BSc. Computer Science

Multi-criteria optimization for sustainable last-mile delivery with flexible time-windows

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BACHELOR THESIS

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Abstract

This thesis investigates the optimization of last-mile delivery with flexible time-windows, exploring the applicability of three distinct algorithms: Greedy, 2-Opt, and Genetic algorithms. The central research question driving this inquiry is whether these algorithms can enhance the utilization and sustainability of last-mile delivery operations.

The Greedy algorithm, known for its simplicity and efficiency, is evaluated for local decision-making optimization. The 2-Opt algorithm, recognized for its optimization using edge-swapping, is scrutinized in the context of last-mile delivery with flexible time-windows. The Genetic algorithm, inspired by natural selection processes, is implemented to assess its potential for finding globally optimal solutions.

The study uses a methodology utilizing 2 types of datasets: clustered- and unclustered nodes. It evaluates the algorithms based on multiple objectives, including the cost, emission, and customer dissatisfaction.

The greedy algorithm showed consistent performance for its simplicity. The 2-opt got stuck in local optima, therefore the algorithm was ineffective to solve the route delivery problem. The genetic algorithm showed similar consistent performance, and managed to achieve zero-emission in the unclustered dataset.

Based on the findings the genetic algorithm is most suitable for solving a last mile route delivery minimization problem with flexible time windows. Further research could be done on more advanced meta heuristic techniques to solve this problem.

Contents

1 Introduction

The parcel delivery industry is rapidly growing [Sta23]. It is becoming increasingly important in all sectors of business. This comes with a high costs and carbon footprint. In this multi-step delivery process, last mile delivery is the most polluting one. 20% to 30% of a city's total carbon dioxide emissions can be attributed to last-mile delivery activities [Eur22]. Due to the complexity and scale of this optimization problem, Insights in how this multi-objective delivery process can be optimized using algorithms could contribute to lowering the total cost and emissions of this industry.

1.1 Studies of Significance

The optimization of last-mile delivery operations, particularly in the context of flexible time windows, has been a subject of growing interest in logistics and transportation research. Notably, Koskosidis et al. (1992) [KPS92] conducted a seminal study on the optimization of vehicle routing and scheduling with soft time window constraints. Their work, focusing on an optimization-based heuristic that extends the cluster-first, route-second algorithm, has provided valuable insights into the challenges and solutions associated with last-mile delivery logistics. The current literature shows that research on vehicle routing and scheduling problem structures with time window constraints has seen significant advances, offering insights for future research (Solomon & Desrosiers, 1988)[SD88].

1.2 Focus and Scope

This study will concentrate on the multi-criteria optimization problem associated with sustainable last-mile delivery. The primary goals are to minimize delivery costs, minimize emissions, and minimizing customer dissatisfaction. The study will examine how various optimization algorithms and techniques can effectively balance these objectives while considering the flexibility of time windows. The scope of the optimization problem will be determined by research that considers diverse geographic regions, delivery time periods, and consumer preferences. This led to the research question of this study:

Can the utilization and sustainability of last-mile delivery with flexible time-windows be further optimized by applying a greedy-, 2-opt- or genetic algorithm to the multi-objective optimization process?

1.3 Objectives of the Research

This thesis aims to achieve the following objectives:

1. Assess the efficiency of the greedy algorithm, the 2-opt heuristic, and the genetic algorithm in the context of last-mile delivery.

2. Evaluate the impact of these algorithms on the optimization of delivery routes and schedules, in the presence of flexible time windows.

3. Provide insights into the synergies and trade-offs between algorithmic efficiency, environmental sustainability, and customer satisfaction.

1.4 Overview of the Thesis Structure

Chapter 2 of the thesis will provide a literature review on the use of algorithms, last mile delivery practises and flexible time windows. Chapter 3 will explain the last mile delivery problem in detail. After that, chapter 4 outlines the methodology and the algorithms that are used. Chapter 5 contains the results of the research. In Chapter 6 the discussion and conclusion will be presented.

2 Related work

2.1 General trends in last mile delivery

Last-mile delivery has garnered significant attention from logistics researchers and the broader community, driven by the surge in e-commerce and online shopping [TPJ18]. In the current era of the circular economy, sustainable service quality has become an important factor for selecting logistics providers worldwide. The major delivery businesses have set company-wide emission goals ranging from "zero emissions" to "net-zero emissions" [HdL21]. Gupta et al. (2021) [Gup21] findings underscore the importance for logistics providers to prioritize sustainable network optimization, reduced response times, reliable green services, flexible green processes, and the establishment of trust with stakeholders. These measures are instrumental in positioning logistics providers as the preferred choice for customers.

2.2 Multi-objective optimization in logistics

The field of logistics and supply chain management has witnessed a notable increase in interest in multi-objective optimization, owing to its capacity to successfully address the challenge of balancing conflicting objectives. It facilitates the ability of decision-makers to make well-informed choices within intricate situations. It has been demonstrated that the created multi-objective optimization is an excellent method for analyzing real-life scenarios with multiple objectives [FZ15].

The vehicle routing problem with stochastic demand was addressed by Cheong et al. (2006) [CTLxX06] with the use of a multi-objective evolutionary algorithm. The primary objective of this study is to enhance the efficiency of vehicle routes in situations when demand is unclear. This research emphasizes the significance of flexibility within the field of logistics.

The contribution made by Eid et al. (2018) [Eid18] to the subject of study was an investigation into the application of simultaneous multi-criteria optimization for the purpose of scheduling linear infrastructure projects. The research conducted by the authors showcases the practicality of employing multi-objective optimization methods within the realm of linear infrastructure projects. It underscores the significance of effective project scheduling in ensuring the accomplishment of project objectives.

2.3 Flexible time windows

Addressing the complexities of time window management in urban freight operations is a prominent concern in modern logistics. Insights from a comprehensive study involving three Dutch retail organizations [AK13] shed light on potential solutions. This study reveals that harmonizing time windows between neighboring cities significantly enhances overall performance. The findings indicate that the conventional time-window policy, as commonly employed, may benefit from substantial improvements in various dimensions of urban freight operations.

The study conducted by Zhao et al. (2020) [Zha20] introduces a novel multi-objective optimization model based on cost, carbon emissions, and customer satisfaction in the cold chain logistics distribution process. This model, along with the proposed ACOMO algorithm, addresses the evolving needs of modern logistics and highlights the importance of considering multiple objectives for efficient and environmentally friendly last-mile delivery solutions. The study's findings underscore the advantages of multi-objective optimization in providing diverse distribution route options, aligning with the concept of flexible time windows and offering valuable insights for logistics companies striving to optimize their operations.

2.4 Algorithms for route optimization

The route optimization algorithm discussed in the study by Aibinu et al. (2016) [ASR+16] is a clustering-based genetic algorithm with polygamy and a dynamic population control mechanism. This algorithm has demonstrated superior performance in solving route optimization problems, converging to a global solution within a limited number of iterations. Furthermore, its characteristics make it particularly suitable for real-time and online applications in the context of last-mile delivery.

Regarding the Traveling Salesman Problem (TSP), noteworthy contributions have been made to enhance its resolution. Cui et al. [CZY+20] proposed an innovative approach by refining the architecture of the Particle Swarm Optimization (PSO) method. Their approach includes a preprocessing multi-subdomain grouping technique, genetic mutation, and a simplified 4-opt strategy. This optimization technique exhibits remarkable performance, particularly for small to medium-sized TSP problems, consistently achieving percentage error values below 4.8%.

2.5 Significance of the research

This thesis concentrates on the evaluation of various algorithms for route optimization. Moreover, it explores the integration of flexible time windows within these algorithms. This focus is crucial because it aligns with the dynamic aspect of last-mile delivery, where timely and sustainable service is paramount. By assessing the effectiveness of these algorithms, this research aims to provide valuable insights into how they can adapt to the specific requirements of last-mile delivery.

3 Problem description

The model used for this last-mile delivery minimization problem is built around three objective functions which represent the cornerstones of the optimization. These functions include minimizing the cost of delivery, minimizing emissions from the hybrid bus, and minimizing consumer dissatisfaction.

3.1 Objective Function 1: Minimize Cost of Delivery

The first objective function targets minimizing the cost of delivery. The cost is calculated by adding the salary of the driver, the product of the total time spent in minutes and salary per minute, the product of the distance traveled using diesel and the cost per kilometer for diesel, and the product of the distance traveled using electricity and the cost per kilometer for electricity. Mathematically, if the distance between any two nodes is less than 20 units, electricity is used, whereas diesel is used if the distance exceeds 20 units.

$$\begin{aligned} \text{Cost} = \text{salary} + (\text{endtime} - \text{begintime}) \times \text{salary\_per\_minute} \\ +(\text{diesel\_distance} \times \text{diesel\_cost\_per\_km}) + (\text{electric\_distance} \times \text{electric\_cost\_per\_km}) \end{aligned} \tag{1}$$

3.2 Objective Function 2: Minimize Emissions

The second objective function aims to minimize the distance traveled using diesel. This function is essentially the summation of all distances above 20 units (where diesel is employed) across the entire route. Minimizing this will result in a reduction in emissions.

3.3 Objective Function 3: Minimize Consumer Dissatisfaction

The third objective function is constructed to minimize consumer dissatisfaction. Each customer is assigned three time slots, each 30 minutes long. The preference is to have all deliveries made during the first time slot. If this is not feasible, the second time slot is utilized, and if that too is not possible, the third time slot is used. In cases where none of the time slots are viable, a penalty is incurred. The weights associated with these options are 0, 1, 2, and 10 respectively. The objective is to minimize the sum of these weights across all customers.

3.4 Combination of Objectives

The optimization problem is solved by combining the three objective functions. We can either solve for each objective separately, providing us with three different solutions or integrate the objectives into a single function by assigning equal weights to each, and then solving for a single solution that best balances the trade-offs among the objectives.

3.5 Geographical Context

The mathematical model is based on a 2D map with positive coordinates. Node 0 represents the depot from which the driver begins and ends the journey. Other nodes represent customers, who are scattered across the map. The x and y coordinates signify the location of the node on the map. The driver operates a hybrid bus and must visit all the nodes/customers and return to the depot while optimally satisfying the aforementioned objectives. The dataset comprises the node number, x and y coordinates, and three time slots for each customer.

3.6 Visualization

To visualize the solution, we plot the route on a 2D map. The customers and the depot are represented by their respective coordinates, which are plotted on the map. The visualization incorporates color coding to represent different aspects of the solution. Specifically:

- If a customer is assigned option 1 (first time slot), the corresponding point on the map is marked in green.
- If a customer is assigned option 2 (second time slot), the corresponding point is marked in blue.
- If a customer is assigned option 3 (third time slot), the corresponding point is marked in orange.
- If a customer is unable to be assigned any of the three options, the corresponding point is marked in red.
- The depot is marked in **black**.

The lines connecting the points on the map represent the distances traveled between consecutive points. If the distance is covered using electricity, the line is displayed in green. If the distance is covered using diesel, the line is displayed in yellow. These visual elements provide an intuitive representation of the solution, highlighting the delivery options, travel modes, and overall satisfaction for each customer. An example of a visualization can be seen in figure 5.

4 Methodology

4.1 Type of Research

This research employs a quantitative approach to address the research question: "Can the utilization and sustainability of last-mile delivery with flexible time-windows be further optimized by applying a greedy-, 2-opt- or genetic algorithm to the multi-criteria optimization process?" The study aims to optimize the last-mile delivery process by utilizing three distinct optimization algorithms. These algorithms are applied to two different datasets of delivery routes and evaluated against multiple criteria.

4.2 Data Collection

4.2.1 Dataset Generation

A dataset of consumers is generated using a randomizer, including information on delivery locations with coordinates and 3 different time-windows.

4.3 Application of Optimization Algorithms

To create delivery routes, 3 different optimization algorithms were used. Each algorithm has different characteristics. The generated routes will be assessed on their performance. The data will be compared in a clustered and unclustered setting.

4.3.1 Greedy Algorithm

The greedy algorithm is implemented to iteratively refine the delivery routes. It starts with an initial solution and explores neighboring solutions by making incremental adjustments.

Algorithm 1: Greedy Algorithm for Route Optimization

```
Data: nodes, weights
Result: Optimized route
current_node = nodes[0];
route = [current_node];
unvisited_nodes = nodes[1:];
while unvisited_nodes is not empty do
    next_node = SelectNextNode(unvisited_nodes, route, weights);
    unvisited_nodes.remove(next_node);
    route.append(next_node);
route.append(nodes[0]);
return route;
```

4.3.2 2-Opt Algorithm

The 2-opt algorithm is applied to improve the order of delivery stops within the routes. It systematically evaluates pairs of delivery stops and performs swaps to minimize delivery cost, emissions and enhance adherence to time-windows.

```
Algorithm 2: 2-Opt Algorithm for Route Optimization
  Data: route, weights
  Result: Optimized route
repeat
    for i = 1 to length(route) - 1 do
        for j = i + 1 to length(route) do
            new_route = 2-OptSwap(route, i, j);
            if calculate_cost(new_route, weights) < calculate_cost(route, weights) then
                route = new_route;
until no improvement is made;
return route;
```

4.3.3 Genetic Algorithm

Genetic algorithms are utilized to evolve and optimize the delivery routes. Routes are represented as chromosomes, and genetic operators such as crossover and mutation are applied to generate new solutions. Fitness evaluation considers the objective functions.

```
Algorithm 3: Genetic Algorithm for Route Optimization
  Data: nodes, weights, population_size, generations
  Result: Optimized route
Initialize a population of routes with random chromosomes;
for generation = 1 to generations do
    Evaluate the fitness of each route in the population using the given weights;
    Select routes for the next generation using roulette wheel selection or other methods;
    Apply crossover to create new routes in the next generation;
    Apply mutation to introduce diversity in the population;
Select the best route from the final generation based on fitness;
return best_route;
```

4.4 Data Analysis

4.4.1 Performance Metrics

The assessment criteria used in this study assess the efficiency of the algorithms utilized on the datasets. The metrics used in this analysis are as follows:

1. Objective Functions: The evaluation of algorithmic performance was conducted with respect to multiple objective functions, including cost, diesel emissions and customer dissatisfaction. These objective functions are essential in characterizing the efficacy of the dataset configurations in real-world applications.

2. Combined Scores: In addition to the evaluation of individual objective functions, a normalized score was calculated for each algorithm to create a combined score. These combined scores provide a holistic view of the overall performance of each algorithm and allow us to investigate trade-offs between various objectives.

4.5 Mitigation of Research Biases

4.5.1 Randomization

Randomization is used during the initial generation of solutions in the genetic algorithm to reduce any inherent biases. The mean of 10 runs was taken to asses the performance for each objective function. All algorithms used a randomly generated route to perform the route optimization.

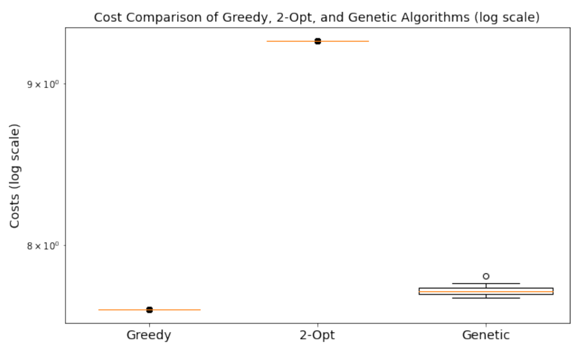
4.5.2 Clustered and unclustered dataset

The focus of this analysis is on two main datasets: the clustered and unclustered versions of a collection of nodes. The clustered dataset configuration is characterized by a map consisting of three cities, whereby customers are situated in relatively close range inside each city. In contrast, the unclustered dataset configuration contains a randomly generated map where customers are spread out across the entire area. Both configurations were assessed on their performance for each algorithm. By examining the algorithms' performance in both clustered and unclustered scenarios, the risk of research bias associated with exclusively focusing on one type of dataset is reduced.

5 Results

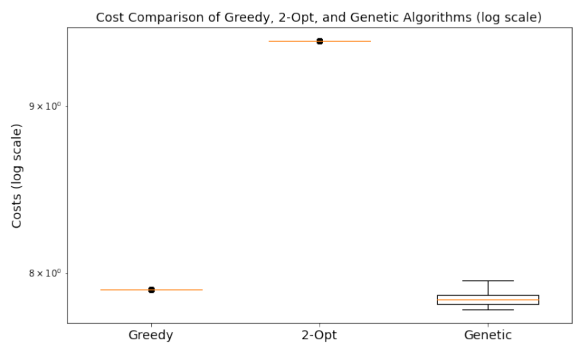
The research objectives of this thesis involved assessing the effectiveness of algorithms applied to a last mile delivery problem. The goal was to gain a better understanding of the trade-offs and benefits linked to different algorithms, and to measure the performance of each algorithm for each objective function.

5.1 Objective function 1



(a) Objective Function 1: Cost Comparison for clustured dataset

Algorithm	Cost
Greedy	2068.61
2-Opt	10785.30
Genetic (Mean)	2311.39



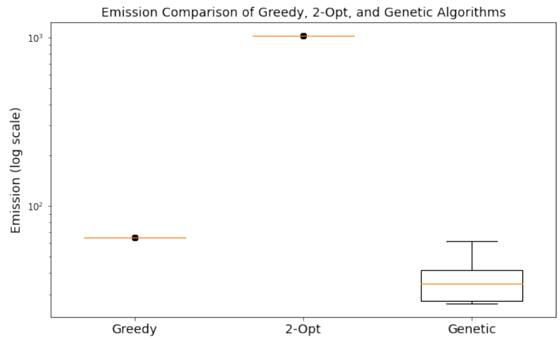
(b) Objective Function 1: Cost Comparison for unclustured dataset

Algorithm	Cost
Greedy	2712.70
2-Opt	12381.53
Genetic (Mean)	2580.25

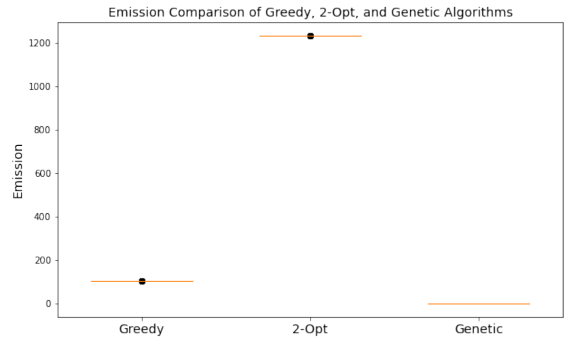
Figure 1: Comparison of algorithms for OF1

In figure 1, the Greedy algorithm generally performed well, especially in the clustered dataset. The 2-Opt algorithm, on the other hand, exhibited higher costs in both scenarios, indicating potential limitations. The Genetic algorithm, with mean costs, positioned itself as a robust alternative, showing competitive performance in both clustered and unclustered datasets.

5.2 Objective function 2



(a) Objective Function 2: Emission Comparison for clustered dataset



(b) Objective Function 2: Emission Comparison for unclustered dataset

Algorithm	Emission
Greedy	65.26
2-Opt	1028.30
Genetic (Mean)	36.85

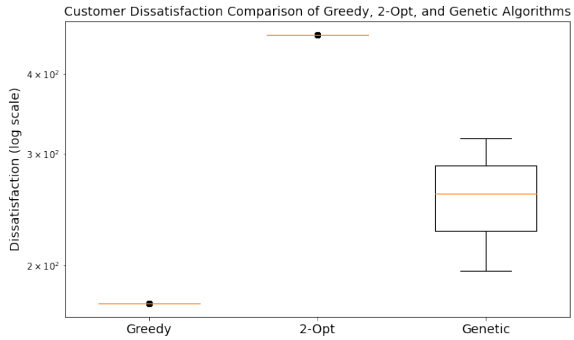
Algorithm	Emission
Greedy	104.95
2-Opt	1236.09
Genetic (Mean)	0.00

Figure 2: Comparison of algorithms for OF2

In figure 2 the Genetic algorithm, with zero emissions in the unclustered dataset, stands out as an environmentally conscious solution. This can be seen in figure 10 where all edges are green. The Greedy algorithm showed moderate emissions, while the 2-Opt algorithm exhibited higher emissions in both clustered and unclustered datasets. The environmental efficiency of the Genetic algorithm, especially in the absence of clustering, positions it as a promising choice for sustainability.

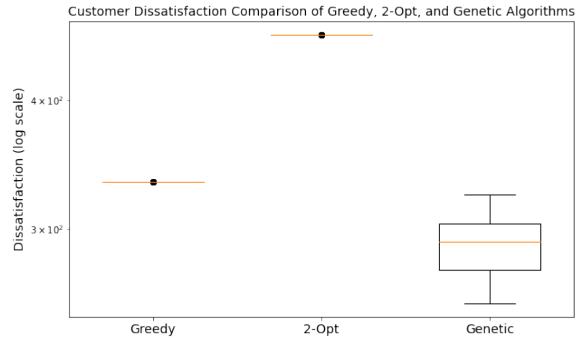
5.3 Objective function 3

In figure 3, in the clustered dataset, the Greedy algorithm outperforms the Genetic algorithm, suggesting its efficiency in optimizing routes for closely grouped customers. Conversely, in the unclustered dataset, the Genetic Algorithm excels, showcasing its effectiveness in handling dispersed customer distributions. These results may emphasize the need for algorithm choice based on dataset characteristics, highlighting the trade-off between the two.



(a) Objective Function 3: Customer Dissatisfaction Comparison for clustered dataset

Algorithm	Customer Dissatisfaction
Greedy	174.0
2-Opt	462.0
Genetic (Mean)	257.1

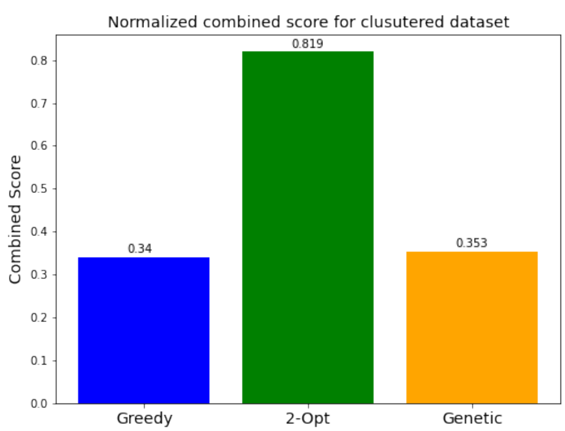


(b) Objective Function 3: Customer Dissatisfaction Comparison for unclustered dataset

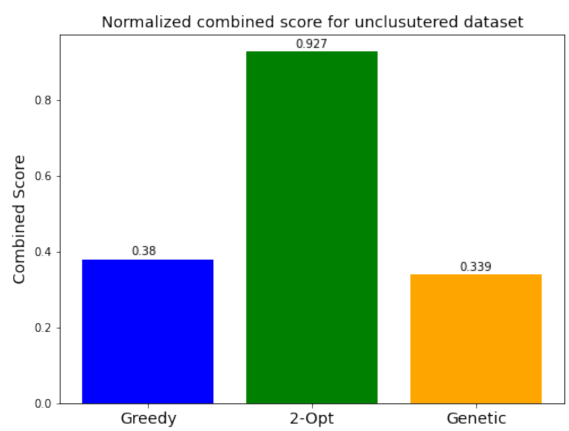
Algorithm	Customer Dissatisfaction
Greedy	333.0
2-Opt	463.0
Genetic (Mean)	289.1

Figure 3: Comparison of algorithms for OF3

5.4 Combined weights



(a) Combined weights Comparison for clustered dataset



(b) Combined weights Comparison for unclustered dataset

Figure 4: Comparison of Combined weight scores

5.4.1 Clustered approach

In the clustered approach, the normalized scores reveal interesting insights into the performance of the algorithms. The Greedy algorithm demonstrates the best performance, obtaining a normalized score of 0.34. This indicates that, within the clustered setting, the Greedy algorithm has a good balance among the considered objectives. On the other hand, the 2-Opt algorithm appears to struggle, yielding a high normalized score of 0.82. This suggests that 2-Opt might be converging to a local optimum, consistently producing similar routes across various objective functions and resulting in less favorable scores. This is visualized in figure 7.

In contrast, the Genetic algorithm, with a normalized score of 0.35, displays competitive performance in the clustered approach. The ability of the Genetic algorithm to explore diverse solutions seems to contribute to its effectiveness in tackling multi-objective optimization problems, showcasing its versatility in addressing different criteria simultaneously.

5.4.2 Unclustered approach

Moving to the unclustered approach, the landscape changes. Greedy, which performed well in the clustered setting, now exhibits a higher normalized score of 0.38. This might indicate that the simplicity of the Greedy algorithm becomes a limitation in a more complex, unclustered scenario. On the other hand, 2-Opt continues to struggle, with a notably high normalized score of 0.93. This reinforces the hypothesis that 2-Opt is susceptible to getting stuck in local optima, visible in figure 8.

Remarkably, the Genetic algorithm in the unclustered setting achieves a normalized score of 0.34, comparable to its performance in the clustered scenario. Additionally, it manages to achieve zero emissions. This is a significant finding, suggesting that the Genetic algorithm has the potential to provide environmentally sustainable solutions in last-mile delivery scenarios with flexible time windows.

Algorithm	Normalized Score
Greedy	0.34
2-Opt	0.819
Genetic	0.353

Table 1: Normalized scores in the clustered approach.

Algorithm	Normalized Score
Greedy	0.38
2-Opt	0.927
Genetic	0.339

Table 2: Normalized scores in the unclustered approach.

5.5 Balance of scores

Analyzing the percentage contributions to the combined scores provides insights into how each objective function influences the overall score for each algorithm. The percentage contributions can be seen in table 3 and 4.

5.5.1 Greedy Algorithm

For the Greedy algorithm, dissatisfaction significantly influences the combined score, emphasizing a potential area for improvement. The contributions from cost and emission, while present, are comparatively lower.

5.5.2 2-Opt Algorithm

In contrast, the 2-Opt algorithm demonstrates a more balanced contribution across cost, emission, and customer dissatisfaction. However, this result is not representative because of the overall bad performance of the algorithm.

5.5.3 Genetic Algorithm

The Genetic algorithm, intriguingly, achieves 0% diesel emission, showcasing an environmentally friendly characteristic. Dissatisfaction remains a dominant factor, indicating potential enhancements in parameter optimization that could be done to get better scores. This requires more process power and time.

5.5.4 Overall balance

The combined scores seem to have a good balance, representing the scores of the individual results. The dissatisfaction contribution is high across the scores, it was the hardest task for all algorithms. Therefore, there is no overcompensation witnessed in the results.

Algorithm	**Cost (%)**	**Diesel Emission (%)**	**Dissatisfaction (%)**
Greedy	15.71	4.27	80.03
2-Opt	35.15	27.90	36.95
Genetic	19.20	4.59	76.21

Table 3: Percentage Contribution to Combined Score for Each Algorithm in the Clustured dataset.

Algorithm	**Cost (%)**	**Diesel Emission (%)**	**Dissatisfaction (%)**
Greedy	18.48	5.68	75.84
2-Opt	35.78	29.63	34.59
Genetic	18.05	0.00	81.95

Table 4: Percentage Contribution to Combined Score for Each Algorithm in the Unclustered dataset.

6 Conclusion and Discussion

6.1 Conclusion and contributions

In addressing the research question— "Can the utilization and sustainability of last-mile delivery with flexible time-windows be further optimized by applying a greedy-, 2-opt-, or genetic algorithm to the multi-objective optimization process?"— each algorithm played a distinct role in optimizing the delivery process. The Greedy algorithm demonstrated solid performance for its simplicity , the 2-Opt algorithm revealed to be unuseful in all cases, and the Genetic algorithm showcased to be capable of achieving zero-emissions in an unclustered setting. The results showed that the genetic algorithm is the best suited algorithm for solving a last mile delivery problem with flexible time windows.

This thesis makes contributions to the field of sustainable last mile delivery. Specifically, it advances the understanding of applying certain algorithms to a minimization problem and provides practical advise for parcel delivery companies. The integration of algorithms and the use of flexible time windows has widened the scope of research in last mile delivery route optimization.

6.2 Limitations and future work

The limitations of this study include the reliance on two datasets and a fixed set of parameters. Further studies could explore the sensitivity of the algorithms to different dataset characteristics and parameter settings. Additionally, the focus on three specific objectives leaves room for the addition of more nuanced criteria, such as vehicle capacity or dynamic traffic conditions.

To build on this research, future studies could delve deeper into other algorithms that perform well on route optimization problems. While our study focused on the performance of greedy, 2-opt, and genetic algorithms, there are several emerging algorithms and variations that warrant investigation. Exploring advanced meta-heuristic techniques, such as specific meta-heuristic, may offer novel perspectives on enhancing route optimization in last-mile delivery. Furthermore, exploring specific variables' impact on optimization and tailoring algorithms to unique constraints within last-mile delivery contexts offers promising research directions. Continuous exploration of diverse algorithms and factors is crucial for advancing knowledge in last-mile delivery optimization.

In conclusion, this research has shed light on the subject of sustainable last mile delivery through the lens of multi-objective optimization algorithms. The findings highlight the influence of algorithm choice on last-mile delivery optimization, emphasizing the superior performance of the genetic algorithm, potential pitfalls of 2-opt, and the contextual nuances between clustered and unclustered approaches. It is clear that the optimization of last-mile delivery is a multifaceted challenge that requires ongoing exploration and innovation.

References

[AK13] D. Akyol and R. Koster. Non-dominated time-window policies in city distribution. *Production and Operations Management*, 22:739–751, 2013.

[ASR+16] A. Aibinu, H. Salau, Najeeb Arthur Rahman, M. Nwohu, and C. Akachukwu. A novel clustering based genetic algorithm for route optimization. *Engineering Science and Technology, an International Journal*, 19:2022–2034, 2016.

[CTLxX06] C. Cheong, K. Tan, Dikai Liu, and Jian xin Xu. A multiobjective evolutionary algorithm for solving vehicle routing problem with stochastic demand. *2006 IEEE International Conference on Evolutionary Computation*, pages 1370–1377, 2006.

[CZY+20] Ying Cui, Jiabao Zhong, Fengru Yang, Shixin Li, and Penghao Li. Multi-subdomain grouping-based particle swarm optimization for the traveling salesman problem. *IEEE Access*, 8:227497–227510, 2020.

[Eid18] M. Eid. Simultaneous multi-criteria optimization for scheduling linear infrastructure projects. *International Journal of Construction Management*, 2018.

[Eur22] The carbon cost of home delivery and how to avoid it, 2022.

[FZ15] Mazen Farran and T. Zayed. Fitness-oriented multi-objective optimisation for infrastructures rehabilitations. *Structure and Infrastructure Engineering*, 11:761 – 775, 2015.

[Gup21] Anchal Gupta. Evaluation of logistics providers for sustainable service quality: Analytics based decision making framework. *Annals of Operations Research*, 2021.

[HdL21] Ilona Hartlief and David Ollivier de Leth. Parcel delivery on a warming planet. Technical report, 11 2021.

[KPS92] Y. A. Koskosidis, Warrren B Powell, and M. Solomon. An optimization-based heuristic for vehicle routing and scheduling with soft time window constraints. *Transp. Sci.*, 26:69–85, 1992.

[SD88] M. Solomon and J. Desrosiers. Survey paper - time window constrained routing and scheduling problems. *Transp. Sci.*, 22:1–13, 1988.

[Sta23] Statista. Last mile delivery market size worldwide 2020-2027, 3 2023.

[TPJ18] Noppakun Tiwapat, Choosak Pomsing, and Peerapop Jomthong. Last mile delivery: Modes, efficiencies, sustainability, and trends. *2018 3rd IEEE International Conference on Intelligent Transportation Engineering (ICITE)*, pages 313–317, 2018.

[Zha20] Banglei Zhao. Cold chain logistics path optimization via improved multi-objective ant colony algorithm. *IEEE Access*, 2020.

A Appendix

A.1 Route Visualizations

B Code

The GitHub repository of this project can be found at the following URL: https://git.liacs.nl/s2713330/last-mile-delivery-thesis.git

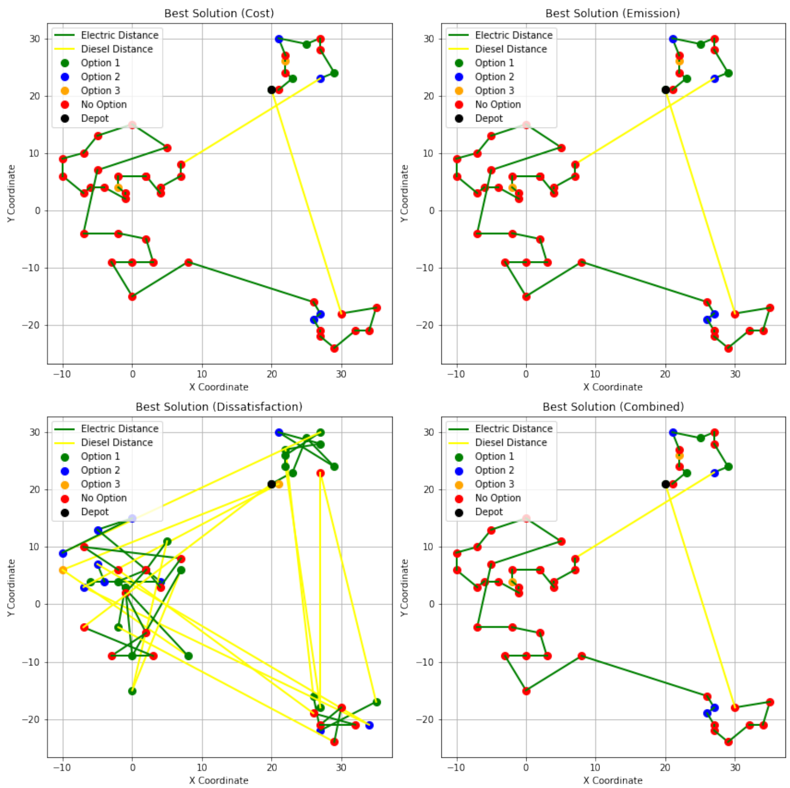


Figure 5: Greedy Algorithm Route Visualization for Clustered Data

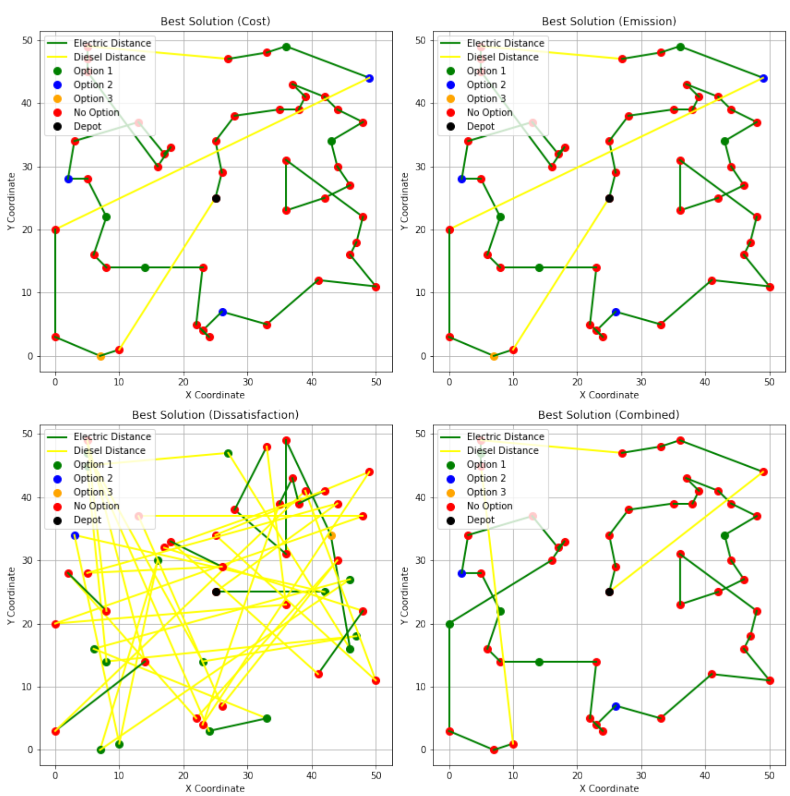


Figure 6: Greedy Algorithm Route Visualization for Unclustered Data

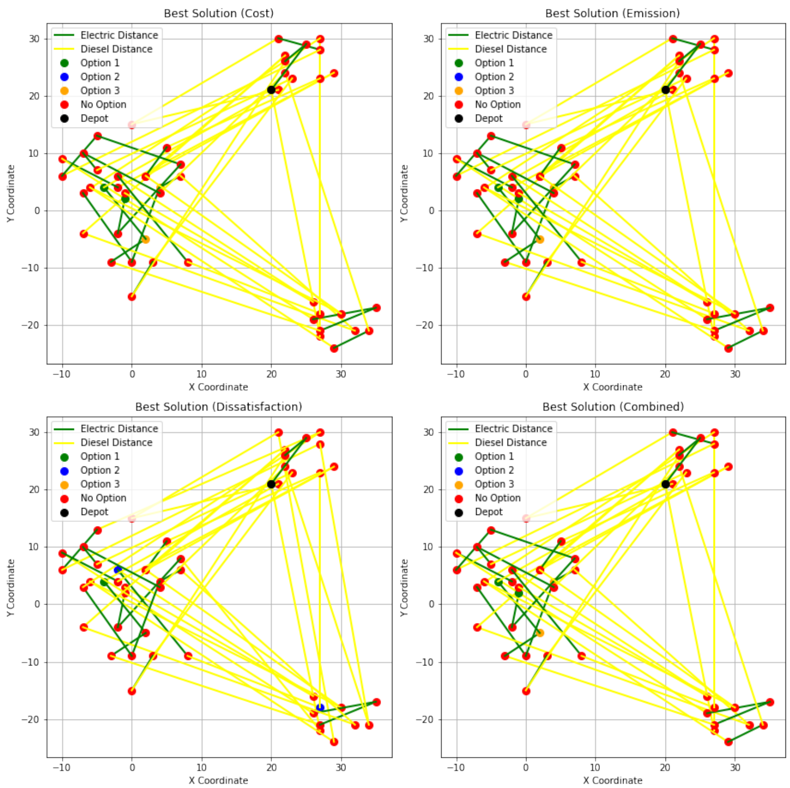


Figure 7: 2-Opt Algorithm Route Visualization for Clustered Data

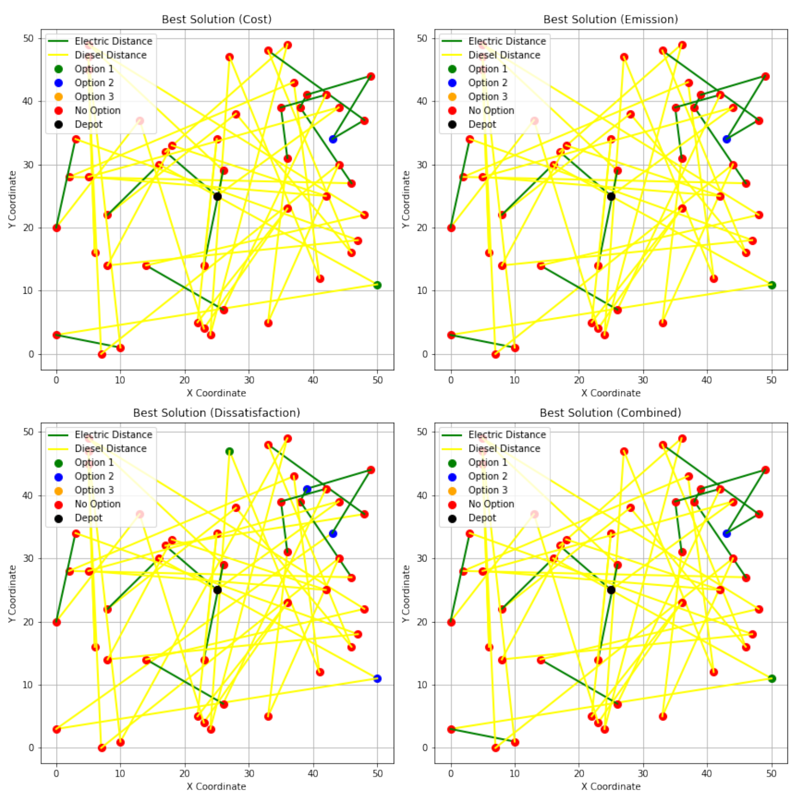


Figure 8: 2-Opt Algorithm Route Visualization for Unclustered Data

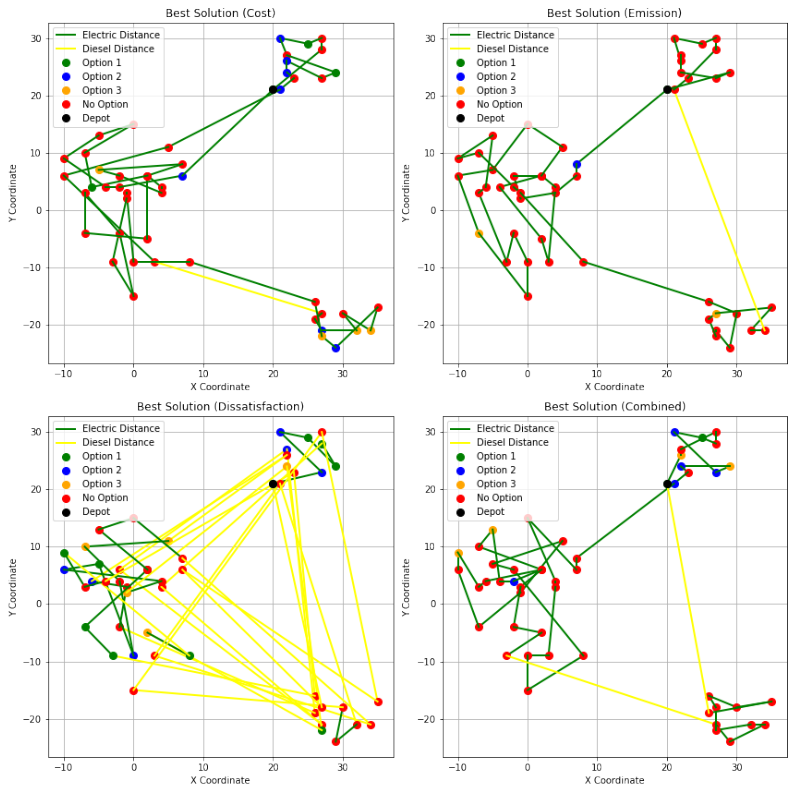


Figure 9: Genetic Algorithm Route Visualization for Clustered Data

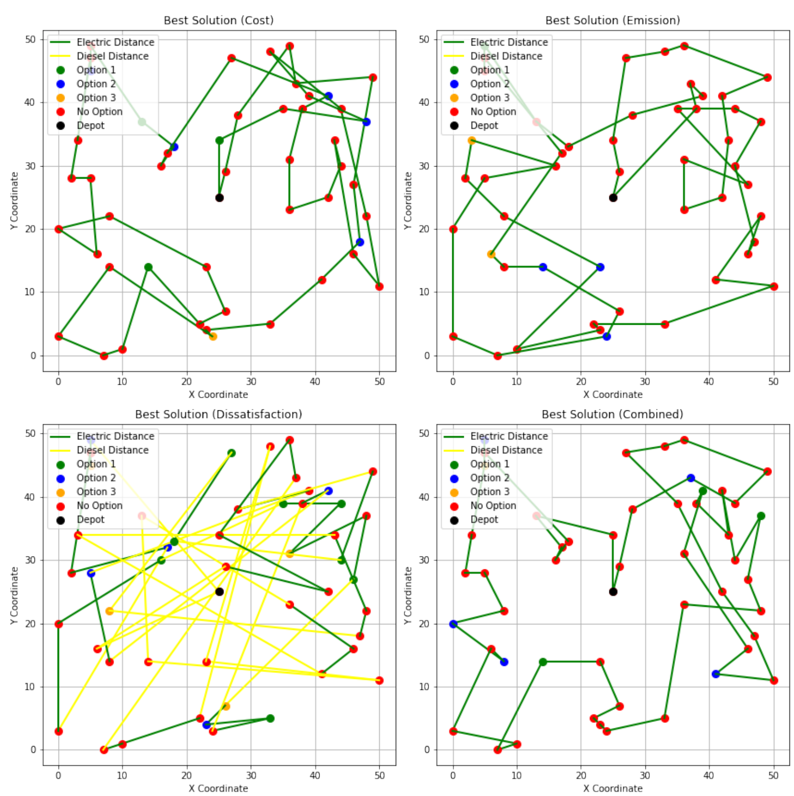


Figure 10: Genetic Algorithm Route Visualization for Unclustered Data