.135 ± 0.046	0.496 ± 0.017	40.476 ± 3.367
	EVMD-PMB-CMHA-TCN	0.1312 ± 0.0043	0.1023 ± 0.0025	4.097 ± 0.108	0.509 ± 0.033	36.905 ± 6.411
	SVMD-TCN	0.1225 ± 0.0017	0.0936 ± 0.0013	3.739 ± 0.053	0.573 ± 0.012	45.238 ± 5.709
	SVMD-CMHA-TCN	0.1209 ± 0.0017	0.0907 ± 0.0012	3.627 ± 0.049	0.584 ± 0.012	53.571 ± 6.521
	SVMD-PMB-TCN	**0.1189** ± 0.0011	**0.0890** ± 0.0009	**3.558** ± 0.031	**0.598** ± 0.007	**55.357** ± 4.494
	SVMD-PMB-CMHA-TCN	0.1247 ± 0.0059	0.0949 ± 0.0031	3.794 ± 0.136	0.556 ± 0.042	48.809 ± 9.144
March 2025	Diff-TCN [27]	0.1934 ± 0.0000	0.1156 ± 0.0001	4.750 ± 0.002	−0.233 ± 0.001	48.925 ± 1.202
	TCN	0.1929 ± 0.0008	0.1156 ± 0.0003	4.751 ± 0.014	−0.227 ± 0.010	50.000 ± 6.106
	Diff-TCN	0.1902 ± 0.0007	**0.1146** ± 0.0003	**4.717** ± 0.010	−0.192 ± 0.009	40.323 ± 2.464
	CMHA-TCN	0.1903 ± 0.0022	0.1154 ± 0.0003	4.755 ± 0.011	−0.194 ± 0.027	45.161 ± 4.562
	Diff-CMHA-TCN	0.1931 ± 0.0008	0.1155 ± 0.0003	4.748 ± 0.011	−0.230 ± 0.010	48.387 ± 5.268
	EVMD-TCN	0.1885 ± 0.0003	0.1179 ± 0.0002	4.838 ± 0.010	−0.171 ± 0.003	52.688 ± 2.404
	EVMD-CMHA-TCN	0.1872 ± 0.0004	0.1170 ± 0.0004	4.812 ± 0.018	−0.156 ± 0.005	53.226 ± 1.613
	EVMD-PMB-TCN	0.1884 ± 0.0007	0.1171 ± 0.0005	4.812 ± 0.022	−0.171 ± 0.009	50.538 ± 3.041
	EVMD-PMB-CMHA-TCN	**0.1865** ± 0.0008	0.1161 ± 0.0008	4.769 ± 0.032	**-0.146** ± 0.010	**54.301** ± 1.202
	SVMD-TCN	0.1878 ± 0.0002	0.1185 ± 0.0002	4.888 ± 0.010	−0.163 ± 0.002	43.011 ± 3.041
	SVMD-CMHA-TCN	0.1885 ± 0.0004	0.1173 ± 0.0004	4.834 ± 0.019	−0.172 ± 0.005	45.699 ± 2.217
	SVMD-PMB-TCN	0.1884 ± 0.0005	0.1161 ± 0.0005	4.787 ± 0.022	−0.170 ± 0.007	45.699 ± 2.217
	SVMD-PMB-CMHA-TCN	0.1873 ± 0.0007	0.1168 ± 0.0001	4.814 ± 0.009	−0.157 ± 0.009	46.237 ± 2.404
April 2025	Diff-TCN [27]	0.0838 ± 0.0000	0.0571 ± 0.0000	2.771 ± 0.000	0.401 ± 0.000	50.556 ± 1.242
	TCN	0.0838 ± 0.0000	0.0573 ± 0.0001	2.778 ± 0.004	0.401 ± 0.001	46.111 ± 4.045
	Diff-TCN	**0.0829** ± 0.0002	**0.0568** ± 0.0001	**2.755** ± 0.006	**0.414** ± 0.003	50.000 ± 1.925
	CMHA-TCN	0.0829 ± 0.0004	0.0572 ± 0.0002	2.780 ± 0.009	0.414 ± 0.005	48.889 ± 7.617

Month	Model	RMSE	MAE	MAPE	R2	DA
	Diff-CMHA-TCN	0.0836 ± 0.0004	0.0570 ± 0.0002	2.768 ± 0.008	0.404 ± 0.005	50.556 ± 1.242
	EVMD-TCN	0.0856 ± 0.0002	0.0603 ± 0.0002	2.916 ± 0.010	0.375 ± 0.003	42.778 ± 2.992
	EVMD-CMHA-TCN	0.0849 ± 0.0001	0.0598 ± 0.0001	2.891 ± 0.003	0.386 ± 0.002	38.889 ± 5.984
	EVMD-PMB-TCN	0.0851 ± 0.0003	0.0605 ± 0.0005	2.933 ± 0.023	0.382 ± 0.004	37.778 ± 3.685
	EVMD-PMB-CMHA-TCN	0.0845 ± 0.0004	0.0594 ± 0.0004	2.869 ± 0.018	0.390 ± 0.005	45.556 ± 5.329
	SVMD-TCN	0.0872 ± 0.0002	0.0595 ± 0.0003	2.889 ± 0.013	0.352 ± 0.003	51.111 ± 1.571
	SVMD-CMHA-TCN	0.0861 ± 0.0005	0.0586 ± 0.0006	2.842 ± 0.027	0.368 ± 0.007	46.667 ± 2.722
	SVMD-PMB-TCN	0.0858 ± 0.0003	0.0592 ± 0.0003	2.870 ± 0.013	0.372 ± 0.004	46.111 ± 4.479
	SVMD-PMB-CMHA-TCN	0.0861 ± 0.0007	0.0586 ± 0.0004	2.842 ± 0.021	0.368 ± 0.011	**54.444** ± 3.685
May 2025	Diff-TCN [27]	0.0761 ± 0.0000	0.0549 ± 0.0000	2.339 ± 0.000	0.620 ± 0.000	45.161 ± 0.000
	TCN	0.0761 ± 0.0001	0.0547 ± 0.0004	2.329 ± 0.019	0.621 ± 0.001	50.000 ± 4.839
	Diff-TCN	0.0756 ± 0.0003	0.0549 ± 0.0000	2.337 ± 0.001	0.626 ± 0.003	51.075 ± 2.217
	CMHA-TCN	0.0758 ± 0.0001	0.0546 ± 0.0002	2.322 ± 0.011	0.624 ± 0.001	**54.839** ± 5.587
	Diff-CMHA-TCN	0.0762 ± 0.0001	0.0549 ± 0.0000	2.340 ± 0.001	0.620 ± 0.001	45.161 ± 3.725
	EVMD-TCN	0.0767 ± 0.0001	0.0561 ± 0.0002	2.388 ± 0.007	0.615 ± 0.001	43.011 ± 3.566
	EVMD-CMHA-TCN	0.0764 ± 0.0001	0.0562 ± 0.0003	2.392 ± 0.012	0.618 ± 0.001	40.323 ± 2.464
	EVMD-PMB-TCN	0.0764 ± 0.0003	0.0568 ± 0.0004	2.418 ± 0.017	0.617 ± 0.003	39.785 ± 3.566
	EVMD-PMB-CMHA-TCN	0.0763 ± 0.0007	0.0563 ± 0.0005	2.395 ± 0.023	0.619 ± 0.007	42.473 ± 1.202
	SVMD-TCN	0.0727 ± 0.0002	0.0541 ± 0.0003	2.308 ± 0.015	0.654 ± 0.002	46.237 ± 6.361
	SVMD-CMHA-TCN	0.0728 ± 0.0001	0.0545 ± 0.0002	2.325 ± 0.007	0.653 ± 0.001	40.860 ± 2.404
	SVMD-PMB-TCN	**0.0721** ± 0.0001	**0.0537** ± 0.0004	**2.292** ± 0.019	**0.660** ± 0.001	48.387 ± 5.889
	SVMD-PMB-CMHA-TCN	0.0725 ± 0.0006	0.0542 ± 0.0006	2.314 ± 0.030	0.655 ± 0.006	52.688 ± 3.566

Table 67: Average results of the *extended experiments* across 6 repetitions per split $M_1, \ldots, M_{36}$ corresponding to months June 2022 to May 2025 in relation to forecasting $\mathbf{S}_{\text{Close}}$ with respect to XRP/USD using the novel framework.

G Supplementary Experimental Analysis

G.1 Split Analysis: Default Input

G.1.1 Benchmark Experiment

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)
BTC/USD	M_1	June 2021	0.207	0.060	**5.924**	-20.341	**60.230**
	M_2	July 2021	0.351	0.078	4.303	-3.977	56.841
	M_3	August 2021	0.612	0.019	3.409	**34.119**	41.824
	M_4	September 2021	0.273	0.056	3.643	1.243	52.989
	M_5	October 2021	0.588	0.038	4.015	26.889	56.174
	M_6	November 2021	0.263	0.068	3.094	5.625	51.839
	M_7	December 2021	0.582	0.021	3.661	-18.368	54.616
	M_8	January 2022	0.611	0.042	2.898	-16.136	52.503
	M_9	February 2022	0.530	0.066	3.502	-0.760	46.921
	M_{10}	March 2022	0.280	0.096	4.373	3.675	52.725
	M_{11}	April 2022	0.489	0.038	2.715	0.255	52.529
	M_{12}	May 2022	**0.689**	**0.012**	3.805	-24.082	53.170
	-	Mean	0.456	0.050	3.778	-0.988	52.697
ETH/USD	M_1	June 2021	0.411	0.048	**8.807**	-24.451	51.034
	M_2	July 2021	0.222	0.083	5.440	-7.594	52.058
	M_3	August 2021	0.686	0.024	4.048	**46.327**	43.715
	M_4	September 2021	0.570	0.062	4.906	8.902	**64.368**
	M_5	October 2021	0.642	0.043	4.613	15.781	54.505
	M_6	November 2021	0.508	0.041	3.677	16.964	53.793
	M_7	December 2021	0.207	0.062	4.396	-8.277	53.281
	M_8	January 2022	0.740	0.018	3.649	-23.883	57.397
	M_9	February 2022	0.368	0.070	4.583	-5.061	39.532
	M_{10}	March 2022	0.371	0.075	4.361	1.119	44.049
	M_{11}	April 2022	0.555	0.038	3.034	10.211	51.264
	M_{12}	May 2022	**0.755**	**0.011**	4.372	-29.477	53.281
	-	Mean	0.503	0.048	4.657	0.047	51.523
LTC/USD	M_1	June 2021	0.480	0.029	**11.360**	**-39.164**	57.356
	M_2	July 2021	0.461	0.055	5.842	-17.667	45.495
	M_3	August 2021	**0.737**	0.033	4.449	34.322	43.938
	M_4	September 2021	0.413	0.078	6.718	7.155	57.356
	M_5	October 2021	0.443	0.043	5.030	8.023	46.051
	M_6	November 2021	0.521	0.039	5.706	23.478	50.920
	M_7	December 2021	0.558	0.030	6.420	-29.607	44.939
	M_8	January 2022	0.460	0.051	4.513	-19.458	54.505
	M_9	February 2022	0.309	0.077	5.560	-9.377	50.246
	M_{10}	March 2022	0.479	0.047	5.514	-2.935	**62.625**
	M_{11}	April 2022	0.290	0.038	4.279	-0.788	57.931
	M_{12}	May 2022	0.728	**0.013**	7.844	-38.123	47.942
	-	Mean	0.490	0.044	6.103	-7.012	51.609
XMR/USD	M_1	June 2021	0.296	0.064	**12.527**	-24.594	**66.092**
	M_2	July 2021	0.261	0.039	6.604	-15.228	48.053
	M_3	August 2021	0.652	0.025	3.902	**33.530**	38.932
	M_4	September 2021	0.498	0.044	5.451	-3.424	51.264
	M_5	October 2021	0.351	0.067	4.580	4.669	52.725
	M_6	November 2021	0.166	0.075	4.279	-6.269	50.000
	M_7	December 2021	0.601	0.023	5.109	-21.646	51.390
	M_8	January 2022	0.565	0.070	5.588	-5.144	36.040
	M_9	February 2022	0.387	0.069	5.804	-14.196	45.690
	M_{10}	March 2022	0.366	0.058	7.263	19.812	58.065
	M_{11}	April 2022	**0.748**	**0.013**	4.883	29.820	65.057
	M_{12}	May 2022	0.503	0.054	7.696	-24.064	48.832
	-	Mean	0.450	0.050	6.141	-2.228	51.012

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)
XRP/USD	M_1	June 2021	0.423	0.022	**11.403**	-38.529	56.667
	M_2	July 2021	0.547	0.039	7.587	-21.989	58.954
	M_3	August 2021	0.684	0.027	6.443	**79.257**	46.719
	M_4	September 2021	0.296	0.060	7.461	12.870	48.851
	M_5	October 2021	0.375	0.053	5.266	3.582	56.174
	M_6	November 2021	0.297	0.076	4.298	2.263	54.138
	M_7	December 2021	0.621	0.034	4.777	-23.345	52.169
	M_8	January 2022	0.644	0.052	4.533	-17.833	54.727
	M_9	February 2022	0.612	0.050	6.330	6.384	47.906
	M_{10}	March 2022	0.301	0.062	5.936	9.550	54.950
	M_{11}	April 2022	0.483	0.035	3.829	-6.597	**60.230**
	M_{12}	May 2022	**0.801**	**0.011**	7.193	-44.120	50.501
	-	Mean	0.507	0.043	6.255	-3.209	53.499

Table 68: Statistics of the *default* close price input across the windows in $\mathbf{X}_{\text{Test}}$ for splits $M_1, \ldots, M_{12}$ of the benchmark experiment across *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD*.

G.1.2 Extended Experiment

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)
BTC/USD	M_1	June 2022	0.518	0.059	**4.706**	-22.801	51.034
	M_2	July 2022	0.363	0.059	4.110	-8.325	40.267
	M_3	August 2022	0.380	0.046	3.188	4.953	42.492
	M_4	September 2022	0.355	0.062	3.662	-11.983	54.483
	M_5	October 2022	0.217	0.099	2.507	-0.646	49.722
	M_6	November 2022	0.711	0.048	3.893	-10.858	41.149
	M_7	December 2022	0.203	0.065	2.680	-2.903	54.394
	M_8	January 2023	0.607	0.042	1.951	20.916	53.059
	M_9	February 2023	0.229	0.064	2.769	19.241	57.635
	M_{10}	March 2023	0.630	0.080	3.477	7.434	49.166
	M_{11}	April 2023	0.412	0.040	2.847	17.583	58.851
	M_{12}	May 2023	0.391	0.069	2.128	-4.529	51.724
	M_{13}	June 2023	0.362	0.080	2.343	0.852	58.851
	M_{14}	July 2023	0.534	0.039	1.948	9.394	53.059
	M_{15}	August 2023	0.609	0.028	1.497	-7.343	58.509
	M_{16}	September 2023	0.238	0.062	2.096	-5.512	41.264
	M_{17}	October 2023	0.667	0.034	1.755	12.757	50.501
	M_{18}	November 2023	0.515	**0.010**	2.397	25.022	45.977
	M_{19}	December 2023	0.624	0.026	2.514	16.590	57.731
	M_{20}	January 2024	0.237	0.078	2.740	0.580	60.623
	M_{21}	February 2024	0.720	0.040	2.177	16.018	49.584
	M_{22}	March 2024	0.606	0.028	3.528	**37.352**	47.386
	M_{23}	April 2024	0.299	0.080	3.424	-2.248	54.368
	M_{24}	May 2024	0.474	0.053	2.874	-0.539	50.834
	M_{25}	June 2024	0.516	0.044	2.025	1.400	58.966
	M_{26}	July 2024	0.624	0.039	2.309	-4.308	47.275
	M_{27}	August 2024	0.386	0.061	3.365	-4.202	54.171
	M_{28}	September 2024	0.537	0.085	2.674	0.938	53.448
	M_{29}	October 2024	0.538	0.061	2.011	8.706	47.608
	M_{30}	November 2024	**0.845**	0.013	2.750	30.752	44.943
	M_{31}	December 2024	0.344	0.040	2.589	15.385	**61.068**
	M_{32}	January 2025	0.404	0.070	2.341	1.833	43.715
	M_{33}	February 2025	0.511	0.042	2.015	-3.933	46.182
	M_{34}	March 2025	0.413	0.037	3.410	-10.823	52.392
	M_{35}	April 2025	0.391	0.087	2.874	1.319	57.931
	M_{36}	May 2025	0.710	**0.010**	2.115	19.696	51.724
	-	Mean	0.476	0.052	2.714	4.660	51.447
ETH/USD	M_1	June 2022	0.650	**0.013**	5.827	-36.517	49.080
	M_2	July 2022	0.501	0.055	**6.115**	5.718	43.159
	M_3	August 2022	0.532	0.040	5.339	29.898	50.389

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)
	M_4	September 2022	0.549	0.068	4.837	-12.914	51.724
	M_5	October 2022	0.306	0.060	3.315	-7.006	53.504
	M_6	November 2022	0.628	0.045	5.659	-3.938	50.805
	M_7	December 2022	0.185	0.072	4.001	-3.424	**64.850**
	M_8	January 2023	0.640	0.039	2.374	19.588	50.501
	M_9	February 2023	0.152	0.068	3.070	12.624	49.015
	M_{10}	March 2023	0.401	0.087	3.169	2.894	54.171
	M_{11}	April 2023	0.566	0.029	2.910	15.653	56.207
	M_{12}	May 2023	0.211	0.064	2.527	-3.481	62.069
	M_{13}	June 2023	0.283	0.081	2.218	-1.619	55.517
	M_{14}	July 2023	0.290	0.069	2.314	4.490	59.066
	M_{15}	August 2023	0.587	0.033	1.545	-7.023	54.505
	M_{16}	September 2023	0.294	0.030	1.868	-7.755	52.529
	M_{17}	October 2023	0.313	0.099	1.878	1.963	29.922
	M_{18}	November 2023	0.642	0.015	2.667	20.900	37.701
	M_{19}	December 2023	0.468	0.041	2.812	13.890	56.730
	M_{20}	January 2024	0.314	0.070	3.128	4.968	54.171
	M_{21}	February 2024	0.705	0.052	2.440	14.845	47.562
	M_{22}	March 2024	0.622	0.038	3.080	34.963	54.171
	M_{23}	April 2024	0.347	0.057	4.072	-10.144	57.586
	M_{24}	May 2024	0.602	0.066	3.429	1.968	55.840
	M_{25}	June 2024	0.536	0.031	3.092	9.876	54.943
	M_{26}	July 2024	0.623	0.053	2.597	-8.023	52.503
	M_{27}	August 2024	0.563	0.053	4.222	-18.605	53.059
	M_{28}	September 2024	0.498	0.055	3.386	-6.037	53.333
	M_{29}	October 2024	0.183	0.086	2.569	2.581	45.495
	M_{30}	November 2024	0.637	0.054	3.538	22.549	40.115
	M_{31}	December 2024	0.579	0.035	3.789	19.516	62.625
	M_{32}	January 2025	0.242	0.075	3.324	-8.156	55.617
	M_{33}	February 2025	0.602	0.020	3.446	-19.297	64.778
	M_{34}	March 2025	0.580	0.019	5.229	-25.127	55.172
	M_{35}	April 2025	0.517	0.047	4.681	-16.439	45.172
	M_{36}	May 2025	**0.720**	0.022	4.800	**42.066**	52.836
	-	Mean	0.474	0.051	3.480	2.374	52.401
LTC/USD	M_1	June 2022	0.474	0.023	**9.847**	-36.179	56.897
	M_2	July 2022	0.267	0.090	8.700	0.906	51.168
	M_3	August 2022	0.346	0.039	6.307	14.941	42.047
	M_4	September 2022	0.351	0.081	7.029	-4.804	50.575
	M_5	October 2022	0.119	0.058	4.673	-8.915	53.615
	M_6	November 2022	0.542	0.057	8.780	37.812	44.368
	M_7	December 2022	0.595	0.034	6.933	19.634	56.396
	M_8	January 2023	0.655	0.034	3.914	27.629	42.937
	M_9	February 2023	0.389	0.039	4.301	20.961	58.005
	M_{10}	March 2023	0.578	0.059	5.526	-13.956	47.831
	M_{11}	April 2023	0.269	0.052	5.063	12.634	51.954
	M_{12}	May 2023	0.444	0.074	4.248	-6.385	61.068
	M_{13}	June 2023	0.494	0.063	4.881	-3.108	50.460
	M_{14}	July 2023	0.440	0.059	7.513	18.209	46.051
	M_{15}	August 2023	**0.659**	**0.014**	4.180	-27.995	55.061
	M_{16}	September 2023	0.270	0.055	4.467	-17.314	53.448
	M_{17}	October 2023	0.221	0.080	3.274	2.690	46.830
	M_{18}	November 2023	0.495	0.045	3.206	15.191	49.540
	M_{19}	December 2023	0.209	0.084	3.567	3.961	47.831
	M_{20}	January 2024	0.215	0.100	4.583	-8.343	47.052
	M_{21}	February 2024	0.234	0.073	3.081	3.328	43.520
	M_{22}	March 2024	0.569	0.045	6.330	40.774	39.933
	M_{23}	April 2024	0.531	0.069	7.459	-1.090	**64.138**
	M_{24}	May 2024	0.154	0.077	4.089	-7.131	58.843
	M_{25}	June 2024	0.577	0.043	2.930	-8.628	55.402
	M_{26}	July 2024	0.464	0.057	4.868	-12.281	56.841
	M_{27}	August 2024	0.393	0.068	5.581	-13.574	46.830
	M_{28}	September 2024	0.260	0.089	3.823	5.577	38.851
	M_{29}	October 2024	0.380	0.079	3.685	7.924	40.601
	M_{30}	November 2024	0.499	0.055	5.307	29.603	46.437
	M_{31}	December 2024	0.636	0.040	8.191	**59.117**	56.285
	M_{32}	January 2025	0.327	0.071	6.564	1.186	54.060
	M_{33}	February 2025	0.250	0.096	6.797	7.196	42.734
	M_{34}	March 2025	0.539	0.038	6.290	-22.453	57.953
	M_{35}	April 2025	0.527	0.035	5.549	-20.345	60.460

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)
	M_{36}	May 2025	0.569	0.028	4.850	28.062	51.502
	-	Mean	0.415	0.058	5.455	4.023	50.764
XMR/USD	M_1	June 2022	0.611	0.050	7.741	-21.181	45.172
	M_2	July 2022	0.554	0.036	6.118	4.420	49.722
	M_3	August 2022	0.341	0.038	4.465	18.289	57.620
	M_4	September 2022	0.226	0.069	5.039	-6.226	62.759
	M_5	October 2022	0.090	0.087	3.529	-3.188	62.403
	M_6	November 2022	0.553	0.069	4.683	-5.823	58.276
	M_7	December 2022	0.413	0.051	3.252	8.476	49.277
	M_8	January 2023	0.727	0.040	2.195	17.196	57.620
	M_9	February 2023	0.471	0.042	3.509	-3.377	58.128
	M_{10}	March 2023	0.301	0.042	3.496	-7.307	45.495
	M_{11}	April 2023	0.243	0.045	3.043	6.094	**67.701**
	M_{12}	May 2023	0.287	0.050	1.858	-3.692	53.281
	M_{13}	June 2023	0.526	0.034	2.318	-5.075	51.954
	M_{14}	July 2023	0.198	0.040	2.078	15.363	47.386
	M_{15}	August 2023	0.774	0.013	1.787	-9.270	55.172
	M_{16}	September 2023	0.275	0.054	2.355	-5.487	47.241
	M_{17}	October 2023	0.673	0.019	1.660	9.616	56.062
	M_{18}	November 2023	0.478	0.053	2.242	8.599	49.080
	M_{19}	December 2023	0.321	0.074	1.913	3.874	54.616
	M_{20}	January 2024	0.487	0.053	3.494	-10.676	61.290
	M_{21}	February 2024	0.327	0.046	**10.386**	-20.040	48.751
	M_{22}	March 2024	0.424	0.047	5.506	2.678	47.164
	M_{23}	April 2024	0.384	0.055	4.632	-3.418	51.609
	M_{24}	May 2024	0.641	0.037	3.985	10.883	57.175
	M_{25}	June 2024	0.642	0.022	3.250	29.212	37.816
	M_{26}	July 2024	0.274	0.069	3.225	-4.203	55.617
	M_{27}	August 2024	0.519	0.063	2.863	-2.756	56.396
	M_{28}	September 2024	0.418	0.040	2.816	10.909	43.333
	M_{29}	October 2024	0.550	0.046	3.452	-9.897	46.941
	M_{30}	November 2024	0.074	0.077	2.681	2.750	41.839
	M_{31}	December 2024	0.530	0.047	6.728	29.313	54.060
	M_{32}	January 2025	0.374	0.060	4.681	7.345	57.842
	M_{33}	February 2025	0.197	0.069	3.734	9.735	51.232
	M_{34}	March 2025	0.297	0.071	3.307	-4.597	50.501
	M_{35}	April 2025	0.451	0.094	2.738	1.287	55.517
	M_{36}	May 2025	**0.930**	**0.011**	3.381	**58.844**	43.048
	-	Mean	0.433	0.050	3.726	3.574	52.475
XRP/USD	M_1	June 2022	0.486	**0.024**	7.187	-29.364	51.839
	M_2	July 2022	0.371	0.083	6.250	-2.386	53.838
	M_3	August 2022	0.403	0.043	4.715	8.373	53.059
	M_4	September 2022	0.611	0.042	5.860	14.240	59.425
	M_5	October 2022	0.380	0.052	7.187	41.613	55.395
	M_6	November 2022	0.447	0.047	8.243	-20.906	51.034
	M_7	December 2022	0.378	0.060	5.711	-10.307	53.949
	M_8	January 2023	0.638	0.038	4.014	6.867	59.066
	M_9	February 2023	0.239	0.043	3.996	5.940	65.148
	M_{10}	March 2023	0.416	0.053	4.806	6.294	59.733
	M_{11}	April 2023	0.423	0.035	6.891	37.114	65.977
	M_{12}	May 2023	0.480	0.047	3.314	- 10.093	48.832
	M_{13}	June 2023	0.578	0.044	3.659	14.877	52.414
	M_{14}	July 2023	0.496	0.033	**9.286**	37.934	63.960
	M_{15}	August 2023	0.668	0.032	7.475	-1.218	48.610
	M_{16}	September 2023	0.376	0.040	3.415	-15.599	49.770
	M_{17}	October 2023	0.284	0.081	2.628	4.688	49.944
	M_{18}	November 2023	0.577	0.041	3.750	29.123	47.241
	M_{19}	December 2023	0.171	0.084	3.211	-0.711	57.620
	M_{20}	January 2024	0.472	0.037	3.386	-13.154	55.395
	M_{21}	February 2024	0.550	0.034	2.784	-4.623	50.178
	M_{22}	March 2024	0.482	0.037	5.275	22.825	56.396
	M_{23}	April 2024	0.491	0.042	5.465	-16.260	54.713
	M_{24}	May 2024	0.104	0.093	3.788	-4.795	62.069
	M_{25}	June 2024	0.465	0.050	2.511	-7.397	60.920
	M_{26}	July 2024	0.668	0.039	4.652	11.684	54.394
	M_{27}	August 2024	0.215	0.084	6.243	12.538	49.277
	M_{28}	September 2024	0.459	0.078	3.514	0.198	64.023

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)
	M_{29}	October 2024	0.435	0.063	3.730	-7.887	**67.408**
	M_{30}	November 2024	**0.770**	0.049	5.180	105.275	52.989
	M_{31}	December 2024	0.524	0.029	8.529	**235.805**	41.157
	M_{32}	January 2025	0.546	0.048	5.168	21.544	50.501
	M_{33}	February 2025	0.525	0.058	4.783	-8.313	46.675
	M_{34}	March 2025	0.052	0.090	8.177	-7.258	52.280
	M_{35}	April 2025	0.405	0.062	4.791	-10.691	50.690
	M_{36}	May 2025	0.468	0.039	3.498	11.064	48.721
	-	Mean	0.446	0.051	5.085	12.695	54.573

Table 69: Statistics of the *default* close price input across the windows in $\mathbf{X}_{\text{Test}}$ for splits $M_1, \ldots, M_{12}$ of the *extended experiment* across *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD*.

G.2 Split Analysis: EVMD Input Modes

G.2.1 Benchmark Experiment

Crypto	Split	Month	ADF (Min)	ADF (Mean)	ADF (Max)	ADF (%)	KPSS (Min)	KPSS (Mean)	KPSS (Max)	KPSS (%)	Residual Energy (%)	Mode Overlap (%)	Energy Ratio (%)
BTC/USD	M_1	June 2021	0.000	0.197	0.843	37.22	0.060	0.074	0.085	30.00	0.013	13.11	99.23
	M_2	July 2021	0.000	0.227	0.853	48.92	0.065	0.080	0.100	24.19	0.017	15.37	99.77
	M_3	August 2021	0.000	0.180	0.839	33.87	0.060	0.072	0.085	31.72	0.017	15.02	99.40
	M_4	September 2021	**0.002**	0.285	0.762	39.44	0.060	0.072	0.100	31.11	0.015	15.37	**99.81**
	M_5	October 2021	0.000	0.223	0.842	46.24	**0.059**	0.072	0.100	33.87	0.015	14.77	99.12
	M_6	November 2021	0.000	0.287	**0.897**	54.44	0.060	0.072	0.090	**35.00**	0.013	14.62	99.74
	M_7	December 2021	0.000	0.299	0.894	47.85	0.070	0.074	0.100	29.03	**0.043**	**17.17**	99.34
	M_8	January 2022	0.000	**0.352**	0.883	**65.05**	0.060	0.075	0.085	27.96	0.019	15.48	99.72
	M_9	February 2022	0.000	0.302	0.844	58.93	0.067	0.077	0.088	26.19	0.022	12.70	99.58
	M_{10}	March 2022	0.000	0.265	0.862	47.31	0.062	0.090	0.100	12.90	0.023	17.06	99.76
	M_{11}	April 2022	0.000	0.239	0.815	54.44	0.067	0.076	0.100	26.67	0.023	14.92	99.65
	M_{12}	May 2022	0.000	0.229	0.866	39.78	0.060	**0.069**	**0.078**	34.95	0.027	15.26	99.45
	-	Mean	0.000	0.257	0.850	47.79	0.063	0.075	0.093	28.63	0.02	15.07	99.55
ETH/USD	M_1	June 2021	0.000	0.131	0.582	29.17	0.028	0.069	0.100	35.83	**2.314**	19.69	98.16
	M_2	July 2021	0.000	0.139	0.729	43.55	0.041	0.076	0.100	24.19	1.595	18.29	99.39
	M_3	August 2021	0.000	0.246	0.848	**59.68**	0.055	0.066	0.078	38.71	0.988	19.08	99.21
	M_4	September 2021	0.000	0.178	0.715	35.00	0.056	0.077	0.100	25.00	1.402	20.80	99.54
	M_5	October 2021	0.000	0.265	0.823	48.39	0.028	0.065	0.100	38.71	1.142	22.33	99.46
	M_6	November 2021	0.000	**0.282**	0.778	50.83	**0.026**	0.061	0.087	**45.83**	1.038	23.01	**99.83**
	M_7	December 2021	0.000	0.156	0.684	29.03	0.058	0.077	0.100	25.00	1.160	18.66	99.78
	M_8	January 2022	0.000	0.136	0.619	35.48	0.054	0.067	0.078	38.71	0.678	23.74	99.69
	M_9	February 2022	0.000	0.258	0.856	50.00	0.058	**0.082**	0.100	19.64	0.817	20.51	99.28
	M_{10}	March 2022	0.000	0.184	0.468	29.03	0.058	0.077	0.100	25.81	0.824	17.50	99.60
	M_{11}	April 2022	0.000	0.210	0.827	52.50	0.055	0.064	0.100	40.00	0.517	21.03	99.63
	M_{12}	May 2022	0.000	0.229	**0.878**	51.61	0.041	0.061	**0.077**	45.16	0.685	**24.11**	99.59
	-	Mean	0.000	0.201	0.734	42.86	0.046	0.070	0.093	33.55	1.10	20.73	99.43
LTC/USD	M_1	June 2021	0.000	0.181	0.753	46.67	**0.033**	**0.060**	**0.070**	**45.56**	**2.743**	**31.64**	97.45
	M_2	July 2021	0.000	0.113	0.726	35.48	0.070	0.070	**0.070**	33.33	2.094	30.28	99.25
	M_3	August 2021	0.001	**0.359**	0.830	**60.22**	0.044	0.064	0.100	41.94	1.293	27.96	99.53
	M_4	September 2021	0.003	0.279	0.818	53.33	0.059	0.074	0.100	28.89	1.598	25.15	99.33
	M_5	October 2021	0.000	0.296	0.683	46.24	0.043	0.065	0.100	41.94	0.986	26.78	99.52
	M_6	November 2021	0.001	0.206	0.690	42.22	0.064	0.071	0.100	32.22	1.542	27.19	99.30
	M_7	December 2021	**0.042**	0.328	0.765	**60.22**	0.044	0.067	0.100	37.63	1.849	27.85	99.28
	M_8	January 2022	0.000	0.182	0.594	46.24	0.045	0.067	0.071	37.63	1.385	27.69	99.48
	M_9	February 2022	0.001	0.235	0.617	57.14	0.062	0.081	0.100	20.24	1.432	26.32	98.90
	M_{10}	March 2022	0.000	0.286	0.675	44.09	0.046	0.065	0.100	36.56	1.810	25.97	99.41
	M_{11}	April 2022	0.000	0.155	**0.874**	32.22	0.043	0.064	0.100	43.33	1.391	30.68	**99.61**
	M_{12}	May 2022	0.000	0.146	0.776	47.31	0.070	0.070	**0.070**	33.33	2.173	26.19	99.17
	-	Mean	0.004	0.231	0.733	47.61	0.052	0.068	0.090	36.05	1.69	27.81	99.19
XMR/USD	M_1	June 2021	**0.001**	0.129	0.648	32.92	0.058	0.077	0.089	26.25	**2.000**	18.01	95.06
	M_2	July 2021	0.000	0.135	0.666	35.89	0.059	0.071	0.089	34.27	1.560	22.40	92.43
	M_3	August 2021	0.000	0.164	0.774	38.71	0.059	0.069	0.089	35.48	0.622	20.81	96.70
	M_4	September 2021	0.000	0.128	0.644	27.50	0.055	0.072	0.100	31.67	0.805	19.99	98.49
	M_5	October 2021	0.000	0.140	0.537	27.82	0.053	**0.068**	**0.079**	**36.69**	0.641	21.86	99.28
	M_6	November 2021	0.000	0.137	0.721	33.33	0.058	0.076	0.100	27.50	0.751	18.86	**99.70**
	M_7	December 2021	0.000	0.192	0.721	38.71	0.061	**0.068**	0.085	35.48	1.008	22.52	98.35
	M_8	January 2022	0.000	0.207	0.689	43.15	**0.050**	0.075	0.089	28.63	0.996	20.91	97.20
	M_9	February 2022	0.000	0.154	0.719	33.04	0.057	0.072	0.090	31.70	0.966	**23.97**	95.86
	M_{10}	March 2022	0.000	0.144	0.762	33.87	0.063	0.073	0.093	30.65	1.202	22.77	98.08
	M_{11}	April 2022	**0.001**	**0.284**	**0.799**	**50.42**	0.059	0.070	0.089	33.33	0.856	23.78	96.93
	M_{12}	May 2022	0.000	0.142	0.717	39.11	0.059	0.073	0.100	31.45	1.301	20.51	95.98
	-	Mean	0.000	0.163	0.700	36.21	0.058	0.072	0.091	31.93	1.06	21.37	97.01
XRP/USD	M_1	June 2021	0.000	0.186	0.758	42.50	0.040	0.063	0.078	42.50	**2.443**	30.07	94.70
	M_2	July 2021	0.000	0.179	0.708	49.19	0.055	0.059	0.078	45.97	1.802	36.78	96.43
	M_3	August 2021	0.000	0.249	**0.878**	54.84	0.055	0.060	0.078	45.16	1.370	35.00	92.97
	M_4	September 2021	0.001	0.178	0.537	48.33	0.055	0.059	0.083	**47.50**	1.861	32.87	95.49
	M_5	October 2021	0.000	0.197	0.754	48.39	**0.035**	0.063	0.100	41.94	1.294	38.46	99.18
	M_6	November 2021	0.001	0.188	0.720	42.50	0.042	0.078	0.100	25.00	1.141	**38.82**	**99.75**
	M_7	December 2021	0.003	0.190	0.636	55.65	0.055	0.064	0.100	39.52	1.274	34.92	98.58
	M_8	January 2022	0.007	**0.304**	0.705	59.68	0.055	0.061	0.079	44.35	1.056	36.10	99.07
	M_9	February 2022	0.003	0.222	0.684	56.25	0.055	0.070	0.100	32.14	1.615	36.26	98.28
	M_{10}	March 2022	**0.048**	0.293	0.807	52.42	0.055	0.071	0.100	36.29	1.555	31.84	99.26
	M_{11}	April 2022	0.000	0.129	0.651	45.83	0.055	0.074	0.100	29.17	0.971	32.91	99.50
	M_{12}	May 2022	0.017	0.292	0.721	**60.48**	0.040	**0.057**	**0.075**	46.77	1.380	30.78	96.02
	-	Mean	0.007	0.217	0.713	51.34	0.050	0.065	0.089	39.69	1.48	34.57	97.44

Table 70: Statistics of the EVMD modes across the windows in $\mathbf{X}_{\text{Test}}$ for splits $M_1, \ldots, M_{12}$ of the benchmark experiment across *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD*.

G.2.2 Extended Experiment

Crypto	Split	Month	ADF (Min)	ADF (Mean)	ADF (Max)	ADF (%)	KPSS (Min)	KPSS (Mean)	KPSS (Max)	KPSS (%)	Residual Energy (%)	Mode Overlap (%)	Energy Ratio (%)
BTC/USD	M_1	June 2022	0.000	0.289	0.872	58.89	0.060	0.074	0.085	30.00	0.035	14.33	99.06
	M_2	July 2022	0.000	0.185	0.795	43.01	0.060	0.070	0.086	34.95	0.048	15.84	99.09
	M_3	August 2022	0.000	0.257	0.742	48.39	0.060	0.072	0.100	33.87	0.045	15.76	99.69
	M_4	September 2022	0.000	0.142	0.647	30.56	0.070	0.080	0.100	22.22	0.050	12.83	99.64
	M_5	October 2022	0.000	0.284	0.870	60.75	0.065	0.084	0.100	17.20	0.054	15.64	**99.93**
	M_6	November 2022	0.000	0.314	0.901	54.44	0.060	0.078	0.100	26.11	0.054	12.12	99.49
	M_7	December 2022	0.000	0.085	0.785	18.82	0.070	0.076	0.085	27.96	0.062	17.21	99.73
	M_8	January 2023	0.000	0.281	0.928	51.08	0.070	0.076	0.100	26.88	0.059	14.35	99.46
	M_9	February 2023	0.000	0.129	0.743	38.69	0.062	0.076	0.085	27.38	0.046	13.33	99.58
	M_{10}	March 2023	0.000	**0.387**	0.887	**66.13**	0.070	0.085	0.100	18.82	0.044	13.16	99.57
	M_{11}	April 2023	0.000	0.191	0.850	34.44	0.070	0.077	0.085	25.56	0.034	15.96	99.67
	M_{12}	May 2023	0.000	0.230	0.829	48.92	0.070	0.074	0.095	29.57	0.035	14.52	99.90
	M_{13}	June 2023	0.000	0.131	0.739	37.78	0.060	0.083	0.100	19.44	0.039	11.91	99.89
	M_{14}	July 2023	0.000	0.188	0.735	46.77	0.060	0.068	0.085	36.02	0.031	14.51	99.77
	M_{15}	August 2023	0.000	0.346	0.840	60.22	0.060	0.071	0.100	34.95	0.034	16.34	99.91
	M_{16}	September 2023	0.000	0.275	0.746	60.00	0.060	0.072	0.085	31.11	0.044	16.08	99.90
	M_{17}	October 2023	0.000	0.314	0.879	51.61	0.060	0.072	0.090	32.26	0.044	17.71	99.85
	M_{18}	November 2023	0.000	0.220	0.847	42.22	0.060	0.072	0.085	31.67	0.121	16.61	99.56
	M_{19}	December 2023	0.000	0.250	0.854	58.06	0.060	0.073	0.085	32.26	0.089	14.33	99.83
	M_{20}	January 2024	0.000	0.142	0.642	32.26	0.055	0.077	0.100	26.88	0.138	16.08	99.89
	M_{21}	February 2024	0.000	0.181	0.799	42.53	0.054	0.076	0.100	26.44	0.097	19.19	99.63
	M_{22}	March 2024	0.000	0.203	0.840	47.31	0.046	0.068	0.078	34.95	0.230	24.40	97.20
	M_{23}	April 2024	0.000	0.172	0.721	41.11	0.051	0.069	0.088	35.56	**0.293**	25.14	98.99
	M_{24}	May 2024	**0.002**	0.201	0.827	44.09	0.042	0.066	0.085	37.10	0.218	**25.77**	99.78
	M_{25}	June 2024	0.001	0.210	0.725	48.89	0.038	**0.064**	0.100	**45.00**	0.133	24.77	99.90
	M_{26}	July 2024	0.000	0.257	0.901	51.08	**0.036**	0.066	0.100	40.32	0.176	24.28	99.69
	M_{27}	August 2024	0.000	0.232	0.849	48.92	0.051	0.075	0.100	27.96	0.182	22.51	99.74
	M_{28}	September 2024	0.000	0.165	0.730	33.89	0.053	0.080	0.100	23.89	0.129	22.49	99.84
	M_{29}	October 2024	0.000	0.286	**0.940**	59.14	0.048	0.073	0.088	30.65	0.119	21.63	99.77
	M_{30}	November 2024	0.000	0.163	0.747	36.11	0.047	0.066	**0.070**	37.22	0.157	24.49	98.59
	M_{31}	December 2024	0.000	0.101	0.497	24.19	0.047	0.066	0.085	38.71	0.135	24.80	97.62
	M_{32}	January 2025	0.000	0.258	0.898	55.38	0.061	0.070	0.085	33.33	0.121	21.79	99.68
	M_{33}	February 2025	0.000	0.166	0.787	40.48	0.047	0.075	0.100	29.17	0.138	23.89	99.91
	M_{34}	March 2025	0.000	0.220	0.768	47.85	0.041	0.066	0.074	38.17	0.232	23.74	99.56
	M_{35}	April 2025	0.000	0.175	0.809	38.33	0.045	0.072	0.097	31.11	**0.293**	22.40	99.72
	M_{36}	May 2025	0.000	0.222	0.711	49.46	0.046	0.068	0.085	36.56	0.127	23.69	99.30
	-	Mean	0.000	0.218	0.797	45.88	0.056	0.073	0.091	30.87	0.11	18.71	99.51
ETH/USD	M_1	June 2022	0.000	0.194	0.722	49.17	0.040	0.066	**0.078**	39.17	1.324	21.69	99.05
	M_2	July 2022	0.000	0.227	0.817	52.42	0.040	0.063	0.100	41.13	1.587	25.60	98.76
	M_3	August 2022	0.000	0.117	0.681	33.06	0.055	0.071	0.094	32.26	1.518	24.13	99.48
	M_4	September 2022	0.002	0.168	0.762	46.67	0.058	0.074	0.100	30.00	**1.760**	18.56	99.37
	M_5	October 2022	0.000	0.162	0.773	37.10	0.056	0.067	0.100	36.29	0.739	23.87	99.71
	M_6	November 2022	**0.003**	0.213	0.785	47.50	0.055	0.067	0.100	38.33	1.300	19.25	99.09
	M_7	December 2022	0.000	0.159	0.719	50.81	0.055	0.071	0.100	33.06	1.413	19.57	99.59
	M_8	January 2023	0.000	0.305	**0.957**	**59.68**	0.055	0.066	0.100	40.32	0.716	20.33	99.66
	M_9	February 2023	0.000	0.188	0.764	40.18	0.055	0.068	0.080	36.61	1.069	22.86	99.82
	M_{10}	March 2023	0.002	0.243	0.628	43.55	0.059	0.082	0.100	20.97	0.980	20.71	99.81
	M_{11}	April 2023	0.000	0.161	0.570	43.33	0.057	0.070	**0.078**	33.33	1.135	22.51	99.82
	M_{12}	May 2023	0.000	0.240	0.751	45.97	0.059	0.075	0.100	28.23	1.096	18.27	99.86
	M_{13}	June 2023	0.001	0.179	0.666	41.67	0.057	0.077	0.100	25.00	0.623	17.51	99.90
	M_{14}	July 2023	**0.002**	0.188	0.570	41.13	0.056	0.067	0.100	38.71	0.821	20.85	99.90
	M_{15}	August 2023	0.002	0.260	0.799	54.03	0.056	0.067	0.100	37.90	0.503	**25.69**	**99.95**
	M_{16}	September 2023	0.000	0.145	0.647	43.33	0.058	0.068	**0.078**	36.67	0.588	19.75	**99.95**
	M_{17}	October 2023	0.000	0.239	0.641	44.35	0.063	0.085	0.100	16.94	0.472	19.39	99.92
	M_{18}	November 2023	0.000	0.194	0.670	40.83	0.055	0.064	**0.078**	40.00	0.975	20.51	99.81
	M_{19}	December 2023	0.000	0.097	0.648	26.61	0.060	0.074	**0.078**	29.03	0.935	21.36	99.87
	M_{20}	January 2024	0.001	0.230	0.732	51.61	0.065	0.075	0.083	25.00	0.913	18.24	99.86
	M_{21}	February 2024	0.001	0.205	0.843	57.76	0.055	0.072	0.100	32.76	0.628	17.48	99.64
	M_{22}	March 2024	0.001	0.269	0.866	54.03	0.051	0.063	**0.078**	41.94	0.760	20.34	99.56
	M_{23}	April 2024	0.000	0.214	0.582	40.83	0.057	0.074	0.100	30.00	1.144	23.05	99.76
	M_{24}	May 2024	0.000	0.179	0.777	42.74	0.059	0.077	0.100	25.81	1.028	24.07	99.72
	M_{25}	June 2024	0.000	0.198	0.834	48.33	0.055	0.064	0.100	41.67	0.863	22.35	99.61
	M_{26}	July 2024	0.000	0.274	0.818	51.61	0.055	0.070	0.100	34.68	0.849	22.25	99.83
	M_{27}	August 2024	0.000	0.124	0.699	37.90	0.055	0.070	0.100	33.06	1.329	19.69	99.35
	M_{28}	September 2024	0.000	0.138	0.711	37.50	0.058	0.070	0.100	34.17	0.827	17.96	99.76
	M_{29}	October 2024	0.002	0.252	0.803	51.61	0.041	0.074	0.089	31.45	0.848	16.12	99.78
	M_{30}	November 2024	0.000	0.188	0.705	45.83	**0.036**	0.065	0.095	40.00	1.118	22.14	99.56
	M_{31}	December 2024	0.000	0.198	0.794	46.77	0.056	0.065	0.100	39.52	1.271	21.84	99.71
	M_{32}	January 2025	0.001	0.210	0.865	50.00	0.055	0.074	0.099	29.03	1.177	18.99	99.76
	M_{33}	February 2025	0.000	0.108	0.517	34.82	0.056	0.067	**0.078**	36.61	1.265	23.13	99.73
	M_{34}	March 2025	0.002	0.211	0.689	51.61	0.040	0.069	**0.078**	35.48	1.326	20.34	99.61
	M_{35}	April 2025	0.000	0.222	0.853	55.00	0.056	0.071	**0.078**	31.67	1.628	16.82	99.56
	M_{36}	May 2025	0.000	**0.312**	0.800	56.45	0.055	**0.061**	0.100	**46.77**	1.254	24.21	99.10
	-	Mean	0.001	0.200	0.735	46.00	0.054	0.070	0.093	33.99	1.05	20.87	99.64
LTC/USD	M_1	June 2022	0.000	0.127	0.579	42.22	0.049	0.067	**0.070**	36.67	2.388	30.77	98.66
	M_2	July 2022	0.000	0.275	0.670	50.54	0.061	0.072	0.100	31.18	**2.611**	31.02	98.59
	M_3	August 2022	0.000	0.264	0.655	45.16	0.058	0.073	0.100	30.11	2.560	23.68	99.47
	M_4	September 2022	0.000	0.297	0.640	55.56	0.062	0.080	0.100	21.11	2.443	30.23	99.28
	M_5	October 2022	0.000	0.145	0.699	34.41	0.057	0.071	0.100	31.18	1.323	33.86	99.65
	M_6	November 2022	0.003	0.369	0.882	64.44	0.068	0.070	0.072	33.33	2.493	29.44	98.72
	M_7	December 2022	0.000	0.320	0.800	60.22	0.044	0.065	0.100	39.78	2.001	32.98	99.11
	M_8	January 2023	0.004	**0.406**	**0.974**	**68.82**	0.040	0.060	0.100	45.16	0.988	31.83	99.57
	M_9	February 2023	0.000	0.164	0.497	42.86	0.070	0.071	0.082	33.33	1.641	23.80	99.73

Crypto	Split	Month	ADF (Min)	ADF (Mean)	ADF (Max)	ADF (%)	KPSS (Min)	KPSS (Mean)	KPSS (Max)	KPSS (%)	Residual Energy (%)	Mode Overlap (%)	Energy Ratio (%)
	M_{10}	March 2023	0.002	0.344	0.685	62.37	0.066	0.077	0.100	25.81	2.125	25.24	99.43
	M_{11}	April 2023	0.000	0.160	0.623	46.67	0.040	0.072	0.100	32.22	1.271	28.80	99.64
	M_{12}	May 2023	0.008	0.335	0.696	56.99	0.070	0.077	0.100	26.88	1.195	19.52	99.72
	M_{13}	June 2023	0.000	0.228	0.788	45.56	0.070	0.072	0.100	31.11	1.233	24.06	99.49
	M_{14}	July 2023	0.000	0.339	0.683	55.91	0.042	0.071	0.100	32.26	2.107	32.37	99.01
	M_{15}	August 2023	0.000	0.286	0.797	52.69	0.052	0.069	**0.070**	34.41	1.176	25.49	99.65
	M_{16}	September 2023	0.000	0.178	0.606	40.00	0.048	0.074	0.100	28.89	1.392	28.43	99.58
	M_{17}	October 2023	0.000	0.243	0.586	44.09	0.070	0.077	0.100	26.88	0.898	23.57	99.82
	M_{18}	November 2023	0.000	0.259	0.798	47.78	0.044	0.067	0.100	37.78	1.035	26.86	99.80
	M_{19}	December 2023	0.000	0.281	0.646	49.46	0.064	0.078	0.100	23.66	1.082	30.59	99.80
	M_{20}	January 2024	0.002	0.223	0.842	39.78	0.070	0.071	0.100	32.26	1.297	24.00	99.67
	M_{21}	February 2024	0.000	0.277	0.622	47.13	0.049	0.071	0.100	32.18	0.905	29.78	99.87
	M_{22}	March 2024	0.002	0.267	0.755	53.76	0.056	0.068	**0.070**	33.33	1.768	32.63	99.20
	M_{23}	April 2024	0.000	0.229	0.565	43.33	0.057	0.071	0.100	30.00	2.402	30.99	98.95
	M_{24}	May 2024	0.000	0.228	0.772	37.63	0.049	0.072	0.100	31.18	1.178	29.71	99.63
	M_{25}	June 2024	0.009	0.400	0.691	62.22	0.042	**0.060**	0.100	**47.78**	1.147	27.88	**99.87**
	M_{26}	July 2024	0.004	0.176	0.669	48.39	0.068	0.077	0.100	25.81	1.468	22.35	99.62
	M_{27}	August 2024	0.000	0.320	0.798	53.76	0.051	0.070	0.100	33.33	1.227	31.53	99.38
	M_{28}	September 2024	**0.041**	0.367	0.691	60.00	0.039	0.088	0.100	11.11	0.932	30.16	99.76
	M_{29}	October 2024	0.000	0.294	0.599	60.22	0.070	0.073	0.099	31.18	0.952	33.93	99.74
	M_{30}	November 2024	0.003	0.250	0.875	50.00	0.040	0.065	0.074	40.00	1.531	**34.45**	99.49
	M_{31}	December 2024	0.001	0.220	0.655	45.16	0.039	0.070	0.100	33.33	2.063	28.38	98.73
	M_{32}	January 2025	0.002	0.278	0.625	49.46	0.044	0.070	0.100	33.33	1.847	23.61	99.33
	M_{33}	February 2025	0.002	0.283	0.672	52.38	0.070	0.081	0.100	21.43	1.858	29.39	99.23
	M_{34}	March 2025	0.000	0.284	0.681	41.94	0.043	0.064	0.100	39.78	2.431	32.82	99.11
	M_{35}	April 2025	0.000	0.211	0.826	50.00	0.063	0.072	0.100	30.00	1.537	31.79	99.50
	M_{36}	May 2025	0.008	0.272	0.865	53.76	**0.033**	0.065	0.100	39.78	1.433	24.88	99.61
	-	Mean	0.003	0.267	0.709	50.41	0.054	0.071	0.095	31.88	1.61	28.63	99.43
XMR/USD	M_1	June 2022	0.000	0.183	0.812	42.08	0.060	0.075	0.089	27.08	**1.369**	20.53	96.09
	M_2	July 2022	0.000	0.128	0.846	38.31	0.051	0.078	0.100	24.60	1.320	22.02	92.19
	M_3	August 2022	0.000	0.146	0.655	34.27	**0.049**	0.069	0.089	34.27	0.879	22.46	98.61
	M_4	September 2022	0.000	0.166	0.679	42.08	0.059	0.073	0.089	30.83	1.031	21.19	99.41
	M_5	October 2022	0.000	0.217	0.851	49.60	0.066	0.074	0.091	29.03	0.577	21.66	99.88
	M_6	November 2022	0.000	0.096	0.569	33.33	0.058	0.079	0.100	25.00	0.694	18.74	99.65
	M_7	December 2022	0.000	0.134	0.701	32.26	0.064	**0.083**	0.100	19.76	0.488	19.87	99.69
	M_8	January 2023	0.000	0.085	0.601	27.82	0.055	0.069	0.081	35.48	0.422	20.63	99.18
	M_9	February 2023	0.000	0.129	0.735	34.38	0.061	0.074	0.100	29.02	0.580	19.56	98.38
	M_{10}	March 2023	0.000	0.224	0.727	51.61	0.059	0.068	0.089	34.68	0.581	20.68	99.64
	M_{11}	April 2023	0.000	0.110	0.607	33.75	0.055	0.067	0.089	36.67	0.367	22.34	99.81
	M_{12}	May 2023	0.000	0.165	0.574	34.68	0.059	0.069	0.100	33.87	0.286	22.86	**99.93**
	M_{13}	June 2023	0.000	0.206	0.845	47.50	0.063	0.074	0.100	29.58	0.315	21.17	99.68
	M_{14}	July 2023	0.000	**0.266**	0.863	58.87	0.059	0.071	0.100	34.68	0.216	20.82	99.47
	M_{15}	August 2023	0.000	0.241	0.823	50.40	0.054	0.068	0.089	35.89	0.261	21.12	99.70
	M_{16}	September 2023	0.000	0.119	0.741	35.42	0.058	0.069	0.089	35.42	0.456	19.04	99.56
	M_{17}	October 2023	0.000	0.172	0.670	35.89	0.059	0.067	0.079	37.10	0.250	22.27	99.82
	M_{18}	November 2023	0.000	0.116	0.624	30.42	0.059	0.074	0.089	29.17	0.309	20.62	99.41
	M_{19}	December 2023	0.000	0.257	**0.917**	**60.08**	0.060	0.079	0.092	24.60	0.260	18.79	99.43
	M_{20}	January 2024	0.000	0.164	0.825	39.11	0.059	0.078	0.100	25.81	0.521	19.54	99.68
	M_{21}	February 2024	**0.001**	0.181	0.720	40.95	0.059	0.072	0.089	31.47	1.316	16.78	98.00
	M_{22}	March 2024	0.000	0.156	0.645	45.56	0.058	0.073	0.100	29.44	0.884	**23.26**	96.36
	M_{23}	April 2024	0.000	0.062	0.373	27.50	0.059	0.073	0.089	29.17	0.673	21.07	98.93
	M_{24}	May 2024	0.000	0.168	0.807	38.31	0.066	0.071	0.090	32.66	0.583	20.75	99.58
	M_{25}	June 2024	0.000	0.164	0.841	35.83	0.059	0.071	0.089	32.92	0.447	22.49	97.18
	M_{26}	July 2024	0.000	0.178	0.771	47.18	0.059	0.074	0.098	29.44	0.501	19.11	97.13
	M_{27}	August 2024	0.000	0.181	0.826	41.53	0.061	0.077	0.098	25.00	0.384	20.28	99.64
	M_{28}	September 2024	0.000	0.186	0.762	41.25	0.064	0.069	0.089	35.00	0.397	20.01	99.73
	M_{29}	October 2024	0.000	0.164	0.821	45.16	0.063	0.078	0.100	24.19	0.487	20.40	99.55
	M_{30}	November 2024	0.000	0.163	0.616	29.58	0.057	0.076	0.100	27.92	0.371	20.11	99.72
	M_{31}	December 2024	0.000	0.197	0.676	41.13	0.059	0.069	0.087	35.48	1.145	19.78	98.35
	M_{32}	January 2025	0.000	0.072	0.379	20.16	0.059	0.068	0.088	36.69	0.946	19.33	97.72
	M_{33}	February 2025	0.000	0.152	0.886	33.48	0.059	0.069	0.079	35.27	0.641	17.73	98.06
	M_{34}	March 2025	0.000	0.179	0.761	43.15	0.061	0.070	0.093	34.68	0.562	17.81	99.34
	M_{35}	April 2025	**0.001**	0.180	0.780	42.50	0.057	0.074	0.096	29.58	0.372	21.21	99.83
	M_{36}	May 2025	0.000	0.200	0.693	40.73	0.059	0.065	**0.067**	**39.52**	0.537	21.33	96.07
	-	Mean	0.000	0.164	0.723	39.61	0.059	0.072	0.092	31.14	0.60	20.48	98.73
XRP/USD	M_1	June 2022	0.000	0.083	0.596	26.67	0.048	0.071	**0.078**	32.50	1.598	31.35	95.40
	M_2	July 2022	0.003	0.203	0.589	47.58	0.047	**0.056**	**0.078**	**48.39**	1.254	34.38	98.63
	M_3	August 2022	0.000	0.170	0.651	47.58	0.040	0.069	0.100	36.29	1.038	27.09	98.33
	M_4	September 2022	0.011	0.338	0.743	59.17	0.040	0.062	0.100	44.17	1.316	31.57	98.59
	M_5	October 2022	0.000	0.204	**0.940**	38.71	0.055	0.061	0.085	45.97	1.658	27.65	96.32
	M_6	November 2022	0.004	0.223	0.583	52.50	0.051	0.066	**0.078**	37.50	1.684	38.59	98.32
	M_7	December 2022	0.002	0.246	0.880	49.19	0.032	0.069	0.100	35.48	1.209	37.11	98.75
	M_8	January 2023	0.000	0.120	0.647	27.42	0.055	0.065	0.100	39.52	1.082	39.21	99.19
	M_9	February 2023	0.006	0.339	0.719	58.93	0.042	0.064	0.100	41.96	1.110	41.17	99.19
	M_{10}	March 2023	0.002	0.301	0.930	54.03	0.051	0.058	0.091	47.58	1.166	41.96	99.55
	M_{11}	April 2023	0.001	0.174	0.851	35.00	0.055	0.066	0.100	38.33	1.593	**42.22**	97.15
	M_{12}	May 2023	0.001	0.230	0.516	41.94	0.055	0.059	0.100	45.16	0.772	36.59	99.23
	M_{13}	June 2023	**0.027**	0.302	0.794	50.00	0.055	0.066	0.100	38.33	0.863	38.98	99.54
	M_{14}	July 2023	0.002	0.281	0.843	52.42	0.055	0.062	0.100	44.35	2.258	38.83	96.38
	M_{15}	August 2023	0.000	0.269	0.861	50.00	0.042	0.074	0.100	27.42	1.729	37.25	96.64
	M_{16}	September 2023	0.012	0.256	0.661	53.33	0.055	0.061	0.100	44.17	0.975	36.64	98.11
	M_{17}	October 2023	0.000	0.190	0.626	40.32	0.055	0.059	0.088	45.16	0.721	31.23	99.56
	M_{18}	November 2023	0.002	0.162	0.707	43.33	0.055	0.073	0.100	30.83	0.994	32.32	98.21
	M_{19}	December 2023	0.000	0.257	0.877	47.58	0.052	0.063	0.096	41.94	0.853	35.60	99.55
	M_{20}	January 2024	0.000	0.287	0.569	46.77	0.055	0.064	**0.078**	40.32	1.018	32.85	99.60
	M_{21}	February 2024	0.001	0.182	0.622	48.28	0.055	0.062	0.094	43.10	1.003	34.91	99.31
	M_{22}	March 2024	0.016	0.232	0.695	**62.90**	0.056	0.077	0.100	25.81	1.378	32.17	98.95
	M_{23}	April 2024	0.000	0.283	0.755	60.83	0.058	0.078	0.100	24.17	1.476	25.86	99.10
	M_{24}	May 2024	0.019	**0.361**	0.936	61.29	0.055	0.070	0.100	33.87	1.155	32.06	99.24
	M_{25}	June 2024	0.001	0.287	0.739	57.50	0.055	0.059	**0.078**	45.83	0.713	32.60	**99.85**
	M_{26}	July 2024	0.000	0.262	0.830	55.65	0.055	0.063	0.100	41.94	1.171	35.42	98.92

Crypto	Split	Month	ADF (Min)	ADF (Mean)	ADF (Max)	ADF (%)	KPSS (Min)	KPSS (Mean)	KPSS (Max)	KPSS (%)	Residual Energy (%)	Mode Overlap (%)	Energy Ratio (%)
	M_{27}	August 2024	0.001	0.251	0.690	58.06	0.055	0.080	0.100	21.77	1.478	34.58	98.58
	M_{28}	September 2024	0.001	0.269	0.710	50.83	0.040	0.062	0.093	42.50	0.943	34.84	99.76
	M_{29}	October 2024	0.000	0.201	0.598	47.58	0.055	0.070	0.100	33.06	0.931	31.27	99.68
	M_{30}	November 2024	0.000	0.251	0.744	48.33	0.055	0.064	0.100	40.83	1.427	41.30	92.39
	M_{31}	December 2024	0.000	0.177	0.817	35.48	0.055	0.065	0.100	39.52	**2.529**	27.24	76.23
	M_{32}	January 2025	0.003	0.226	0.850	58.87	0.040	0.058	0.081	47.58	1.343	22.29	97.88
	M_{33}	February 2025	0.000	0.184	0.778	42.86	0.039	0.076	0.100	29.46	0.925	16.21	98.88
	M_{34}	March 2025	0.000	0.226	0.860	43.55	**0.026**	0.075	0.100	28.23	1.231	16.98	99.51
	M_{35}	April 2025	0.000	0.150	0.591	30.83	0.041	0.067	0.079	37.50	0.770	19.03	99.63
	M_{36}	May 2025	0.002	0.249	0.598	51.61	0.033	0.066	0.100	40.32	0.692	21.67	99.67
	-	Mean	0.003	0.234	0.733	48.25	0.049	0.066	0.094	38.36	1.22	32.53	97.88

Table 71: Statistics of the EVMD modes across the windows in $\mathbf{X}_{\text{Test}}$ for splits $M_1, \ldots, M_{36}$ of the *extended experiment* across *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD*.

G.3 Split Analysis: SVMD Input Modes

G.3.1 Benchmark Experiment

Crypto	Split	Month	ADF (Min)	ADF (Mean)	ADF (Max)	ADF (%)	KPSS (Min)	KPSS (Mean)	KPSS (Max)	KPSS (%)	Residual Energy (%)	Mode Overlap (%)	Energy Ratio (%)
BTC/USD	M_1	June 2021	0.000	0.210	0.805	48.33	0.040	0.078	0.100	25.83	**1.153**	14.61	98.78
	M_2	July 2021	0.000	**0.253**	0.834	**51.61**	0.044	0.075	**0.096**	29.84	0.705	13.06	99.75
	M_3	August 2021	0.000	0.165	0.962	37.10	0.040	0.076	0.100	26.61	0.621	18.40	99.11
	M_4	September 2021	0.000	0.193	0.936	40.83	0.034	0.080	0.100	22.50	0.463	9.31	**99.87**
	M_5	October 2021	0.000	0.210	0.818	42.74	0.040	0.072	0.100	32.26	0.545	15.26	98.88
	M_6	November 2021	0.000	0.216	0.733	41.67	0.027	**0.071**	0.100	**33.33**	0.257	15.40	99.83
	M_7	December 2021	0.000	0.201	0.898	37.90	0.040	0.076	0.100	27.42	0.648	16.86	99.59
	M_8	January 2022	0.000	0.213	**0.981**	36.29	**0.026**	0.075	0.100	29.03	0.416	18.27	99.68
	M_9	February 2022	0.000	0.252	0.900	44.64	0.055	0.078	0.100	24.11	0.518	16.62	99.61
	M_{10}	March 2022	0.000	0.190	0.906	41.13	0.041	0.078	0.100	25.81	0.763	13.44	99.74
	M_{11}	April 2022	0.000	0.189	0.958	34.17	**0.026**	0.075	0.100	28.33	0.289	15.50	99.67
	M_{12}	May 2022	0.000	0.169	0.745	41.13	0.040	0.075	0.100	28.23	0.744	**21.69**	99.06
	-	Mean	0.000	0.205	0.873	41.46	0.038	0.076	0.100	27.78	0.59	15.70	99.46
ETH/USD	M_1	June 2021	0.000	0.220	0.981	43.33	0.040	0.076	0.100	25.83	**1.532**	17.37	98.51
	M_2	July 2021	0.000	0.185	0.965	38.71	0.030	0.078	0.100	25.00	1.008	17.50	99.38
	M_3	August 2021	0.000	0.160	0.818	41.94	0.037	0.074	0.100	29.84	0.788	18.06	98.01
	M_4	September 2021	0.000	0.194	0.946	38.33	0.048	0.079	0.100	24.17	0.648	12.26	99.64
	M_5	October 2021	0.000	0.178	0.859	37.10	0.040	0.078	0.100	25.00	0.483	15.94	99.39
	M_6	November 2021	0.000	0.159	0.852	34.17	0.040	**0.071**	0.100	**34.17**	0.319	13.46	99.58
	M_7	December 2021	0.000	0.169	0.755	45.97	0.042	0.076	**0.093**	28.23	0.665	13.40	**99.86**
	M_8	January 2022	0.000	**0.254**	**0.993**	**48.39**	**0.018**	0.075	0.100	28.23	0.446	17.60	99.40
	M_9	February 2022	0.000	0.161	0.947	31.25	0.055	0.078	0.100	25.00	0.676	17.81	99.26
	M_{10}	March 2022	0.000	0.193	0.871	37.90	0.028	0.076	0.100	26.61	0.573	15.32	99.68
	M_{11}	April 2022	0.000	0.227	0.958	42.50	0.049	0.077	0.100	25.00	0.443	16.60	99.45
	M_{12}	May 2022	0.000	0.165	0.944	41.13	0.026	0.076	0.100	27.42	0.977	**22.21**	98.49
	-	Mean	0.000	0.189	0.907	40.06	0.038	0.076	0.099	27.04	0.71	16.46	99.22
LTC/USD	M_1	June 2021	0.000	0.133	0.689	37.78	**0.015**	0.067	0.100	36.67	**2.198**	20.68	96.68
	M_2	July 2021	0.000	0.191	0.872	40.86	0.049	0.067	0.087	37.63	0.885	23.93	99.42
	M_3	August 2021	0.000	0.281	0.938	**49.46**	0.022	0.070	0.100	34.41	0.935	17.33	99.20
	M_4	September 2021	0.000	0.249	0.949	43.33	0.051	0.078	0.100	25.56	1.138	11.00	99.40
	M_5	October 2021	0.000	0.207	**0.953**	45.16	0.021	0.068	0.100	37.63	0.625	19.42	99.52
	M_6	November 2021	0.000	0.216	0.642	48.89	0.023	0.067	0.100	**38.89**	0.794	21.01	99.26
	M_7	December 2021	0.000	**0.290**	0.833	**49.46**	0.021	0.067	0.100	37.63	1.163	20.29	99.11
	M_8	January 2022	0.000	0.207	0.742	**49.46**	0.070	0.071	**0.077**	33.33	0.400	17.49	**99.65**
	M_9	February 2022	0.000	0.194	0.772	40.48	0.051	0.074	0.100	29.76	0.357	**24.12**	98.96
	M_{10}	March 2022	0.000	0.183	0.716	37.63	0.040	0.071	0.100	32.26	0.429	20.37	99.53
	M_{11}	April 2022	0.000	0.175	0.889	42.22	0.021	0.070	0.100	34.44	0.855	20.17	99.58
	M_{12}	May 2022	0.000	0.221	0.922	48.39	0.021	**0.066**	0.100	38.71	1.128	18.82	98.04
	-	Mean	0.000	0.212	0.826	44.43	0.033	0.070	0.097	34.74	0.91	19.55	99.03
XMR/USD	M_1	June 2021	0.000	0.110	0.489	30.00	**0.023**	0.073	0.100	31.11	**2.186**	22.31	98.02
	M_2	July 2021	0.000	0.197	0.804	47.31	0.042	0.070	0.100	33.33	1.373	18.72	99.51
	M_3	August 2021	0.000	0.245	0.983	44.09	0.038	0.069	0.100	34.41	0.801	22.03	99.37
	M_4	September 2021	0.000	0.186	0.887	41.11	0.051	0.075	0.100	30.00	1.060	10.67	99.68
	M_5	October 2021	0.000	0.162	0.648	41.94	0.048	0.072	0.100	33.33	0.585	25.38	99.66
	M_6	November 2021	0.000	0.185	0.598	45.56	0.051	**0.085**	0.100	16.67	0.887	12.65	**99.87**
	M_7	December 2021	0.000	0.214	0.902	47.31	0.041	0.069	0.100	34.41	0.928	15.27	99.69
	M_8	January 2022	0.000	0.224	0.861	48.39	0.053	0.075	0.100	25.81	1.218	17.78	99.21
	M_9	February 2022	0.000	0.152	0.808	33.33	0.051	0.072	0.100	32.14	1.040	**26.29**	98.67
	M_{10}	March 2022	0.000	0.199	0.684	44.09	0.070	0.078	0.100	25.81	1.443	10.45	99.57
	M_{11}	April 2022	0.000	**0.276**	**0.990**	**51.11**	0.040	0.068	0.100	**35.56**	0.829	14.72	99.81
	M_{12}	May 2022	0.000	0.206	0.779	41.94	0.038	0.073	0.100	30.11	1.311	19.91	99.14
	-	Mean	0.000	0.196	0.786	43.01	0.045	0.073	0.100	30.22	1.14	18.02	99.35
XRP/USD	M_1	June 2021	0.000	0.285	0.964	51.67	0.040	0.076	0.100	27.50	0.937	11.56	98.62
	M_2	July 2021	0.000	0.225	0.975	**52.42**	0.040	0.074	0.100	29.03	0.238	15.40	98.93
	M_3	August 2021	0.001	**0.287**	0.863	**52.42**	0.053	0.076	0.100	25.81	0.827	18.03	95.86
	M_4	September 2021	0.000	0.222	0.862	41.67	0.028	0.073	**0.084**	32.50	**0.970**	12.76	99.15
	M_5	October 2021	0.000	0.170	0.834	35.48	0.040	0.075	0.100	29.84	0.559	16.08	99.46
	M_6	November 2021	**0.004**	0.204	0.611	40.83	0.042	**0.070**	0.100	**39.17**	0.424	15.77	99.71
	M_7	December 2021	0.000	0.214	0.909	48.39	0.045	0.078	0.100	24.19	0.610	14.90	99.15
	M_8	January 2022	0.000	0.189	0.841	48.39	**0.026**	0.076	0.100	28.23	0.643	17.45	99.34
	M_9	February 2022	0.000	0.132	0.627	33.93	0.040	0.076	0.100	26.79	0.705	**18.82**	98.13
	M_{10}	March 2022	0.000	0.244	**0.992**	46.77	0.040	0.079	0.100	25.00	0.491	11.54	99.62
	M_{11}	April 2022	0.000	0.170	0.808	39.17	0.054	0.077	0.100	26.67	0.377	13.56	**99.78**
	M_{12}	May 2022	0.000	0.236	0.910	51.61	0.040	0.077	0.100	25.81	0.863	18.77	97.17
	-	Mean	0.000	0.215	0.850	45.23	0.041	0.076	0.099	28.38	0.64	15.39	98.74

Table 72: Statistics of the SVMD modes across the windows in $\mathbf{X}_{\text{Test}}$ for splits $M_1, \ldots, M_{12}$ of the benchmark experiment across *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD*.

G.3.2 Extended Experiment

Crypto	Split	Month	ADF (Min)	ADF (Mean)	ADF (Max)	ADF (%)	KPSS (Min)	KPSS (Mean)	KPSS (Max)	KPSS (%)	Residual Energy (%)	Mode Overlap (%)	Energy Ratio (%)
BTC/USD	M_1	June 2022	0.000	0.213	0.853	41.67	0.044	0.079	0.100	23.33	**0.880**	19.81	98.69
	M_2	July 2022	0.000	0.244	0.944	53.23	**0.026**	0.075	0.100	30.65	0.426	11.74	99.13
	M_3	August 2022	0.000	0.228	0.950	38.71	0.027	0.074	0.100	30.65	0.347	12.87	99.85
	M_4	September 2022	0.000	0.181	0.843	44.17	0.048	0.078	0.100	24.17	0.366	14.67	99.71
	M_5	October 2022	0.000	0.159	0.838	39.52	0.048	0.082	0.100	20.97	0.212	15.62	99.92
	M_6	November 2022	0.000	0.165	0.911	30.00	0.040	0.077	0.100	25.83	0.508	18.77	99.37
	M_7	December 2022	0.000	0.247	0.924	50.81	0.027	0.080	0.100	23.39	0.366	11.73	99.85
	M_8	January 2023	0.000	0.241	0.832	49.19	0.055	0.077	0.100	26.61	0.228	17.80	99.22
	M_9	February 2023	0.000	0.227	0.774	50.00	0.055	0.080	0.100	23.21	0.398	17.27	99.49
	M_{10}	March 2023	0.000	0.230	0.896	43.55	0.034	0.077	0.100	24.19	0.473	16.98	99.53
	M_{11}	April 2023	0.000	0.191	0.970	41.67	0.028	0.076	0.100	26.67	0.505	17.59	99.61
	M_{12}	May 2023	0.000	0.194	0.879	37.90	0.042	0.078	0.100	25.81	0.240	14.70	99.90
	M_{13}	June 2023	0.000	0.227	0.628	43.33	0.043	0.078	**0.099**	26.67	0.300	17.35	99.89
	M_{14}	July 2023	0.000	0.215	0.925	47.58	0.037	0.077	0.100	26.61	0.414	19.12	99.75
	M_{15}	August 2023	0.000	0.275	0.975	50.00	0.055	0.076	0.100	28.23	0.318	15.47	99.91
	M_{16}	September 2023	0.000	0.135	0.644	42.50	**0.026**	0.077	0.100	27.50	0.393	15.30	99.88
	M_{17}	October 2023	0.000	0.151	0.749	27.42	0.040	0.075	**0.099**	29.03	0.194	14.16	99.85
	M_{18}	November 2023	0.000	0.101	0.818	29.17	**0.026**	0.076	0.100	26.67	0.389	18.57	99.37
	M_{19}	December 2023	0.000	0.171	0.959	38.71	**0.026**	0.074	0.100	29.84	0.483	19.72	99.75
	M_{20}	January 2024	**0.004**	0.160	0.748	32.26	0.049	0.080	0.100	23.39	0.413	13.47	99.91
	M_{21}	February 2024	0.000	0.119	0.770	25.00	0.040	0.075	0.100	28.45	0.394	21.78	99.53
	M_{22}	March 2024	0.000	0.079	0.609	25.81	0.040	0.075	0.100	29.03	0.787	**21.94**	98.84
	M_{23}	April 2024	0.000	0.224	0.956	47.50	0.048	0.085	0.100	18.33	0.432	8.21	99.89
	M_{24}	May 2024	0.000	0.220	0.922	42.74	0.027	0.078	0.100	24.19	0.500	10.94	99.89
	M_{25}	June 2024	0.000	0.157	0.938	31.67	0.033	**0.073**	0.100	30.00	0.303	16.79	99.89
	M_{26}	July 2024	0.000	**0.304**	**0.993**	51.61	0.040	0.075	0.100	26.61	0.346	15.15	99.84
	M_{27}	August 2024	0.000	0.146	0.868	35.48	0.040	0.078	0.100	25.00	0.365	15.94	99.73
	M_{28}	September 2024	0.000	0.181	0.750	38.33	**0.026**	0.077	0.100	27.50	0.397	15.20	99.85
	M_{29}	October 2024	0.000	0.285	0.900	45.97	**0.026**	0.076	0.100	27.42	0.334	18.06	99.87
	M_{30}	November 2024	0.000	0.188	0.856	37.50	**0.026**	0.074	0.100	**30.83**	0.558	17.98	99.16
	M_{31}	December 2024	0.000	0.155	0.906	37.10	0.043	0.081	0.100	20.97	0.406	14.19	99.73
	M_{32}	January 2025	0.000	0.240	0.778	**56.45**	0.063	0.079	0.100	25.00	0.252	8.40	**99.94**
	M_{33}	February 2025	0.000	0.139	0.739	38.39	0.037	0.075	0.100	28.57	0.353	15.76	99.90
	M_{34}	March 2025	0.000	0.142	0.927	28.23	**0.026**	0.077	0.100	26.61	0.499	9.99	99.89
	M_{35}	April 2025	0.000	0.258	0.917	55.83	0.037	0.085	0.100	16.67	0.452	11.88	99.90
	M_{36}	May 2025	0.000	0.264	0.981	46.77	**0.026**	0.075	0.100	29.84	0.360	15.76	99.77
	-	Mean	0.000	0.196	0.858	40.99	0.038	0.077	0.100	26.07	0.41	15.58	99.67
ETH/USD	M_1	June 2022	0.000	0.129	0.647	30.00	0.026	0.071	0.100	**34.17**	1.010	21.59	97.61
	M_2	July 2022	0.000	0.207	0.941	40.32	0.027	0.074	0.100	29.84	1.043	17.36	98.50
	M_3	August 2022	0.000	0.183	0.979	36.29	0.034	0.077	0.100	25.81	0.983	16.45	99.35
	M_4	September 2022	0.000	0.216	0.879	40.83	0.055	0.079	0.100	24.17	0.985	18.68	99.41
	M_5	October 2022	0.000	0.185	0.814	43.55	0.026	0.077	0.100	25.81	0.402	18.74	99.61
	M_6	November 2022	0.000	0.199	0.951	39.17	0.040	0.076	0.100	27.50	0.685	17.88	98.84
	M_7	December 2022	0.000	**0.291**	0.954	**56.45**	0.041	0.079	0.100	23.39	0.733	14.39	99.71
	M_8	January 2023	0.000	0.179	0.881	37.90	0.026	0.077	0.100	25.81	0.393	18.14	99.29
	M_9	February 2023	0.000	0.162	0.871	35.71	0.041	0.080	0.100	24.11	0.504	12.78	99.75
	M_{10}	March 2023	0.000	0.234	0.828	46.77	0.078	0.082	0.100	20.97	0.379	13.38	99.82
	M_{11}	April 2023	0.000	0.216	**0.982**	38.33	**0.020**	0.074	0.100	30.00	0.487	16.86	99.80
	M_{12}	May 2023	0.000	0.111	0.719	28.23	0.068	0.080	0.100	21.77	0.468	13.82	99.90
	M_{13}	June 2023	0.000	0.230	0.871	47.50	0.062	0.077	0.100	26.67	0.174	15.60	99.91
	M_{14}	July 2023	0.000	0.195	0.857	41.13	0.044	0.078	0.100	24.19	0.393	12.03	**99.93**
	M_{15}	August 2023	0.000	0.209	0.944	41.94	0.026	0.075	0.100	27.42	0.374	16.49	99.91
	M_{16}	September 2023	0.000	0.144	0.692	36.67	0.026	0.072	0.100	30.83	0.386	14.13	99.90
	M_{17}	October 2023	0.000	0.211	0.735	41.13	0.048	0.079	0.100	25.00	0.235	14.29	99.91
	M_{18}	November 2023	0.000	0.180	0.667	40.00	0.032	0.075	0.100	27.50	0.620	17.83	99.58
	M_{19}	December 2023	0.000	0.198	0.961	41.13	0.026	0.074	0.100	30.65	0.527	16.56	99.85
	M_{20}	January 2024	0.000	0.154	0.756	37.10	0.063	0.079	0.100	24.19	0.446	12.86	99.87
	M_{21}	February 2024	0.000	0.191	0.910	35.34	0.040	0.076	0.100	27.59	0.418	19.10	99.47
	M_{22}	March 2024	0.000	0.202	0.866	47.58	0.026	0.076	0.100	26.61	0.476	20.49	98.78
	M_{23}	April 2024	0.000	0.099	0.699	35.00	0.063	0.076	**0.080**	27.50	0.595	10.47	99.82
	M_{24}	May 2024	0.000	0.227	0.732	43.55	0.055	0.078	0.100	25.00	0.583	16.78	99.68
	M_{25}	June 2024	0.000	0.177	0.905	35.83	0.026	0.074	0.100	29.17	0.603	18.15	99.45
	M_{26}	July 2024	0.000	0.198	0.928	41.13	0.040	0.078	0.100	24.19	0.499	16.08	99.81
	M_{27}	August 2024	0.000	0.141	0.764	32.26	0.026	0.074	0.100	29.03	0.830	**21.80**	99.07
	M_{28}	September 2024	0.000	0.245	0.850	48.33	0.026	0.077	0.100	27.50	0.442	13.16	99.83
	M_{29}	October 2024	0.000	0.168	0.747	35.48	0.041	0.079	0.100	24.19	0.359	17.83	99.81
	M_{30}	November 2024	0.000	0.193	0.817	41.67	0.025	0.074	0.100	28.33	0.658	18.13	99.55
	M_{31}	December 2024	0.000	0.249	0.942	47.58	0.030	0.077	0.100	25.81	0.591	12.56	99.73
	M_{32}	January 2025	0.000	0.209	0.867	50.81	0.038	0.077	0.087	26.61	0.479	10.48	99.84
	M_{33}	February 2025	0.000	0.180	0.727	40.18	0.026	0.073	0.100	30.36	0.649	18.48	99.46
	M_{34}	March 2025	0.000	0.168	0.654	35.48	0.051	0.075	0.100	28.23	0.906	18.19	99.20
	M_{35}	April 2025	0.000	0.281	0.946	48.33	0.051	0.078	0.100	25.00	0.743	13.18	99.71
	M_{36}	May 2025	0.000	0.131	0.835	34.68	0.040	0.077	0.100	25.00	**1.119**	21.60	98.23
	-	Mean	0.000	0.191	0.837	40.37	0.039	0.076	0.099	26.66	0.59	16.29	99.50
LTC/USD	M_1	June 2022	0.000	0.196	0.787	41.11	**0.021**	**0.067**	0.100	37.78	1.706	21.37	98.38
	M_2	July 2022	0.000	0.166	0.709	35.48	0.031	0.077	0.100	26.88	1.709	17.94	98.90
	M_3	August 2022	0.000	0.100	0.702	26.88	0.070	0.075	0.100	29.03	0.975	11.42	99.69
	M_4	September 2022	0.000	0.291	0.964	56.67	0.051	0.083	0.100	20.00	0.977	7.85	99.63
	M_5	October 2022	0.000	0.223	0.780	50.54	0.045	0.074	0.100	30.11	0.579	17.21	99.76
	M_6	November 2022	0.000	**0.306**	**0.998**	53.33	0.033	0.070	**0.083**	35.56	1.702	17.57	99.03
	M_7	December 2022	0.000	0.262	0.921	51.61	**0.021**	**0.067**	0.100	38.71	1.091	**24.84**	99.08
	M_8	January 2023	0.000	0.269	0.900	47.31	0.026	0.069	0.100	34.41	0.653	24.81	99.18
	M_9	February 2023	0.000	0.200	0.734	41.67	0.040	0.073	0.100	30.95	0.680	16.04	99.80

Crypto	Split	Month	ADF (Min)	ADF (Mean)	ADF (Max)	ADF (%)	KPSS (Min)	KPSS (Mean)	KPSS (Max)	KPSS (%)	Residual Energy (%)	Mode Overlap (%)	Energy Ratio (%)
	M_{10}	March 2023	0.000	0.285	0.697	45.16	0.023	0.069	0.100	35.48	0.366	22.71	99.49
	M_{11}	April 2023	0.000	0.238	0.861	46.67	0.051	0.071	0.100	35.56	0.639	12.89	99.76
	M_{12}	May 2023	**0.013**	0.295	0.940	56.99	0.051	0.075	0.100	29.03	0.618	14.27	99.73
	M_{13}	June 2023	0.000	0.223	0.931	35.56	0.045	0.069	0.100	35.56	1.012	21.95	99.49
	M_{14}	July 2023	0.000	0.173	0.839	33.33	0.070	0.079	0.100	23.66	0.971	12.14	99.37
	M_{15}	August 2023	0.000	0.246	0.939	37.63	0.040	0.070	0.100	33.33	0.553	18.47	99.33
	M_{16}	September 2023	0.000	0.173	0.847	38.89	**0.021**	0.076	0.100	27.78	0.758	19.30	99.17
	M_{17}	October 2023	0.000	0.253	0.973	45.16	0.051	0.074	0.100	31.18	0.570	16.55	99.85
	M_{18}	November 2023	0.000	0.194	0.890	42.22	**0.021**	0.072	0.100	33.33	0.562	19.94	99.80
	M_{19}	December 2023	0.000	0.208	0.800	49.46	0.031	0.079	0.100	25.81	0.681	16.85	99.88
	M_{20}	January 2024	0.000	0.160	0.723	34.41	0.051	0.072	0.100	32.26	0.962	16.21	99.72
	M_{21}	February 2024	0.000	0.180	0.825	41.38	0.070	0.083	0.100	19.54	0.584	6.40	99.91
	M_{22}	March 2024	0.000	0.263	0.811	41.94	**0.021**	0.070	0.092	31.18	1.045	22.81	99.20
	M_{23}	April 2024	0.000	0.210	0.555	43.33	0.070	0.072	0.100	31.11	1.748	22.96	99.15
	M_{24}	May 2024	0.000	0.126	0.680	31.18	0.051	0.077	0.100	24.73	0.857	17.31	99.71
	M_{25}	June 2024	0.000	0.227	0.972	48.89	0.050	0.072	0.100	30.00	0.481	16.13	**99.93**
	M_{26}	July 2024	0.000	0.180	0.684	40.86	**0.021**	0.076	0.100	27.96	0.897	14.11	99.66
	M_{27}	August 2024	0.000	0.201	0.929	38.71	0.051	0.072	0.100	33.33	0.856	24.65	99.40
	M_{28}	September 2024	0.000	0.165	0.816	40.00	0.060	0.078	0.100	25.56	0.411	13.46	99.86
	M_{29}	October 2024	0.000	0.163	0.877	36.56	0.051	0.081	0.100	21.51	0.479	15.20	99.83
	M_{30}	November 2024	0.000	0.287	0.896	**62.22**	0.051	0.074	0.100	28.89	0.877	17.20	99.65
	M_{31}	December 2024	0.000	0.209	0.871	48.39	**0.021**	**0.067**	0.100	**39.78**	**1.840**	21.11	98.20
	M_{32}	January 2025	0.000	0.205	0.947	34.41	0.051	0.073	0.100	32.26	1.085	12.71	99.49
	M_{33}	February 2025	0.000	0.143	0.683	33.33	0.051	0.076	0.100	28.57	1.017	16.47	99.37
	M_{34}	March 2025	0.000	0.225	0.809	51.61	0.040	0.071	0.100	31.18	1.016	19.23	99.38
	M_{35}	April 2025	0.000	0.286	0.965	53.33	0.056	0.073	0.100	28.89	1.121	15.35	99.68
	M_{36}	May 2025	0.000	0.190	0.980	45.16	**0.021**	0.069	0.100	35.48	0.988	18.18	99.64
	-	Mean	0.000	0.214	0.840	43.37	0.042	0.073	0.099	30.45	0.92	17.32	99.48
XMR/USD	M_1	June 2022	0.000	0.183	0.885	45.56	**0.021**	0.071	0.100	35.56	1.301	24.46	97.11
	M_2	July 2022	0.000	0.249	0.980	44.09	**0.021**	0.068	0.100	37.63	1.342	22.52	98.39
	M_3	August 2022	0.000	0.079	0.689	20.43	0.040	0.076	0.100	26.88	0.869	10.05	99.84
	M_4	September 2022	0.000	0.231	0.814	48.89	0.032	0.084	0.100	18.89	0.942	6.38	99.86
	M_5	October 2022	0.000	0.165	0.880	40.86	0.051	0.087	0.100	17.20	0.750	9.89	99.91
	M_6	November 2022	0.000	0.150	0.925	33.33	0.062	0.079	0.100	25.56	0.527	14.02	99.77
	M_7	December 2022	0.000	0.241	0.982	44.09	0.044	0.077	0.100	24.73	0.631	12.69	99.87
	M_8	January 2023	0.000	0.256	0.935	45.16	**0.021**	0.073	0.100	31.18	0.500	20.87	99.84
	M_9	February 2023	0.000	0.154	0.755	35.71	0.040	0.076	0.100	26.19	0.422	14.12	99.89
	M_{10}	March 2023	0.000	0.130	0.834	36.56	0.051	0.074	0.100	29.03	0.347	12.61	99.91
	M_{11}	April 2023	0.000	0.192	0.780	43.33	0.051	0.078	0.100	24.44	0.435	8.71	99.95
	M_{12}	May 2023	0.000	0.320	0.932	53.76	0.031	0.070	0.083	35.48	0.238	8.97	**99.98**
	M_{13}	June 2023	0.000	0.221	0.682	45.56	0.043	0.070	0.100	33.33	0.318	17.34	99.89
	M_{14}	July 2023	0.000	0.218	0.682	39.78	**0.021**	**0.067**	0.100	38.71	0.339	25.12	99.52
	M_{15}	August 2023	**0.010**	0.281	0.677	54.84	0.051	0.068	**0.070**	36.56	0.195	12.81	**99.98**
	M_{16}	September 2023	0.000	0.133	0.758	30.00	0.068	0.077	0.100	26.67	0.312	7.52	99.96
	M_{17}	October 2023	0.000	0.253	0.846	51.61	0.051	0.068	0.071	36.56	0.290	14.40	99.97
	M_{18}	November 2023	0.000	0.224	0.982	43.33	**0.021**	0.074	0.100	30.00	0.440	13.25	99.93
	M_{19}	December 2023	0.000	0.170	0.894	45.16	0.051	0.078	0.100	26.88	0.203	11.08	99.97
	M_{20}	January 2024	0.000	0.297	0.886	52.69	**0.021**	0.069	0.100	35.48	0.910	25.43	99.75
	M_{21}	February 2024	0.000	0.149	0.875	33.33	0.070	0.073	0.100	29.89	**1.708**	16.81	99.25
	M_{22}	March 2024	0.000	0.206	0.879	48.39	0.051	0.072	0.100	32.26	0.812	18.54	99.63
	M_{23}	April 2024	0.000	0.181	0.869	40.00	0.051	0.070	0.100	36.67	1.175	18.40	99.68
	M_{24}	May 2024	0.000	0.184	0.813	45.16	**0.021**	0.073	0.100	31.18	0.909	12.04	99.88
	M_{25}	June 2024	0.000	**0.399**	**0.989**	**64.44**	0.040	0.069	0.100	35.56	0.798	21.71	99.55
	M_{26}	July 2024	0.000	0.174	0.754	44.09	0.070	0.076	0.100	27.96	0.642	15.73	99.89
	M_{27}	August 2024	0.000	0.277	0.975	48.39	0.051	0.075	0.100	30.11	0.599	14.80	99.91
	M_{28}	September 2024	0.000	0.107	0.870	24.44	0.070	0.072	0.099	31.11	0.525	12.32	99.91
	M_{29}	October 2024	0.003	0.278	0.942	48.39	**0.021**	**0.067**	0.100	**39.78**	0.861	25.22	99.61
	M_{30}	November 2024	0.000	0.110	0.637	34.44	0.051	0.077	0.100	26.67	0.400	9.64	99.91
	M_{31}	December 2024	0.000	0.238	0.987	44.09	0.031	0.074	0.100	30.11	1.331	13.31	99.54
	M_{32}	January 2025	0.000	0.248	0.808	48.39	0.051	0.077	0.100	25.81	0.679	10.50	99.84
	M_{33}	February 2025	0.000	0.189	0.762	40.48	0.051	0.075	0.093	30.95	0.671	12.79	99.90
	M_{34}	March 2025	0.000	0.151	0.712	39.78	0.051	0.082	0.100	20.43	0.530	12.42	99.89
	M_{35}	April 2025	0.000	0.218	0.657	45.56	0.060	0.079	0.100	23.33	0.515	22.29	99.89
	M_{36}	May 2025	0.000	0.269	0.964	41.94	0.040	0.069	0.100	34.41	0.672	**27.30**	98.41
	-	Mean	0.000	0.209	0.841	42.95	0.043	0.074	0.098	30.09	0.67	15.45	99.67
XRP/USD	M_1	June 2022	0.000	0.229	0.966	46.67	0.026	**0.071**	0.100	**33.33**	0.613	19.31	98.58
	M_2	July 2022	0.000	0.242	0.935	47.58	0.033	0.081	0.100	22.58	0.651	12.16	99.29
	M_3	August 2022	0.000	0.204	0.971	38.71	0.027	0.077	0.100	26.61	0.508	12.55	99.72
	M_4	September 2022	0.000	0.204	0.917	45.83	0.026	0.077	0.100	25.83	0.533	15.33	98.92
	M_5	October 2022	0.000	0.150	0.800	33.87	0.026	0.077	0.100	25.00	0.618	14.48	98.15
	M_6	November 2022	0.000	0.207	0.873	44.17	0.038	0.076	0.100	25.83	0.842	16.47	98.88
	M_7	December 2022	0.000	0.204	0.930	37.90	0.040	0.079	0.100	22.58	0.356	14.61	99.51
	M_8	January 2023	0.000	0.245	0.979	53.23	0.040	0.077	0.100	26.61	0.493	14.88	99.63
	M_9	February 2023	0.000	0.160	0.621	33.93	0.050	0.077	0.100	25.89	0.465	13.79	99.70
	M_{10}	March 2023	0.000	0.221	0.917	47.58	0.029	0.076	0.100	27.42	0.309	12.47	99.65
	M_{11}	April 2023	0.000	0.147	0.891	31.67	0.026	0.076	0.100	28.33	1.003	16.39	98.25
	M_{12}	May 2023	0.000	0.117	0.755	30.65	0.063	0.078	0.100	25.00	0.426	13.42	99.80
	M_{13}	June 2023	0.000	0.162	0.843	34.17	0.055	0.078	0.100	25.00	0.229	14.13	99.65
	M_{14}	July 2023	0.000	0.177	0.880	36.29	0.026	0.072	0.100	32.26	**1.382**	14.33	97.05
	M_{15}	August 2023	0.000	0.243	0.953	47.58	0.026	0.075	0.100	29.03	0.906	16.90	98.57
	M_{16}	September 2023	0.000	0.210	0.882	44.17	0.026	0.077	0.100	25.83	0.345	16.25	99.51
	M_{17}	October 2023	0.000	0.225	0.935	41.13	0.048	0.076	0.100	28.23	0.226	12.27	**99.87**
	M_{18}	November 2023	0.000	0.219	0.636	45.83	0.024	0.075	0.100	29.17	0.417	16.06	98.80
	M_{19}	December 2023	0.000	0.173	0.895	35.48	0.042	0.081	0.100	21.77	0.414	13.34	**99.87**
	M_{20}	January 2024	0.000	0.169	0.848	35.48	0.040	0.077	0.100	25.81	0.440	13.09	99.85
	M_{21}	February 2024	0.000	0.169	0.789	45.69	0.040	0.076	0.100	27.59	0.255	15.41	99.80
	M_{22}	March 2024	0.000	0.253	**0.984**	52.42	0.040	0.080	0.100	23.39	0.386	9.54	99.74
	M_{23}	April 2024	0.000	0.221	0.926	39.17	0.040	0.077	0.100	24.17	0.436	11.63	99.65
	M_{24}	May 2024	0.000	0.169	0.902	39.52	0.056	0.083	0.100	20.16	0.415	10.44	99.77
	M_{25}	June 2024	0.000	0.226	0.958	40.83	0.034	0.077	0.100	25.83	0.241	13.24	99.92
	M_{26}	July 2024	0.000	0.222	0.798	43.55	0.026	0.076	0.100	28.23	0.407	16.85	98.89

Crypto	Split	Month	ADF (Min)	ADF (Mean)	ADF (Max)	ADF (%)	KPSS (Min)	KPSS (Mean)	KPSS (Max)	KPSS (%)	Residual Energy (%)	Mode Overlap (%)	Energy Ratio (%)
	M_{27}	August 2024	0.000	0.184	0.961	35.48	0.044	0.083	0.100	19.35	0.751	11.66	99.12
	M_{28}	September 2024	0.000	0.209	0.904	40.00	0.053	0.074	0.100	31.67	0.291	15.07	99.80
	M_{29}	October 2024	0.000	0.146	0.599	31.45	0.048	0.074	0.100	30.65	0.181	16.56	99.73
	M_{30}	November 2024	0.000	0.285	0.920	48.33	**0.018**	0.074	0.100	29.17	0.750	**20.93**	94.29
	M_{31}	December 2024	0.000	0.184	0.923	34.68	0.026	0.074	0.100	30.65	1.277	19.83	89.52
	M_{32}	January 2025	0.000	**0.288**	0.934	**58.87**	0.026	0.080	0.100	23.39	0.438	11.98	99.25
	M_{33}	February 2025	0.000	0.172	0.858	41.07	0.033	0.074	0.100	30.36	0.710	18.71	99.05
	M_{34}	March 2025	0.000	0.139	0.857	31.45	0.055	0.083	0.100	19.35	0.688	8.24	99.48
	M_{35}	April 2025	0.000	0.175	0.858	36.67	0.040	0.078	0.100	25.83	0.661	14.52	99.63
	M_{36}	May 2025	0.000	0.101	0.938	31.45	0.063	0.074	**0.078**	29.03	0.387	11.09	99.86
	-	Mean	0.000	0.196	0.876	40.63	0.038	0.077	0.099	26.41	0.54	14.39	98.91

Table 73: Statistics of the SVMD modes across the windows in $\mathbf{X}_{\text{Test}}$ for splits $M_1, \ldots, M_{36}$ of the *extended experiment* across *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD*.

G.4 Split Analysis: Expected Outputs

G.4.1 Benchmark Experiment

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)	$\mathbf{Y}_{\text{Test}}$
BTC/USD	M_1	June 2021	0.218	0.100	**5.180**	-4.492	58.621	
	M_2	July 2021	0.102	0.091	3.004	23.749	50.000	
	M_3	August 2021	0.329	0.014	3.156	18.209	50.000	
	M_4	September 2021	0.639	0.018	3.945	-10.216	55.172	
	M_5	October 2021	0.418	**0.012**	3.124	**27.332**	**60.000**	
	M_6	November 2021	0.625	0.023	3.339	-6.502	51.724	
	M_7	December 2021	0.096	0.082	3.294	-19.179	53.333	
	M_8	January 2022	0.307	**0.012**	2.734	-19.395	43.333	
	M_9	February 2022	0.280	0.100	4.369	11.540	48.148	
	M_{10}	March 2022	**0.714**	0.034	3.249	2.452	46.667	
	M_{11}	April 2022	0.530	**0.012**	2.509	-18.695	55.172	
	M_{12}	May 2022	0.192	0.026	4.210	-17.332	53.333	
	-	Mean	0.371	0.044	3.509	-1.044	52.125	-
ETH/USD	M_1	June 2021	0.622	0.013	**5.513**	-13.622	48.276	
	M_2	July 2021	0.932	0.100	3.957	20.159	40.000	
	M_3	August 2021	0.195	0.021	4.092	**34.179**	**66.667**	
	M_4	September 2021	**0.947**	0.011	5.205	-21.590	58.621	
	M_5	October 2021	0.864	**0.010**	3.283	29.526	63.333	
	M_6	November 2021	0.149	0.064	4.301	7.196	48.276	
	M_7	December 2021	0.853	0.018	3.505	-19.785	60.000	
	M_8	January 2022	0.585	**0.010**	4.289	-28.644	46.667	
	M_9	February 2022	0.380	0.100	4.722	4.798	40.741	
	M_{10}	March 2022	0.927	0.020	3.192	10.254	40.000	
	M_{11}	April 2022	0.483	**0.010**	2.948	-21.086	55.172	

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)	$\mathbf{Y}_{\text{Test}}$
	M_{12}	May 2022	0.439	0.012	5.256	-31.256	56.667	
	-	Mean	0.615	0.032	4.188	-2.489	52.035	-
LTC/USD	M_1	June 2021	**0.993**	0.015	5.991	-21.165	48.276	
	M_2	July 2021	0.736	0.100	3.169	5.364	33.333	
	M_3	August 2021	0.284	0.024	4.258	22.229	**66.667**	
	M_4	September 2021	0.141	0.016	6.365	-15.257	48.276	
	M_5	October 2021	0.169	**0.010**	3.639	15.463	60.000	
	M_6	November 2021	0.440	0.100	6.229	5.162	48.276	
	M_7	December 2021	0.017	0.047	4.559	-29.933	46.667	
	M_8	January 2022	0.828	0.021	4.064	-27.387	53.333	
	M_9	February 2022	0.329	0.080	4.964	-1.130	55.556	
	M_{10}	March 2022	0.077	0.012	3.548	10.044	**66.667**	
	M_{11}	April 2022	0.314	0.016	3.533	-23.237	44.828	
	M_{12}	May 2022	0.239	0.018	**6.946**	**-31.118**	56.667	
	-	Mean	0.381	0.038	4.772	-7.580	52.379	-
XMR/USD	M_1	June 2021	0.493	0.020	7.600	-16.259	48.276	
	M_2	July 2021	0.010	0.100	2.932	16.754	36.667	
	M_3	August 2021	0.387	0.016	4.173	21.385	56.667	
	M_4	September 2021	0.395	0.017	5.295	-17.101	51.724	
	M_5	October 2021	0.042	0.100	3.291	6.757	50.000	
	M_6	November 2021	0.378	0.015	4.295	-12.210	48.276	
	M_7	December 2021	0.903	0.100	4.250	-0.824	40.000	
	M_8	January 2022	**0.999**	0.018	4.999	**-41.184**	40.000	
	M_9	February 2022	0.142	0.100	4.776	16.632	55.556	
	M_{10}	March 2022	0.952	**0.010**	5.979	19.831	**63.333**	
	M_{11}	April 2022	0.426	0.100	4.454	-1.969	55.172	
	M_{12}	May 2022	0.172	0.100	**7.757**	-6.277	53.333	

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)	$\mathbf{Y}_{\text{Test}}$
	-	Mean	0.442	0.058	4.962	-1.205	49.917	-
XRP/USD	M_1	June 2021	0.554	**0.010**	**7.211**	-30.125	55.172	
	M_2	July 2021	0.150	0.100	3.843	13.185	53.333	
	M_3	August 2021	0.547	0.017	6.830	**63.712**	53.333	
	M_4	September 2021	0.617	**0.010**	5.953	-22.885	48.276	
	M_5	October 2021	0.017	0.100	3.413	6.774	56.667	
	M_6	November 2021	0.775	0.016	3.868	-8.539	55.172	
	M_7	December 2021	0.130	0.100	4.463	-16.183	53.333	
	M_8	January 2022	0.723	**0.010**	3.365	-27.424	53.333	
	M_9	February 2022	0.242	0.100	6.454	24.268	48.148	
	M_{10}	March 2022	0.816	**0.010**	3.253	3.942	**60.000**	
	M_{11}	April 2022	**0.941**	0.015	3.459	-29.383	41.379	
	M_{12}	May 2022	0.099	0.015	6.201	-30.527	**60.000**	
	-	Mean	0.468	0.042	4.860	-4.432	53.179	-

Table 74: Statistics of $\mathbf{Y}_{\text{Test}}$ for splits $M_1, \ldots, M_{12}$ of the benchmark experiment across *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD*.

G.4.2 Extended Experiment

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)	$\mathbf{Y}_{\text{Test}}$
BTC/USD	M_1	June 2022	0.811	0.012	**4.627**	-33.093	44.828	
	M_2	July 2022	0.270	0.014	3.180	20.817	40.000	
	M_3	August 2022	0.860	0.020	2.798	-13.830	56.667	
	M_4	September 2022	0.575	0.100	3.395	-3.521	55.172	
	M_5	October 2022	0.636	0.100	1.649	6.109	46.667	
	M_6	November 2022	0.422	0.023	4.320	-16.208	37.931	
	M_7	December 2022	0.252	0.068	1.451	- 2.562	63.333	
	M_8	January 2023	0.804	**0.010**	2.270	39.168	60.000	
	M_9	February 2023	0.413	0.100	2.618	-2.491	44.444	

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)	$\mathbf{Y}_{\text{Test}}$
	M_{10}	March 2023	0.895	0.013	3.585	20.468	56.667	
	M_{11}	April 2023	0.016	0.100	2.076	2.743	51.724	
	M_{12}	May 2023	0.056	0.048	1.637	-3.057	43.333	
	M_{13}	June 2023	0.899	0.023	2.476	13.625	**68.966**	
	M_{14}	July 2023	0.760	**0.010**	1.305	-4.426	56.667	
	M_{15}	August 2023	0.756	0.014	2.121	-12.675	46.667	
	M_{16}	September 2023	0.465	0.024	1.161	4.486	48.276	
	M_{17}	October 2023	**0.980**	0.013	2.219	23.746	43.333	
	M_{18}	November 2023	0.214	0.013	2.184	6.500	55.172	
	M_{19}	December 2023	0.008	0.100	2.297	9.309	60.000	
	M_{20}	January 2024	0.376	0.042	2.774	-3.621	63.333	
	M_{21}	February 2024	0.872	**0.010**	2.398	**41.891**	39.286	
	M_{22}	March 2024	0.005	0.100	3.893	14.253	50.000	
	M_{23}	April 2024	0.482	0.031	2.755	-12.890	55.172	
	M_{24}	May 2024	0.323	**0.010**	2.683	15.720	56.667	
	M_{25}	June 2024	0.882	**0.010**	1.717	-7.371	51.724	
	M_{26}	July 2024	0.038	0.018	2.402	2.434	40.000	
	M_{27}	August 2024	0.024	0.100	3.578	-9.762	60.000	
	M_{28}	September 2024	0.770	**0.010**	2.143	10.516	44.828	
	M_{29}	October 2024	0.768	**0.010**	1.853	15.601	60.000	
	M_{30}	November 2024	0.600	**0.010**	3.102	38.724	48.276	
	M_{31}	December 2024	0.469	0.100	2.284	-3.714	56.667	
	M_{32}	January 2025	0.366	0.022	2.231	8.286	43.333	
	M_{33}	February 2025	0.955	0.035	2.011	-16.183	51.852	
	M_{34}	March 2025	0.049	0.100	3.472	-4.084	53.333	
	M_{35}	April 2025	0.848	0.015	2.799	10.585	55.172	
	M_{36}	May 2025	0.466	0.016	1.839	8.397	53.333	

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)	$\mathbf{Y}_{\text{Test}}$
	-	Mean	0.511	0.040	2.537	4.561	51.745	-
ETH / USD	M_1	June 2022	0.746	0.014	6.081	-41.087	37.931	
	M_2	July 2022	0.803	**0.010**	5.509	**58.354**	50.000	
	M_3	August 2022	0.616	0.100	4.694	-4.673	53.333	
	M_4	September 2022	0.588	0.020	4.149	-16.230	55.172	
	M_5	October 2022	0.811	0.036	2.751	19.889	53.333	
	M_6	November 2022	0.369	0.023	**6.243**	-17.993	44.828	
	M_7	December 2022	0.238	0.027	2.450	-6.290	**70.000**	
	M_8	January 2023	0.498	**0.010**	2.712	32.073	46.667	
	M_9	February 2023	0.066	0.100	2.620	-2.220	55.556	
	M_{10}	March 2023	0.798	0.020	3.277	9.386	50.000	
	M_{11}	April 2023	0.116	0.100	2.590	2.708	68.966	
	M_{12}	May 2023	0.134	0.100	2.011	2.343	50.000	
	M_{13}	June 2023	0.599	0.100	2.582	3.868	62.069	
	M_{14}	July 2023	0.070	0.100	1.715	-3.552	50.000	
	M_{15}	August 2023	0.743	0.011	1.890	-12.154	53.333	
	M_{16}	September 2023	0.033	0.100	1.341	2.564	41.379	
	M_{17}	October 2023	0.922	0.052	1.888	4.665	23.333	
	M_{18}	November 2023	0.169	0.036	3.121	11.098	58.621	
	M_{19}	December 2023	0.005	0.100	2.584	9.325	56.667	
	M_{20}	January 2024	0.377	0.100	3.137	-2.929	50.000	
	M_{21}	February 2024	**0.980**	**0.010**	2.013	44.952	46.429	
	M_{22}	March 2024	0.320	0.100	4.064	6.171	56.667	
	M_{23}	April 2024	0.315	0.062	3.539	-13.978	62.069	
	M_{24}	May 2024	0.843	0.015	3.824	26.572	53.333	
	M_{25}	June 2024	0.484	**0.010**	1.850	-9.897	58.621	
	M_{26}	July 2024	0.455	0.100	2.900	-6.085	46.667	

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)	$\mathbf{Y}_{\text{Test}}$
	M_{27}	August 2024	0.001	0.100	4.539	-21.552	60.000	
	M_{28}	September 2024	0.843	0.025	2.690	7.277	44.828	
	M_{29}	October 2024	0.437	0.045	2.462	2.893	53.333	
	M_{30}	November 2024	0.733	0.012	4.024	47.466	51.724	
	M_{31}	December 2024	0.879	0.023	3.328	-9.975	60.000	
	M_{32}	January 2025	0.254	0.050	3.317	-1.767	53.333	
	M_{33}	February 2025	0.388	0.044	3.635	-28.226	66.667	
	M_{34}	March 2025	0.268	0.042	4.921	-17.812	46.667	
	M_{35}	April 2025	0.164	0.100	4.791	-5.846	55.172	
	M_{36}	May 2025	0.431	0.021	4.665	37.536	43.333	
	-	Mean	0.458	0.053	3.331	2.969	52.501	-
LTC / USD	M_1	June 2022	0.019	0.100	5.763	-14.131	55.172	
	M_2	July 2022	0.617	0.013	4.009	16.702	46.667	
	M_3	August 2022	0.621	0.023	3.424	-9.421	50.000	
	M_4	September 2022	0.677	0.022	3.974	-7.121	58.621	
	M_5	October 2022	0.021	0.100	2.217	3.949	53.333	
	M_6	November 2022	0.631	0.035	**6.946**	43.666	41.379	
	M_7	December 2022	0.505	0.018	2.784	-9.578	53.333	
	M_8	January 2023	0.452	**0.010**	2.785	32.689	53.333	
	M_9	February 2023	0.289	0.100	2.947	-6.509	51.852	
	M_{10}	March 2023	0.257	0.100	4.850	-8.396	50.000	
	M_{11}	April 2023	0.151	0.100	3.059	-4.699	58.621	
	M_{12}	May 2023	0.947	0.098	2.878	4.231	56.667	
	M_{13}	June 2023	0.751	0.100	6.095	15.405	41.379	
	M_{14}	July 2023	0.133	0.015	3.033	-13.838	50.000	
	M_{15}	August 2023	0.754	**0.010**	3.553	-31.989	53.333	
	M_{16}	September 2023	0.266	0.100	2.165	4.748	55.172	

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)	$\mathbf{Y}_{\text{Test}}$
	M_{17}	October 2023	0.046	0.100	2.004	1.027	40.000	
	M_{18}	November 2023	0.203	0.100	2.342	-0.786	48.276	
	M_{19}	December 2023	0.000	0.100	2.395	1.761	43.333	
	M_{20}	January 2024	0.015	0.100	3.115	-10.653	46.667	
	M_{21}	February 2024	**0.989**	0.048	2.111	18.330	42.857	
	M_{22}	March 2024	0.279	0.100	6.182	23.730	46.667	
	M_{23}	April 2024	0.577	0.024	4.520	-19.869	**65.517**	
	M_{24}	May 2024	0.152	0.025	2.095	3.792	53.333	
	M_{25}	June 2024	0.540	**0.010**	2.240	-9.787	58.621	
	M_{26}	July 2024	0.254	0.100	3.439	-5.700	50.000	
	M_{27}	August 2024	0.006	0.100	3.636	-6.639	36.667	
	M_{28}	September 2024	0.540	0.025	2.191	5.079	37.931	
	M_{29}	October 2024	0.392	0.019	2.548	9.336	53.333	
	M_{30}	November 2024	0.768	**0.010**	4.983	**46.207**	41.379	
	M_{31}	December 2024	0.587	0.011	6.023	-13.609	60.000	
	M_{32}	January 2025	0.118	0.048	5.534	21.712	46.667	
	M_{33}	February 2025	0.608	0.041	4.961	8.472	48.148	
	M_{34}	March 2025	0.046	0.021	4.077	-33.256	63.333	
	M_{35}	April 2025	0.424	0.100	4.052	-1.148	48.276	
	M_{36}	May 2025	0.487	0.100	3.778	-2.048	56.667	
	-	Mean	0.392	0.059	3.686	1.435	50.459	-
XMR/USD	M_1	June 2022	0.631	0.014	5.829	**-43.109**	44.828	
	M_2	July 2022	0.649	**0.010**	3.388	34.142	50.000	
	M_3	August 2022	0.222	0.027	3.884	-7.094	63.333	
	M_4	September 2022	0.468	0.037	3.838	-4.657	**68.966**	
	M_5	October 2022	0.186	0.100	1.728	6.024	56.667	
	M_6	November 2022	0.308	0.100	4.684	-5.010	58.621	

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)	$\mathbf{Y}_{\text{Test}}$
	M_{7}	December 2022	0.148	0.100	1.434	2.008	53.333	
	M_{8}	January 2023	0.462	**0.010**	2.587	19.529	63.333	
	M_{9}	February 2023	0.202	0.019	2.721	-15.419	48.148	
	M_{10}	March 2023	0.238	0.031	3.144	3.209	56.667	
	M_{11}	April 2023	0.163	0.100	1.854	-1.019	55.172	
	M_{12}	May 2023	0.802	0.027	1.297	-4.453	50.000	
	M_{13}	June 2023	0.012	0.057	2.204	15.027	37.931	
	M_{14}	July 2023	0.146	0.017	1.212	-3.473	60.000	
	M_{15}	August 2023	0.833	**0.010**	2.042	-10.730	50.000	
	M_{16}	September 2023	0.237	0.023	1.366	4.119	48.276	
	M_{17}	October 2023	0.953	0.014	1.741	15.493	53.333	
	M_{18}	November 2023	0.161	0.100	1.778	-0.933	58.621	
	M_{19}	December 2023	0.035	0.100	1.619	-3.960	56.667	
	M_{20}	January 2024	0.151	0.100	3.185	-3.422	56.667	
	M_{21}	February 2024	0.066	0.034	**9.616**	-28.613	46.429	
	M_{22}	March 2024	0.536	0.022	3.450	8.044	50.000	
	M_{23}	April 2024	0.291	0.091	3.546	-2.744	55.172	
	M_{24}	May 2024	0.853	**0.010**	2.157	19.855	50.000	
	M_{25}	June 2024	0.000	0.100	3.254	12.885	48.276	
	M_{26}	July 2024	0.054	0.100	2.129	-6.047	50.000	
	M_{27}	August 2024	0.687	0.025	2.897	7.760	53.333	
	M_{28}	September 2024	0.924	0.100	1.844	-9.079	48.276	
	M_{29}	October 2024	0.267	**0.010**	2.707	7.567	40.000	
	M_{30}	November 2024	0.025	0.100	2.377	3.731	58.621	
	M_{31}	December 2024	0.002	0.100	6.704	18.061	53.333	
	M_{32}	January 2025	0.755	**0.010**	3.364	21.498	53.333	
	M_{33}	February 2025	0.024	0.100	2.975	-7.812	55.556	

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)	$\mathbf{Y}_{\text{Test}}$
	M_{34}	March 2025	0.259	0.100	2.512	-3.906	50.000	
	M_{35}	April 2025	**0.998**	0.020	3.067	28.735	51.724	
	M_{36}	May 2025	0.636	0.022	3.749	19.809	30.000	
	-	Mean	0.372	0.054	2.997	2.389	52.350	-
XRP/USD	M_1	June 2022	0.574	0.043	4.274	-16.558	48.276	
	M_2	July 2022	0.590	0.015	3.160	20.803	56.667	
	M_3	August 2022	0.785	0.012	2.508	-13.558	56.667	
	M_4	September 2022	0.994	0.012	5.788	44.071	62.069	
	M_5	October 2022	0.370	0.093	2.790	-2.377	56.667	
	M_6	November 2022	0.020	0.085	6.750	-12.036	44.828	
	M_7	December 2022	0.703	**0.010**	2.415	-14.613	60.000	
	M_8	January 2023	0.707	**0.010**	2.670	19.782	66.667	
	M_9	February 2023	0.174	0.068	2.200	-8.932	59.259	
	M_{10}	March 2023	0.995	0.016	5.482	40.130	56.667	
	M_{11}	April 2023	0.530	0.033	2.749	-7.655	65.517	
	M_{12}	May 2023	0.980	0.066	2.061	11.121	40.000	
	M_{13}	June 2023	0.449	0.017	2.792	-6.634	**72.414**	
	M_{14}	July 2023	0.461	0.020	**10.494**	47.422	56.667	
	M_{15}	August 2023	0.405	**0.010**	3.346	-27.713	46.667	
	M_{16}	September 2023	0.328	0.100	1.560	3.394	44.828	
	M_{17}	October 2023	0.984	0.056	2.290	14.406	36.667	
	M_{18}	November 2023	0.420	0.091	3.255	-0.362	62.069	
	M_{19}	December 2023	0.000	0.100	2.265	0.506	56.667	
	M_{20}	January 2024	0.911	**0.010**	2.661	-20.035	46.667	
	M_{21}	February 2024	0.820	0.013	2.021	15.994	57.143	
	M_{22}	March 2024	0.004	0.100	5.075	4.640	60.000	
	M_{23}	April 2024	0.548	0.036	3.905	-18.069	55.172	

Crypto	Split	Month	ADF p	KPSS p	Volatility (%)	Trend (%)	Fluctuation (%)	$\mathbf{Y}_{\text{Test}}$
	M_{24}	May 2024	0.126	0.100	1.890	0.019	63.333	
	M_{25}	June 2024	0.614	0.018	1.751	-8.213	65.517	
	M_{26}	July 2024	0.874	**0.010**	4.310	30.608	50.000	
	M_{27}	August 2024	0.602	0.100	4.399	-5.064	60.000	
	M_{28}	September 2024	0.662	0.014	2.533	11.732	65.517	
	M_{29}	October 2024	0.000	0.067	2.541	-14.614	66.667	
	M_{30}	November 2024	**0.997**	**0.010**	6.835	**280.296**	37.931	
	M_{31}	December 2024	0.123	0.012	6.043	-9.160	53.333	
	M_{32}	January 2025	0.620	0.015	4.647	30.148	50.000	
	M_{33}	February 2025	0.403	0.100	4.510	-25.453	59.259	
	M_{34}	March 2025	0.007	0.100	7.816	-4.640	43.333	
	M_{35}	April 2025	0.239	0.033	4.213	2.436	48.276	
	M_{36}	May 2025	0.458	0.100	3.287	-1.740	50.000	
	-	Mean	0.513	0.047	3.813	10.002	55.039	-

Table 75: Statistics of $\mathbf{Y}_{\text{Test}}$ for splits $M_1, \ldots, M_{36}$ of the *extended experiment* across *BTC/USD*, *ETH/USD*, *LTC/USD*, *XMR/USD*, and *XRP/USD*.