Master Computer Science

Multi-objective Optimization of Takeaway Order Allocation based on NSGA-II Algorithm

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Abstract

As the scale of the online-to-offline takeaway market continues to expand, the number of users and orders grows rapidly, and the contradiction between the supply and demand of the industry's delivery capacity becomes increasingly prominent. However, due to the low requirements and professionalism of drivers and the continuous compression of delivery time, drivers rush to deliver orders, resulting in a high rate of illegal driving and traffic accidents. How to slow down delivery drivers is being discussed by all parties.

Higher delivery efficiency and lower driving speeds are a pair of mutually exclusive and conflicting objectives. The NSGA-II algorithm was introduced to explore the equilibrium of the two objectives. Simulation experiments were conducted under different scenarios. The delivery efficiency achieved at various driving speeds is visualized in the Pareto frontiers and provided to platforms and drivers. When driving speed ranges within 300-350m/min, the dual objectives reach the optimal equilibrium point.

The Order Bundle Allocation Model(OBAM) was proposed to improve delivery efficiency. Multiple orders are bundled and assigned to a driver. The experiment results proved that the OBAM is preferable to the Linear Allocation Model(LAM), especially in crowded areas. The increased food preparation time affects delivery efficiency, but it's weakened. And for the OBAM, increasing the number of drivers or their working hours both achieved a better optimization effect. But after driving speed exceeding 400m/min, the impact of speed increased on efficiency improvement gradually decreased. Speeding cannot compensate for the shortage of drivers, and it's more desirable to encourage existing drivers to work more hours.

This study extends the multi-objective optimization research in the field of takeaway delivery by exploring the trade-off between the two objectives of higher delivery efficiency and lower travel speed. The optimization results can expand the ideas of order allocation models and strategy selection for takeaway delivery platforms.

KEY WORDS: takeaway delivery; order allocation model; traffic accident rate; driving speed; multiple objectives optimization; NSGA-II algorithm

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Chapter 1

Introduction

1.1 Background

With the rapid development of smartphones and the 'Internet+', the Online To Offline(O2O) ordering model emerged. People order food without leaving their homes, and drivers pick up the food from restaurants and deliver it to their homes. Especially in high-density urban areas, more and more people are getting used to order food online. The takeaway market continues to expand, the number of online takeaway users in China has reached 544 million by December 2021, which represented an increase of 29.9% over last year and accounted for 52.7% of all internet users[6]. With the proliferation of takeaway orders, users' requirements for the timeliness of takeaway delivery are increasing. The existing capacity of delivery platforms cannot better meet customer demand, so delivery platforms need to increase their capacity, mainly achieved by recruiting a large number of drivers. The Chinese takeaway industry is mainly dominated by two platform start-ups, Meituan and Ele.me. According to their self-reported statistics, Meituan has 3.98 million delivery drivers, while Ele.me has 3.1 million. Such a large number of drivers constitutes China's "*unstable new army*"[26].

Driver salaries constitute a significant expense for takeaway platforms. Takeaway margins are thin, with Meituan Takeaway's profit margin only 4.3% in 2020[24]. By the third quarter of 2021, this figure had even dropped to 3.3%, equivalent to earning only 0.2 RMB per takeaway order. By improving operational efficiency, until the fourth quarter of 2021, the Meituan platform's profit reached 6.5%, but it was still low. Driver costs account for the main cost of the takeaway platform, with Meituan, for 71% of takeaway revenue, with over 5.27 million drivers earning revenue. The financial report shows that Meituan rider expenses reached 68.2 billion RMB in 2021, while

Table 1.1: *Eleme dedicated delivery driver salary*

Delivery orders	**Level 1 Driver**	**Level 2 Driver**	**Level 3 Driver**
400 orders/month	2,360 RMB	2,490 RMB	2560 RMB
400-600 orders	5.9 RMB/order		
600-800 orders	6.4 RMB/order		
800-1000 orders	6.9 RMB/order		
More than 1000	7.4 RMB/order		

delivery revenue was only 54.2 billion RMB. To keep the platform running, Meituan has been backed up by 14 billion RMB in the past year.

1.1.1 Type of Drivers

The current delivery drivers are divided into dedicated drivers and crowdsourcing drivers. Different companies have different performance appraisal models, and payouts vary slightly between dedicated and crowdsourcing drivers. Under the dedicated delivery model, delivery drivers are trained by the platform, dispatched to sites. Sites are places for drivers to rest when there are no orders. Drivers automatically take orders and do not go beyond the site range, and they do not have the right to reject orders. And they basically do not deliver orders over 3 kilometers distance. According to the latest Hungry 2021 takeaway recruitment information, Ele.me dedicated drivers are divided into three levels. As shown in Figure 1.1, the base salary will vary slightly. The platform will automatically promote drivers based on positive feedback and delivered order volume. The platform actively assigns dedicated drivers to complete at least 400 orders per month to get a basic salary. With more than 400 orders per month, the order allowance gradually increasing.

For crowsoursing drivers, people can register themselves as drivers and serve on multiple platforms, choosing their orders to deliver and gaining revenue from delivery orders. Logistics expert Li indicated that the crowdsourcing model is now the mainstream, accounting for about 70% of instant logistics[29]. The ratio of dedicated drivers to crowdsourcing drivers is roughly 6:4 at one of the takeaway sites in Wuhan. In the crowdsourcing model, people can register a driver by providing the Certificate of No Crime and paying a deposit ranging from 99-199 RMB. The crowdsourcing driver's income is mainly commission for running orders, plus distance allowance, time slot allowance(midnight, breakfast), and lousy weather allowance. The order allowance will be calculated based on the distance between the merchant and

Table 1.2: *The difference between dedicated drivers and crowdsourcing driver*

Difference	Dedicated Driver	Crowdsoursing Driver
Job type	Full-time job	Part-time job
Ratio	60%	40%
Salary	Basic salary Fixed order allowance	No basic salary Distance-based allowance
Delivery area	Site proximity Small area	Random location Wide area
Distance	<= 3km	No limits

the customer, which is different from a dedicated delivery driver. According to Beijing News' survey, delivery fees range from 5 to 10 RMB. The cost of orders within two kilometers is about 4.5 RMB, with a distance allowance of 2 RMB per kilometer beyond 2km. There is an additional weather allowance for inclement weather. There are also time allowances for delivering breakfast and late-night snacks. The money earned can be withdrawn to the bank account after the audit and over 100 RMB.

Orders near the site and with short delivery distances are usually assigned to dedicated drivers first, and the remaining orders are offered to crowdsourcing drivers. The difference between dedicated drivers and crowdsourcing drivers can be summarized as in table 1.2.

Both crowdsourcing and dedicated drivers are required to complete orders within a set time limit, racing against time. If the estimated time is exceeded, the driver will have no allowance for that order. The income for takeaway drivers is related to the regional economy, but it is mainly linked to the number of orders delivered. More work is more pay. When orders are completed, users can evaluate and reward drivers with additional rewards. For example, the platforms of Ele.me and Meituan will reward delivery drivers with 1 RMB per order for five-star reviews. Only by delivering orders quickly enough to be rewarded or by delivering more orders can drivers earn more.

1.1.2 Instant Delivery Service

The takeaway platform serves as a hub to connect the information between restaurants and customers, and the delivery driver serves as a transportation carrier to connect the logistics between restaurants and customers. The rapid development of the takeaway industry, social refinement management and service awareness continues to increase, the demand for higher levels of delivery, the current contradiction between the supply of logistics capacity and demand in the industry is increasingly prominent, requiring a large number of drivers to supplement the lack of capacity. The threshold to become a delivery driver is low, with a smartphone and an electric car, after completing a simple online exam on the platform can be qualified for delivery, in the actual delivery process, except for the delivery of orders within the specified time, no other constraints.

The takeaway platforms regard timeliness as the most important metric. Delivery time was constantly compressed. The Ele.me platform take 'Everything 30min' as its mission. Initially requiring five drivers to complete the delivery task, after optimization, only four people can complete the delivery. The algorithm learning system and takeaway platform are a continuous improvement and breakthrough. However, the drivers often need to deliver multiple orders simultaneously. With shorter delivery times for the same order and higher timeliness requirements, drivers need to save time on the road to ensure that they deliver all orders in time without complaints or fines.

Drivers take more orders in order to get more revenue, but some orders cannot be delivered on time due to unreasonable arrangement of delivery path, unfamiliarity with road conditions, too many orders, etc. But delivery times are linked to customer satisfaction, bad reviews, complaints and driver revenue. Penalties will be incurred. Drivers decide how fast to driver based on the required delivery time, and if they perceive that an order will not be delivered on time, they will try to complete the delivery on time by speeding up or going against the clock.

In the process of delivery, drivers often commit traffic violations in order to save time, including reversing driving, overspeeding, driving through red lights, crossing the road, and weaving in and out of the road at will, which corresponds to the continuous increase in traffic accident rates of delivery drivers in recent years. In September 2018, Guangzhou traffic police investigated and dealt with 2,000 traffic violations, of which Meituan and Ele.me drivers accounted for the highest percentage. Data released by the Shanghai Public Security Bureau Traffic Police Headquarters in the first half of 2017 showed that drivers accounted for an even higher proportion of electric bikes driving illegally, with an average of one driver killed or injured every 2.5 days. According to the Shanghai Statistical Yearbook 2020, the injury rate of motor vehicle drivers in traffic accidents was 12.9%, while the injury rate of non-motor vehicle drivers in traffic accidents was 44.8%. Non-motorized drivers are more likely to be injured in traffic accidents, so driver safety should be taken seriously.

According to *The Electric Bicycle Safety Technical Specification GB 17761-2018* issued by the Chinese government, the driving speed of electric bicycle shall not exceed 25km/h, which is equivalent to 417.7m/min, otherwise it will be judged as over speeding and fined.

Safety of delivery drivers raises concerns. The Chinese Ministry of Human Resources and Social Security, the State Federation of Trade Unions, and the China Enterprise Confederation, among others, jointly issued *the Guidance on Implementing the Responsibility of Online Catering Platforms to Effectively Safeguard the Rights and Interests of Takeaway Delivery Workers* on 15 January 2020. After the document was issued, takeaway platforms launched many plans and measures to improve the overall welfare of drivers, such as Ele.me announcing the first 300 million yuan for delivery driver protection. At the same time, Meituan continued to promote the ”same boat plan.” On the one hand, guide enterprises to reduce the working hours of outdoor workers to a greater extent through the adjustment of working hours, scheduling, reducing labor intensity, etc. On the other hand, guide the platform to extend the delivery time frame and other measures to protect the personal safety of delivery drivers.

1.2 Research Meanings

This study has both theoretical and practical meanings.

Theoretical meaning: The vehicle path problem is a traditional research problem that has been widely studied, from the traveling merchant problem to the vehicle path problem and later derived from the simultaneous pickup and delivery problem. As the takeaway industry continues to grow, the vehicle path optimization problem for takeaways has received more and more attention, and many researchers have conducted research in this area. But in addition, the study of order distribution cannot be neglected as well. A number of researchers have already started working in this area. The industry is also constantly updating and iterating the algorithms, considering more practical and different scenarios.

In this paper, a multi-objective optimization model for takeaway order allocation is developed by qualitative and quantitative analysis, taking driver traffic safety as the entry point. Motorcycle safety and accident probability research has attracted the attention of many scholars. During busy periods, each driver may have multiple orders, how to assign orders to couriers reasonably so that they can secure delivery efficiency while also ensuring safe speed. However, due to the specificity of traffic accident rate, it cannot be directly used as an optimization objective in the model. We introduce driving speed and first analyze the study of driving speed and traffic accident rate. The objective function is a dual objective in the highest delivery efficiency and the lowest courier driving speed. In this paper, we introduce the NSGA-II algorithm and finally derive the corresponding Pareto optimal curves, which provides a different perspective of optimization methods and perspectives to complement the study of delivery order allocation in O2O delivery industry.

Practical meaning: Drivers' safety is threatened by more traffic accidents due to frequent illegal driving in the delivery process. There are two main reasons why drivers frequently drive illegally: firstly, drivers perceive that they cannot deliver orders within the specified time and speed up, and secondly, drivers want to deliver more orders per day to get more revenue and speed up. For this problem, a reasonable order allocation and route arrangement can control the number of orders received by the driver and ensure that the delivery speed is optimal and the orders are delivered on time. At the same time, traffic accidents can be controlled and reduced to a certain extent by giving driver optimal enough time. In the process of optimizing, whether in crowdsourcing or dedicated delivery mode, the cost of the platform and customer satisfaction should not be the only considerations but also drivers' right and safety issues. For takeaway platforms, in addition to considering their costs and customer satisfaction, adding a reasonable, safe and effective time and order planning that considers drivers' interests can attract more drivers to join, helping to improve the competitiveness of the platform and expand the market scale.

1.3 Research Methods

This paper integrates and applies theoretical knowledge of operations research, management and road traffic using the following research methods:

(1) **Literature research method**: Organise and analyse information on the vehicle path optimisation problem, refine and extend the issue to the takeaway delivery problem, define the interrelationship between the two cases through in-depth research, and analyse the strengths and weaknesses of the existing study, improve and add explanations to the problem points or deficiencies that have not been considered, and propose practical solutions.

(2) **Mathematical modelling method**: Firstly, we understand the actual scenario of takeaway delivery, determine the research objectives, constraints and optimisation directions according to the real situation and needs, combine the theoretical knowledge with the actual scenario, and construct the corresponding mathematical model reasonably.

(3) **Contrast analysis method**: The focus of this paper is to consider the safety of drivers and reduce the incidence of traffic accidents by reducing the driving speed of couriers. To improve the delivery efficiency, an Order Bundle Allocation Model is constructed in this paper to compare with the

optimization results of the traditional Linear Allocation Model. The NSGA-II algorithm is used to explore the optimal solution under the dual-objective equilibrium of reducing driving speed and improving distribution efficiency. The results are analyzed to compare the optimization results of the two models and to explore the performance of the Order Bundle Allocation Model in different settings, and to provide some suggestions to the platform.

Chapter 2

Literature Review

2.1 O2O Food Delivery Service

There are many researches studied in the area of O2O food delivery service. Compared to traditional delivery problems, O2O takeaway delivery problems are more time-sensitive and need to be delivered more quickly, without going through a warehouse or distribution center during the delivery process. The driver goes directly to the restaurant to pick up the food and then delivers the takeaway to complete the delivery process. Takeaway delivery is characterized by short distances, high customer variability, high delivery frequency, and small goods that are more sensitive to time. This paper focuses on the elements of the takeaway delivery problem including the customers, merchants, platforms, and drivers.

(1)**Customer**: The core node in path optimization can directly influence the time window setting and customer satisfaction. Compared to traditional customers, the time requirement is higher, and the delivery of goods for takeaway needs to be delivered quickly. If the goods are not delivered for a long time, it will affect the customer experience. Overtime delivery affects the platform's competitiveness, while the takeaway dining experience suffers, and the restaurant may lose customers. It is essential for the restaurant and the platform to deliver within the time expected by the customer.

(2)**Merchant/Restaurant**: Merchants are also the core node, the sender of the goods, the customer for the takeaway platform and the merchant for the ordering user. Its responsibility is to deliver meals within the specified time so that drivers can pick up their meals on time without waiting too long. Most merchants in food takeaway problems are restaurants. In addition, the restaurant is responsible for the packaging of the takeaway to ensure that the takeaway is delivered on time and does not affect the customer's dining experience.

(3)**Platform**: The platform is the takeaway platform, providing an online platform responsible for connecting drivers, restaurants and users, similar to traditional distribution centres but without distribution, providing only a platform and transport capacity. Merchants pay commissions for transactions in the takeaway platform and rely on the platform's traffic to transact with customers. Users place orders on the takeaway platform to pay for meals and delivery, and the platform recruits drivers to deliver orders to customers.

(4)**Driver/Courier**: Drivers are equivalent to vehicles in the traditional vehicle path problem. The delivery worker drives a vehicle in takeaway delivery, mostly an electric bike or a shared bike. If not subject to road congestion restrictions, but low security. As takeaway is a just-in-time order and has a time window, the driver needs to pick up the food from the restaurant and deliver it to the customer on time within the specified time and will be subject to an overtime penalty if overtime is exceeded.

2.1.1 Vehicle Routing Problem (VRP)

The Vehicle Routing Problem(VRP) originated by Dantzig and Ramser[7]. They developed and designed a mathematical model and solution for the problem of delivering petrol to a petrol station to minimize the total distance traveled by car. After it was proposed, more scholars joined the research in this field, and it gradually evolved into a classical problem in the field of operations research.

The standard vehicle path problem typically consists of a distribution centre, multiple vehicles(multiple drivers), and multiple customers. Under definite or uncertain constraints, researchers explore optimal time efficiency or cost to reach a demand or desired equilibrium point through rational planning of distribution paths, customer access sequences.

There are many studies on the vehicle path problem. Through the joint efforts of scholars at home and abroad and the increasing integration with practical scenarios, the vehicle path problem has expanded into various forms, such as the classical vehicle path problem with capacity constraints, the vehicle path problem with time windows, the vehicle path problem with multiple distribution centers, the dynamic vehicle path problem, the vehicle path problem with simultaneous pick-up and delivery. In this paper, the takeaway delivery path problem can be categorized as a single distribution center, mixed time window, multi-vehicle delivery, pick-up-and-deliver vehicle delivery path problem.

The vehicle path problem has been studied in various directions, such as minimising mileage, reducing costs and improving transport efficiency.

Goel et al.[11] consider the vehicle path problem with stochastic demand and stochastic service time windows and develop a model to minimise total transport costs and maximise customer satisfaction. Ahkamiraad and Wang[1] develop a VRP mixed integer linear programming model with pick-up, delivery, and time windows to minimize transport costs and fixed costs and solve it using a hybrid genetic algorithm and particle swarm optimization algorithm. Shi et al.[15] considered the total cost of delivery along with transport efficiency and proposed a joint delivery service to optimise the vehicle delivery path. The model is based on a multi-objective distribution optimization model with the minimum number of vehicles used, the minimum total transport mileage and the lowest customer dissatisfaction. customer inconvenience costs.

As the business scenario becomes more complex, the service time requirements of customer points become more stringent and vehicles need to arrive at the customer point within the time window to complete the delivery. The implementation of the JIT concept in urban freight transport was first described and demonstrated by Bhusiri et al.[2, 3] as a Vehicle Path Problem with Soft Time Windows for Simultaneous Pick-up and Delivery(VRPSTWSPD). By extending the time window constraint for convenience stores to incorporate JIT perfectly, the results show that it is possible to reduce costs and process waste while maintaining satisfaction. Ghannadpour et al.[10] described customer time preference by a convex fuzzy function on service time satisfaction. And they developed and solved a multi-objective dynamic Vehicle Path Problem with Fuzzy Time Windows(DVRPFTW) with the objectives of minimising the total number of vehicles, total distance travelled, waiting time and maximising service time satisfaction. Wang et al.[34] constructed a vehicle scheduling model based on fuzzy time windows under certain satisfaction levels, quantifying customer service satisfaction as a fuzzy subordination function of the start time of delivery service. The optimal service time is determined by local adjustment of customer service time to reduce distribution costs and save capacity resources.

The vehicle path problem have studied from several aspects, which can provide theoretical guidance for the subsequent O2O delivery path research. From the perspective of optimisation objectives, the existing research mainly focuses on optimisation in various aspects: shortest total mileage, smallest transport cost, smallest fixed cost, lowest number of vehicles used, highest transport efficiency, lowest route variance, lowest carbon emission and improved customer satisfaction, but as customers' requirements for service quality improve, the requirements for delivery time and ensuring customer time satisfaction are increasingly emphasized. In general, current research has considered numerous practical business scenarios, but less consideration has been given to the safety of the people involved in the delivery. Suppose path planning or results are implemented at too fast a driving speed. In that case, it will be dangerous for the delivery personnel and other people involved in the traffic, so this paper considers traffic accident rates in addition to the sections mentioned above.

Table 2.1: *VRP classification based on taking and delivery characteristics*

Type	Characteristic	Scenarios
Normal VRP	1. delivery center 2. deliver in order 3. only deliver	Normal deliver scenario Only deliver deliver oil or produce materials
Pick-up and deliver meanwhile VRP	1. delivery center 2. pick-up and deliver at same time 3. same customer for taking and delivering	Normal delivery scenarios, including return products Inverse scenarios Shops; Supermarket; Return products
Pick-up first, and then deliver VRP	1. no delivery center 2. firstly pick up the product, then deliver to customers 3. pick-up and deliver to different customers	Mainly takeaway platforms, such as Meituan, Ele.me, Uber Eat and Didi

2.1.2 O2O Food Delivery Problem

With the continuous development and improvement of the takeaway system algorithm, order allocation, driving speed, user address delivery difficulties, and other factors gradually began to take into account.

The Most common researches of O2O delivery problem is vehicle route planning, but is different from the traditional vehicle route problem, as shown in the Table 2.1. The O2O problem also involves delivery mode, operation mode, profit sharing and high timeliness requirements. The takeaway platform provides capacity as a third-party platform, connecting restaurants, customers and drivers, all three of which have no direct relationship, but are mainly directly related to the takeaway platform. The platform dispatches the drivers to realise the process of picking up and delivering the food. The drivers first pick up the food from the restaurant and then deliver the takeaway to the customer.

There has been some research into takeaway delivery models. From the perspective of the platform, Li et al.[16] used the sum of incremental takeaway delivery costs as the objective function. It introduced a time penalty cost to measure takeaway delivery exceeding the time window based on the solution strategy of the simultaneous delivery and pick-up VRP problem. Between 2016 and 2017, a platform compressed the maximum time frame for delivery of 3km orders from 1 hour to 38 minutes [35], developing a pre-system output of order delivery path as a straight-line path between two points, with crossings and retrograde traffic occurring.

After joining the takeaway platform, merchants can use the platform's capacity for delivery or deliver on their own. Xing et al.[37] analyse the three operational modes of merchant delivery, platform delivery and merchant self-built platform+platform delivery from different perspectives, construct profit functions for each of the three operational modes, and optimise the optimal quality control strategy and optimal profit for members of the O2O takeaway service supply chain under different modes. Lou [31] included the number of vehicle inputs to create a multi-objective distribution optimization model with the lowest number of vehicles used, the lowest total transport mileage and the lowest customer dissatisfaction. Pan and Fu[33] added the whole vehicle waiting time to this model.

In addition to the above, Researchers have conducted research on O2O takeaway delivery route optimisation by considering the actual scenarios in the delivery process. Yu et al.[19] developed a dual-objective delivery path optimisation model to minimise delivery costs and maximise customer satisfaction based on the merchant-run model, responding to the high time requirements of fresh food delivery. Zhao et al.[36] considered the uncertainty of driving time in the delivery process of takeaway. It carried out route optimisation intending to minimise the operating cost of the platform. Lu et al.[17] proposed different mathematical models to quantitatively evaluate different operation modes of crowdsourcing delivery. Chen et al.[38] conducted a vehicle path optimisation study to minimise transport costs and the maximum length difference between each delivery path, taking into account vehicle capacity and distance constraints. For takeaway delivery, minimising the maximum length difference between paths can equalise the benefits for the delivery drivers, provided that the order remains unchanged.

The paths need to be updated in real time as the delivery orders are generated instantaneously and the drivers grab orders in real time during the delivery process. The dynamics are based on the static vehicle path problem. Zhang et al.[27] classify takeaway orders in terms of customer priority, and establish a dynamic, multi-site, multi-objective pickup and delivery vehicle path model. They considers customer priority with time windows, from two perspectives: customer satisfaction and more realistic delivery cost. In addition to customer priority in the subsequent optimisation process, priority can also consider the type of takeaway, such as giving more priority to fresh food delivery. Chen and Li [40] established an O2O delivery path optimisation model intending to maximise customer time satisfaction. The model greatly improves customer time satisfaction, but does not consider driver earnings. Mu et al.[30] constructed a mathematical model to maximize the earnings of delivery drivers to ensure acceptable customer satisfaction. But they ultimately did not consider the travel time, which was longer when the earnings of crowdsourcing drivers were greater, and the driver's earnings were not improved. Therefore, this paper analyses driver revenue in terms of average driver revenue and driver revenue per unit of time, taking into account both average driver revenue and travel time.

Most of the researchers considers customer time satisfaction and other scenarios, but most of the current optimization focuses on platform costs or customer satisfaction, not delivery drivers. But the rights and lives of the delivery drivers are not fully protected. According to reports, by 2021, a crowdsourcing driver in Beijing had an accident during delivery and was only covered by a premium of 1.6 yuan, with the insurance company paying out 30,000 yuan. Moreover, the platform was also compensated only 2,000 yuan had sparked a hot debate [29].

2.2 Traffic Accident Rate

Delivery driver traffic accidents have raised concerns. There are numerous causes of accidents. Takeaway platforms are paid on a piece-rate basis, and the wages of drivers are directly related to the volume of orders completed. Zhou[23] believes that the piece-rate payment can improve the motivation of the driver to deliver more orders. Due to the limited working time, drivers are "fast" to get a higher income. Some of them ignoring traffic safety issues, driving over standard electric bikes, speeding, running red lights, using cell phones while driving, and other illegal behaviours are common[22].

On the other hand, the delivery time is constantly compressed, and drivers need to faster deliver the goods needed by customers. Drivers can only speed up by improving driving speed or taking shortcuts. In the platform system settings, delivery time is the most important indicator, and overtime is not allowed, and once it happens, it means terrible reviews, lower income, and even elimination. In the social media platform Baidu where takeaway drivers gather, a driver wrote,"Delivery is a race to the death, and traffic police and red lights as friends"[35].

In recent years, the delivery process of takeaway drivers has seen many traffic accidents, which endanger their safety and the safety of others and traffic orders. Traffic injuries may be the third leading cause of loss of life or disability[13]. Moreover, in crashes, motorcycle drivers are 38 times more likely to be injured than those who drive, and motorcycle drivers are more likely to be injured than people in other motor vehicles[9]. Bicycles and motorcycles (electric vehicles) are also precisely what delivery drivers do for transportation. Ye and Lu[22] found that most the electric bicycles driven by delivery drivers have safety hazards.

Solomon began studying the relationship between traffic accidents and speed in 1964. The variation of driving speed in the study was attributed as one of the leading causes of accidents, and the Solomon model was established, where the accident rate increases with the more significant the difference with the average traffic speed while the accident rate increases. 1993, Monash University conducted a simulation experiment on the current state of roads in Australia[4], which proved the Solomon model. The greater the speed gradient, the higher the traffic accident rate when the vehicle speed is greater than the average speed of the road section.

In 1989, Sweden reduced the road speed limit from 110km/h to 90km/h. After two months of the experiment, the average driving speed was reduced by 11km/h. The traffic accident rate was reduced by 27%, and the number of casualties was 21% less than in the same period in 1988. On the other hand, Brownie and Waltz[5] analyzed seven years of traffic accidents and showed that speeding behavior also increases the probability of personal injury and death in accidents. The study proved that controlling and reducing the operating speed is beneficial in reducing the traffic accident rate and accident casualty rate.

Studies on traffic accidents have shown that driver safety has attracted the attention of many scholars. Although there are many uncertainties in the process of takeaway delivery, it is of practical significance to consider them in delivery route optimization[40]. Many factors affect the safety of drivers, such as driving against the traffic rules, overspeeding, fatigue, using cell phones while delivering, not wearing helmets, etc. The inability to reduce the speed due to time constraints is an important reason why the traffic accident and casualty rates are difficult to ignore. While strengthening education on traffic rules, we should think about how to make delivery drivers "slow down" [28].

Some studies explored the driving speed as the optimization objective. Yu and Jiang[20] explored the delivery efficiency and defined it as the shortest time used per order. They explore the applicability of the model when varying parameters such as delivery capacity limits, number of delivery agents, and order density. A time-dependent model with a speed window is invoked to the direct delivery model[1]. Chen[39] explores the optimization of a crowdsourcing delivery strategy considering order destination preference. Three models are developed considering the service speed of the delivery system as the optimization objectives. The models are validated by designing examples to minimize the customer waiting time with respect to the order matching range radius, the ideal order distribution rate, and the base revenue of the deliverer. The model proposed in this paper based on queuing theory can better portray the characteristics of actual takeaway crowdsourcing delivery, and the relevant findings have theoretical value and practical significance for the operation and management of the takeaway industry.

Moreover, ensuring driver safety requires the joint efforts of multiple parties[28, 32], takeaway platforms, drivers, ordering users together to move forward. On the platform side, Ying[26] proposed to reduce the pressure of the driver time limit. The platform should give a more reasonable time penalty mechanism, such as comprehensive service to better drivers. If the overtime order volume is small and overtime time is short, there is no need to take responsibility. The takeaway platform's "algorithm" for path optimization should not ignore the safety and rights of drivers[25]. He and Deng[18] propose to include drivers in the scope of work-related injury insurance, with joint contributions from platform companies and delivery drivers, supplemented by commercial work-related injury insurance, to protect drivers' labor safety and health rights.

2.3 Multi Objectives Optimization

There is common that multiple objectives need to be balanced in the area of takeaway. They are mostly considered from the platform side to balance reduced operating costs, delivery costs, or improved user time satisfaction and profitability. Few studies take driver satisfaction or benefits into account.

Bao and Lu [21] considered employee satisfaction on the basis of customer satisfaction, and established a multiple objective satisfaction model considering both employees and customers; Huang [41] considers the delivery timeliness and delivery cost and optimizes the goal of delivering to the location specified by the customer within the desired delivery time at the least cost to the customer; Chen et al.[38] combined with ant colony algorithm to seek the Pareto optimal solution for minimizing the transportation cost and the maximum length difference between paths; Zhao et al.[36] developed a dual-objective model for platforms to optimize operating costs and improve stability; Lou [31] Lou developed a scalar triple objective model with minimum vehicle usage, minimum total transportation mileage, and minimum customer dissatisfaction; Ghannadpour [10] explores the required total fleet size, minimization of total vehicle travel distance and waiting time, and maximization of overall customer preference for service in the courier delivery process; Zhang [27] also considers delivery service level and minimize the delivery cost.

Multi-objective optimization evolutionary algorithms are mainly introduced when multiple objectives need to be optimized. Vector evaluated genetic algorithm (VEGA), first proposed by Schaffer in 1985, was the first multi-objective evolutionary algorithm. Since then, researchers have experimented with different strategies for assigning adaptation values, selection strategies, diversity preservation strategies, elite strategies, and constraint handling strategies. Horn et al. proposed the Niched Pareto Genetic Algorithm (NPGA) in 1994. Srinivas and Deb designed the Nondominated Sorting Genetic Algorithm (NSGA) in the same year. In 2000, Deb proposed the NSGA-II algorithm based on the NSGA algorithm[8].

The NSGA-II is one of the most widely used multi-objective genetic algorithms, which adopts a fast non-dominated sorting algorithm and greatly reduces the computational complexity compared with NSGA. It adopts the crowding degree and crowding degree comparison operator to make the Pareto solution set uniformly distributed and ensure the diversity of the population. Furthermore, it introduces the elite strategy, and the parent and the newly generated children are combined for the non-dominated sorting. The elite strategy is introduced, in which the parents are combined with the newly generated children for non-dominated sorting. Then the new off-spring generation are selected, which expands the sampling space, prevents the loss of the best individuals, and improves the convergence speed and robustness of the algorithm.

The NSGA-II algorithm is applied to the multi-objective optimization of takeaway delivery. Zhao et al.[36] used NSGA-II to calculate the optimal operating cost and the Pareto curve with the highest robustness for different orders. When comparing the results with those of the forbidden algorithm, NSGA-II is effective and can be solved quickly, providing more decision options for the third-party takeaway platforms.

For takeaway platforms, the goal is to maintain minimum costs and customer satisfaction, without considering driver safety and revenue. The rights and safety deserve more considerations and concerns. The traffic accident rate cannot be taken as the goal of delivery optimization, as it's inevitable that traffic accidents will occur in any case. The delivery optimization process, taking into account the time window, manpower input and driving speed, can make the work of delivery drivers slower and reduce the number of traffic violations, thus reducing the incidence of accidents and ensuring personal safety of drivers.

Chapter 3

Modelling: Order Allocation Models

3.1 Question Description

The volume of the takeaway market continues to expand, requiring more capacity to support the market, which is supplemented by various forms of recruitment. The main body of takeaway delivery can be divided into takeaway platform delivery and merchant-owned personnel delivery. Takeaway platform delivery can be divided into two modes: dedicated and crowdsourcing delivery, and the delivery workers can be referred as drivers. They all get orders from platform and deliver them to customers in a limited period. In recent years, drivers report a high rate of traffic accidents.

According to data released by the Qingdao Traffic Police, traffic accidents involving electric bicycles accounted for 31.2% of the total number of traffic accidents in the first half of the year in Qingdao's West Coast New Area alone, with the majority of these accidents involving electric bicycles used for food delivery. Traffic injuries are probably the third leading cause of loss of life or disability. Such deaths and injuries occur mainly among vulnerable road users, pedestrians, cyclists, and motorcyclists (e-bikes). Motorcyclists are 38 times more likely to be injured in crashes than those who drive. While pursuing order timeliness, platforms should focus on drivers' safety rather than making them a race against time and trading unsafe driving for revenue.

As a typical instant delivery service, the delivery driver may encounter accidental factors such as traffic congestion, sudden weather changes, different road conditions, etc., and the instant delivery speed cannot be determined. The research problem in this paper can be described as a takeaway platform during a peak meal period. We explore a better order allocation model to optimize drivers' delivery speed and efficiency. The platform dictates that drivers depart from the delivery center to pick up food from restaurants and deliver it to each customer. Each driver can serve multiple customers, and one order can only be served by one driver.

For drivers, there are actually two types of delivery drivers mentioned in the background section: dedicated drivers and crowdsourcing drivers. There are commonalities between the two types of drivers in that they both receive orders from the platform and need to accept orders and complete them within a specified time frame. The two order allocation models are applicable to these two types of drivers.

How to correlate the traffic accident rate with order allocation is the key to build the model. After reviewing literature and comprehensive analysis, the driving speed is determined as the main influencing factor of traffic accident rate. There are many studies showing the association between driving speed and traffic accident rate. The earliest study by Solomon found that on the basis of average speed, the faster the speed the higher the accident rate and the likelihood of a serious accident also increased. Slowing down drivers has become a topic of concern from all walks of life. On the other hand, in the pursuit of time-sensitive instant delivery services, delivery efficiency is a goal that cannot be ignored.

This paper considers the constraints of time window, maximum load capacity, and distance travelled to optimize a safe driving speed and order bundling allocation to maximize the safety of drivers while ensuring delivery efficiency. A more reasonable order distribution model is established to explore the balance between courier speed reduction and delivery efficiency. Based on the historical data and previous literature, this paper assumes that the travel time between the delivery drivers and the customers is also random and satisfies the gamma distribution.

3.2 Aim Functions

In the scenario of instant delivery scheduling, the decision variable is the allocation of orders to drivers, the number of variables is the number of orders, and the range is the number of drivers. The safety of drivers were taken into account. Drivers speed up while delivering, which increases the possibility of traffic accidents. Orders may appear at any minute, and the model accumulates the orders generated in a time interval(n minutes) into an order set O, which is assigned to the drivers on duty.

Higher delivery efficiency and lower driving speeds are a pair of mutually exclusive and conflicting objectives. In this paper, the optimization objective of the instant delivery order allocation problem is set as the lowest average speed of drivers and the shortest average delivery time per order, which can be expressed as follows:

$$\begin{cases} ming_1(\Omega) = \overline{V} \\ ming_2(\Omega) = \frac{\sum_{m \in C} \sum_{o \in \Omega_m} l_{pos(o_m,B),pos(o_m,C)} + l_{pos(o_k,B),pos(o_k,C)}}{\sum_{m \in C|\Omega_m|}} \end{cases}$$

3.3 Linear Allocation Model (LAM)

The Linear Allocation Model is the simplest order allocation model, and serves as the standard case for comparison. Orders are assigned to drivers individually, and drivers start the next order after delivering last order.

3.3.1 Symbols Definitions

There are some symbols involved in the model, which are defined as follows:

$o_i \in O, i = 1, 2, ..., I$, the order o, order set O, the number of orders is I.

or_i, the ordering moment of order i.

og_i, the issuing time of order i.

$pos(o_i, B)$, pick-up location of the order i.

$pos(o_i, C)$, delivery location of the order i.

$r_j \in R, j = 1, 2, ..., J$, restaurant r, restaurant set R, the total number of restaurants is J.

$pos(r_j)$, the geographical location of j hotel.

$c_k \in C, k = 1, 2, ..., K$, driver c, the driver set C, a total number of drivers is K.

$pos(c_k)$ the current position of the driver K.

$time(c_k, on)$, driver K's start working hours.

$time(c_k, off)$, driver K's off-duty time.

$l_pos1, pos2$, the navigation distance from position 1 to position 2.

$\overline{V}$, average speed of delivery

Navigation distance uses Manhattan distance.

$$l_{pos1,pos2} = \mid x_1 - x_2 \mid + \mid y_1 - y_2 \mid \tag{3.1}$$

Ω_k, set K of tasks assigned by the driver

$fr(o_i, B)$, the pick-up time of the order i

$fr(o_i, C)$, the arrival time of the order i

3.3.2 Assumptions and Constraints

The model constraints and assumptions are as follows:

(1) The delivery of the order should be carried out after the driver picks up the meal, which can be expressed as:

$$fr(0_i, B) + \frac{l(pos(o_i, B), pos(o_i, C))}{\overline{V}} \leq fr(o_i, C), \forall o_i \in O \tag{3.2}$$

(2) The order o_i can only be picked up after the order is issued.

$$fr(0_i, B) \geq og_i, \forall o_i \in O \tag{3.3}$$

(3)The same order o_i is picked up and delivered by the same driver.

$$\forall (o_i, B), (o_i, C) \in \Omega, \exists j \in 1, 2, ..., K; (o_i, B), (o_i, C) \in \Omega_j \tag{3.4}$$

(4) The driver’ s position will be refreshed after the driver has finished taking and delivering the order o_i.

$$\begin{cases} pos(c_k) = pos(o_i, C), \forall o_i \in \Omega_k, t = fr(o_i, C) \\ pos(c_k) = pos(o_i, B), \forall o_i \in \Omega_k, t = fr(o_i, B) \end{cases}$$

(5) Drivers can only take orders during working hours and can only get off work after delivering the remaining orders.

$$\begin{cases} time(c_k, on) \leq og_i, \forall o_i \in \Omega_k, \forall c-k \in C \\ time(c_k, off) = time(c_k, on) + time(\Omega_k) \end{cases}$$

3.4 Order Bundle Allocation Model (OBAM)

For improving courier delivery efficiency and route optimization, Reyes et al.[14] proposed and analyzed various order allocation models and validated their performance in a large number of data experiments. The basic idea of Order Bundle Allocation Model is orders with similarities are bundled together and assigned to a driver.

3.4.1 Defining order bundles

Although ideally, every order should be picked up at the ready time and delivered as soon as possible. We considers the reality of limited couriers. Especially during the busy period, drivers have no time to pick up the order and deliver it separately. Drivers always needs to deliver multiple orders at same time. We needs to consider which orders be bundle together and assign to a driver. At the optimization time t, the algorithm determines how many orders should be in a bundle (defining the target bundle size) and how they are assigned to drivers in sequence. There are two primary questions for order bundling:

(1) When will orders be bundled?

Since order bundles usually mean that several orders are assigned the same driver, meal freshness and delivery efficiency are somewhat affected. When it is not busy, and the drivers are enough, orders can be delivered with no bundle. In contrast to when it is busy, the orders always need to be bundled due to the limitation of delivery capacity. Bundling orders can reduce the single-average driving distance and thus improve the order delivery rate. We use the parameter Z to measure the strength of the delivery capacity of restaurant r.

$$Z = \frac{Number\ of\ pending\ delivery\ orders}{Number\ of\ available\ drivers} \tag{3.5}$$

Z is a rough measure of the amount of work that must be done with the available resources in a given period. The current delivery capacity is considered weak when Z is more significant than a threshold value. The order bundling mechanism is started to enable the eligible orders to be bundled together and delivered by one driver.

(2) How can qualified orders be bundled in the same package?

The purpose of bundling orders is to reduce the average driving distance and improve the delivery efficiency. Orders from the same restaurant are given priority to be packaged into the same package. However, when two orders from the same restaurant are too far apart, even beyond the distance for separate delivery, they should not be bundled into the same package. Orders with similarities are bundled into one package. We define the similarity factor of orders mainly related to where the orders need to be delivered. The similarity coefficient is defined as the Euclidean distance after the order coordinates have been denormalized.

3.4.2 Symbolic Definitions

Compared with the traditional order allocation model LAM, what is allocated to drivers is no longer a single order but an order package containing several orders. The new symbols in the Order Bundle Allocation Model are defined as follows:

$\Phi_n \in O, i = 1, 2, ..., I$, Φ_n is order package, Z is order package set, the total number of orders is I.

Φr_n, the ordering moment of the order package n.
Φg_n, the delivery time of order package n.
$pos(o\Phi_n, B)$, pick-up location of the package n.
$pos(\Phi_n, C)$, delivery location of the package n.
$fr(v_i, B)$, the pick-up time of the order n
$fr(v_i, C)$, the arrival time of the order n

And there are definitions of the delivery time and meal pick-up position of the package:

$$\begin{cases} \phi g_i = max(og_i : o_i \in \phi) \\ pos(\phi_n(j), C) = pos(r_j) \end{cases}$$

3.4.3 Order Bundling Algorithm Based on Systematic Clustering Method

The bundling rule of the Order Bundle Allocation Model is a systematic clustering method. The order bundling algorithm involved and the specific procedures are introduced in this section.

Firstly, the set of all orders $N_j = o_i \mid pos(o_i, C) = pos(r_j)$ from the restaurant r_j will be optimized, and $\Phi_1, \Phi_2, ..., \Phi_n$ is defined as a set of divisions N_j. The division method is as follows:

$$\begin{cases} \Phi_i(j) = o_i \mid o_i \in N_j, i = 1, 2, .., \mid N_j \mid \\ \forall m \neq n, \Phi_n(j) \bigcap \Phi_m(j) = \oslash, \bigcup{}_{i=1}\Phi_i(j) = N_j \end{cases}$$

Moreover, we can explore how many orders packed together is the optimal solution in this model. The target bundle size can be defined as a fixed number over the entire operation cycle or over a predefined time interval(such as lunch and dinner time). However, in order to introduce robustness and responsiveness into our solution, we have dynamically defined such a goal, which is directly related to the score of Z. It's a rough measure of the amount of work that must be completed with available resources in a given period. The bundle size will change with the target beam size. Parameters of target beam size Z_t when optimizing time is t is defined as:

$$Z_t = [\frac{\sum^{r_j \in R} \mid N_j \mid}{\mid c_k \mid t \leq t(c_k) \mid}] \tag{3.6}$$

The procedures of order bundling algorithm based on the system clustering method is as follows:

Step 1 Calculate the distance between sets and define the distance between clusters as the single connection distance:

$$l(\Phi_i, \Phi_j) = minl(pos(o_i, o_j)), \forall o_i, o_j \in \Phi_i, \Phi_j \tag{3.7}$$

Among them, the distance between samples is Manhattan distance;

Step 2 According to the calculated distance between samples, the two nearest classes are merged into a new class;

Step 3 Loop the step 2 until the number of orders in any order bundle is greater than the target bundle size Φ_n, and the algorithm ends.

Chapter 4

Algorithm Design: NSGA-II Algorithm

Heuristic algorithms have been widely used in complex optimization problems. The non-dominated sorting genetic algorithm-II(NSGA-II) proposed by Deb [8] is one of the most widely used multi-objective genetic algorithms.

The fast non-dominated sorting algorithm is adopted, and the computational complexity is significantly reduced compared with NSGA; the crowding degree and crowding degree comparison operators are adopted, which make the Pareto solution set uniformly distributed and ensure the diversity of the population; the elite strategy is introduced, and the parents are combined with the newly generated offspring for non-dominated sorting, and then the new offspring is selected, which expands the sampling space and can prevent the loss of the best individuals and improve the convergence of the algorithm speed and robustness of the algorithm.

The current situation where platforms and drivers are obsessed with delivery efficiency and order arrival timeliness needs to be improved. We also take the driving speed as the new consideration. But in the delivery process, if drivers only consider their safety, they can keep driving as slow as possible. The actual number of couriers is limited on the one hand, and the couriers' salaries will likewise be affected. The two objectives cannot be considered separately. We cannot only consider the safety of the driving speed but also need to ensure the efficiency of order delivery. Therefore, according to the characteristics of the proposed problem and the model built, the NSGA-II algorithm was chosen to solve the trade-off the dual objectives, and the Pareto frontier (Pareto optimal solution) of the problem is obtained.

As shown in the Figure 4.1, the processing steps of the algorithm follow the flowchart summarized by Lukic et al [12].

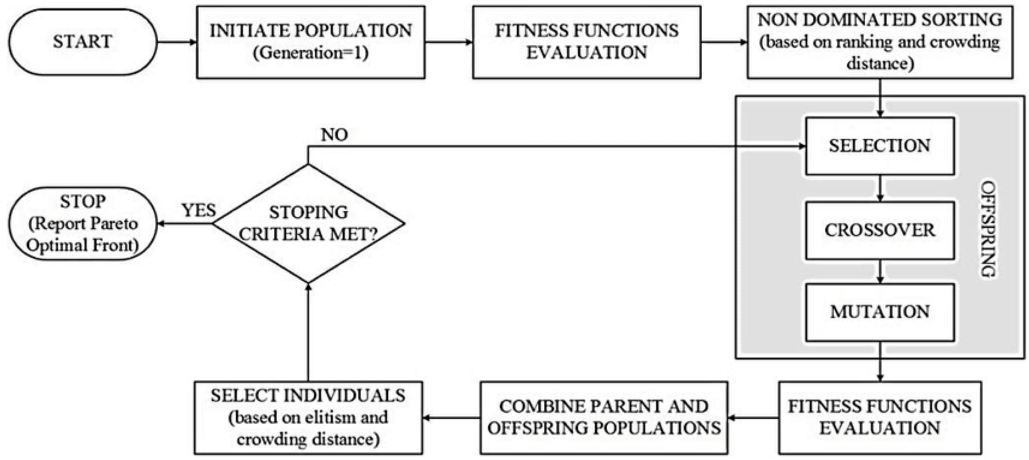


Figure 4.1: *The flowchart of the NSGA-II algorithm*

The specific steps of the algorithm are as follows:

Step 1 Firstly, when t = 1, the initial population P_t is randomly generated, the fitness of each individual in P_t is evaluated under different scenarios, and the non-dominated sorting and crowding distance calculation of the initial population P_t are carried out;

Step 2 Once the stop condition is met, the obtained Pareto optimal solution is output; Otherwise, go to Step3;

Step 3 Select individuals to form parent population P_p through roulette and elite strategy, and cross and mutate P_p to generate offspring population P_o;

Step 4 Combine the offspring population P_o and P_t to form a new initial population P_t+1. Return to step 2.

4.1 Non-dominated Sorting Algorithms with Elite Algorithms

After fast non-dominance ranking and crowding calculation, each n in the population obtains two attributes: non-dominance rank n_{rank} and crowding degree n_d. We can use these two attributes to distinguish between dominant and non-dominant relationships of any two individuals in the population. The crowding degree comparison operator is defined as $\geq_n$, and the comparison of individual superiority is based on: $i \geq_n j$, i.e., individual i is superior to individual j when and only when $i_{rank} < j_{rank}$ or $i_{rank} = j_{rank}$ and $i_d > j_d$. In the selection operation, the individual with a smaller n_{rank} value and larger n_d value will be selected first.

4.2 Selection Operations

The selection operation will be based on the non-dominated ranking and the congestion distance. After non-dominance ranking and crowding calculation, each parent has two attributes n_{rank} and n_d. Based on the dominance relationships among individuals, the current population is divided into K Pareto fronts$PF_1, PF_2, ..., PF_K$. For any two frontiers PF_i and PF_j, if i < j, all individuals in PF_j are dominated by individuals in PF_i. For individuals in the same frontier, crowding distance is a strategy used to ensure population diversity, a criterion that ensures that Pareto frontiers are evenly distributed.

An elite retention strategy is used in the selection operation, in which the parent is merged with the newly generated offspring. Then the new offspring is selected in a non-dominated ranking to prevent the loss of the best solution of the Pareto frontier. A roulette wheel strategy is used, in which individuals with smaller Pareto frontier order (n_{rank}) will have a higher chance of being selected, i.e., the selection process is not precisely based on the size of n_{rank} value, but with a certain probability of acceptance, for those individuals with the same n_{rank} value, the individual with a larger crowding distance(n_d) will be selected in preference. If there is no "acceptance by probability," the selection is done in the order of n_{rank} each time, so it is easy to fall into the local optimum but not to obtain the global optimum solution.

4.3 Crossover and Variation Operations

The coding method used in this paper is integer coding. Each chromosome consists of 2n elements. The first n elements represent the sequence of customers(concerning the distribution of takeaway orders), and the last n elements are the sequences of merchants corresponding to the previous customers. The chromosomes are coded in the following way:

The formula solves for the chromosome of the i individuals in the population after t iterations of the algorithm; where i = 1, 2, ..., pop; t = 1, 2, ..., N, pop denotes the population size, and N is the maximum number of evolutionary generations; x - part is the sequence of customer numbers; y - part is the sequence of merchant numbers corresponding to the customer orders.

$$\overrightarrow{x_{i,t}} = \left(\overbrace{x_{i,1,t}, x_{i,2,t}, \ldots, x_{i,n,t}}^{x-part}, \underbrace{x_{i,n+1,t}, x_{i,n+2,t}, \ldots, x_{i,2n,t}}_{y-part} \right)$$

After the initial population is evaluated for fitness and non-dominated sorting, the parent individuals are selected for crossover and variation by the selection operator, which is the primary method for generating new individuals and determines the global search capability of the algorithm[34]. In this paper, the crossover operator adopts a two-point crossover, which performs the crossover operation on both the x-part and y-part parts of the selected individuals.

For the operation of the variation operator, the variation operator used in this paper contains both permutation variation and inverse variation. The children generated by the crossover operator are judged to satisfy inverse and permutation variation conditions. If the reverse-order mutation condition is satisfied, two mutation points on the chromosome are randomly selected, and the gene fragments between the mutation points are arranged in reverse order to form a new offspring; if the pairwise mutation condition is satisfied, two mutation points on the chromosome are randomly selected, and the values corresponding to the two points are exchanged.

4.4 Simulation-based Adaptation Evaluation

In real life, drivers are also assigned orders during the process of going to a merchant to pick up food and going to a customer's point of delivery. The route selection for delivery is changed according to the orders to be delivered. The order assignment not only affects the actual arrival time of the current customers but also affects the delivery of subsequent customers. In this model, drivers may have multiple delivery assignments at a given time and only retake orders after completing the accepted orders.

In the model objective with the delivery speed as the optimization, the travel time per unit distance is not determinable. We consider the average speed of the delivery process to provide drivers sufficient time to guarantee a safe speed.

In addition, the route planning that makes the objective function optimal cannot be found due to uncertainties in the delivery process. A series of delivery scenarios are simulated by solving different order assignment models and situations to evaluate a more reasonable order assignment. In this paper, SimulationTimes is used to represent the scale of the distribution simulation scenario, and its value is used to control the scale of the simulation in the algorithm.

Chapter 5

Experiment Result and Analysis

In order to test the rationality of the Linear Allocation Model and Bundle Order Allocation Model proposed in this paper and the effectiveness of the NSGA-II algorithm, we will use actual data and construct test instances for simulation experiments. The test instances will be introduced and we will explore, compare and analyze the results of the two models under different conditions. The algorithms used in the experiments are written in MATLAB 2022a, and the computer used is a MacBook Pro with a 1.7 GHz quad-core Intel Core i7 processor.

In the actual case, as users order meals, the order information enters the platform system and is dynamically recorded into the order list. In our simulation experiments, each order has a time window, and orders are assigned according to the order generation time. For the Order Bundle Allocation Model, the orders generated in each time interval n are allocated once, and the time interval n is also used as the optimization interval for this simulation experiment.

The results of Pareto optimization for the two order allocation models for the base case and the different meal preparation speed cases will be analyzed and compared first. In the second part, we concentrate on presenting the optimal Pareto frontiers of the Order Bundle Allocation Model. There are some differences in the optimal solutions of the models for different target beam sizes, number of couriers and the couriers' working time.

5.1 Test Instances

In this section, the test instances and data are introduced. Each test instance contains the data of merchants, customers, delivery personnel and orders. In the test instances, the travel time per unit distance satisfies the probability distribution function, and the expected travel time of the delivery person in all experiments is proportional to the Euclidean distance between two points. All the data provided by Reyes et al.[14] on GitHub of following link:

http://github.com/grubhub/mdrplib

Though the two order allocation models are applicable to these two types of drivers. Crowdsourcing drivers are temporary workers and have only low accident insurance, which provides less guarantee compared to contracted dedicated delivery personnel. When we considering the safety problems of couriers, crowdsourcing drivers deserve more attention. In the data instances used in the simulation experiments, the drivers all matched the characteristics of crowdsourcing mode, with random starting locations and inconsistent commuting times.

There are 240 instance examples of different sizes constructed by collecting actual data from different cities and dates. For each instance, they include the data of orders, restaurants and drivers. The specific data are as follows.

- **Orders**: serial number; the location of customers(x,y); restaurant number; placement_time; ready_time
- **Restaurants**: serial number; location (x,y)
- **Drivers**: serial number; location (x,y); working time(on_time, off_time)

5.2 Parameter Settings

The parameters settings for the NSGA-II algorithm are as follows:

Population size PopSize = 50;

MaxIteration = 300;

Crossover probability pc = 0.7;

Variance probability pm = 0.05;

The processing gap n=30 for order allocation means that orders are assigned once every 30 minutes.

5.3 Comparison of the Two Models

The results and corresponding analysis of the optimal solutions for the two models will be introduced in this section. In the standard situation, a single order is assigned to a single driver, which used the Linear Allocation Model. However, the Order Bundle Allocation Model uses dynamic target bundle sizes to bundle orders before assigning them to couriers, which represented as order bundling situation.

The instance we used in this section is the instance example of 7o50t75s1p100, it contains 1606 orders, 230 restaurants, and 212 delivery drivers/couriers. The Pareto optimal results of two models shown in the Figure 5.1. Overall, the two optimization goals, average driving speed and delivery efficiency should be balanced. The faster the driving speed, the shorter the average time is taken per order.

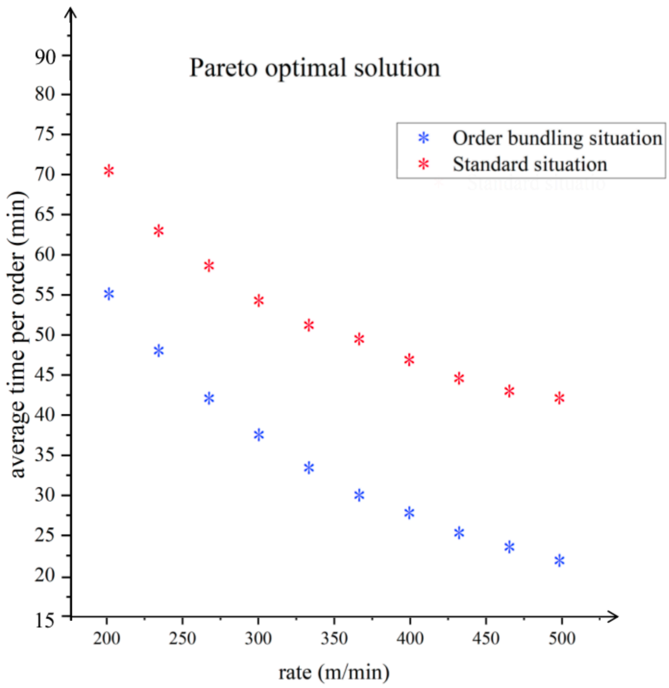


Figure 5.1: *Pareto optimal solutions for the two models*

The red curve represents the case of the Linear Order Allocation Model with a flatter curve. At the slowest average driving speed of 200m/min, the time required for a single order is 70.32min; The average driving speed reaches 500m/min, the delivery efficiency is optimal, and the time required for each order is about 42.44min. The Pareto optimal point is a driving speed of around 233.3m/min, while the average time per order is 48.25min. After the average driving speed exceeds 325m/min, the optimization of efficiency slows down.

The blue curve shows the Pareto frontier of the Order Bundle Allocation Model, and its average time used per order range from 22.50min to 55.20min. The Pareto optimal point is a driving speed of around 300m/min, while the average time per order is 37.9min. In comparison, the delivery efficiency has a better performance at the any driving speed.

5.3.1 Different Food Preparing Speed

In the section, we will explore and analyze how the food preparing speed influence the optimization results of the two models. A variation of the base of the original test example 7o50t75s1p100 is used to test the model's adaptation in different situations.

The food preparation time between when an order starts to be delivered and when it is ordered, is not a fixed value. Different types of restaurants, such as fast food restaurants, sushi restaurants, and fine dining restaurants, have different meal preparation times or different types of food, such as fast food, milk tea drinks, and foods that must be cooked.

The average food preparing time range from 1 to 120 min, and the average food preparing time of the 1606 orders is around 21.3min. For testing whether the optimization results would be significantly different for these two models with different meal preparation speeds, the new example is constructed with a 25% increase in the original preparation time. The food preparation time increased by 5.33min for the new dataset.

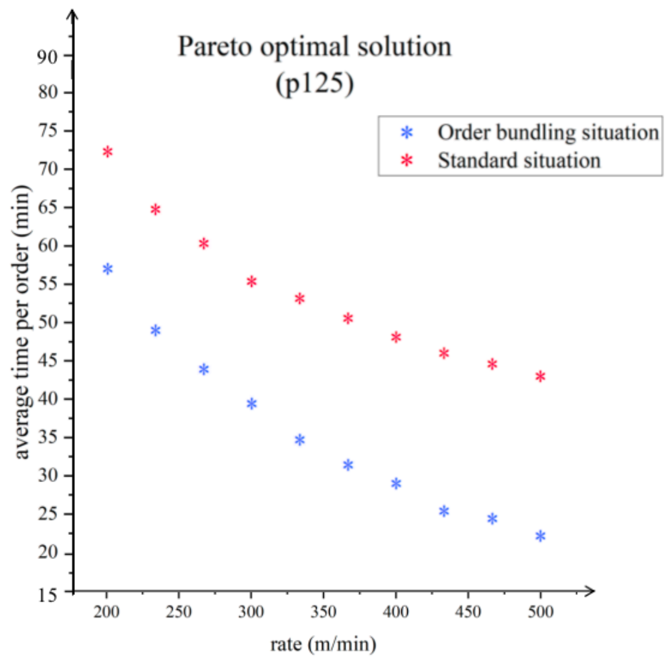


Figure 5.2: *Pareto optimal solution of the two models with 1.25 times food preparing time*

As the Pareto optimal solutions for the new example is shown in Figure 5.2, the trend of both the two models did not change significantly after the increase in meal preparation time, while the time required for average time per order increased in both models. The red curve shows the Pareto frontier of the Linear Allocation Model, and its average time used per order is range from 43.39min to 72.53min. The blue curve shows the Order Allocation Model, and average time used per order range from 22.70min to 57.32min. The positions of driving speed for the Pareto optimal points are not changed. This suggests that meal preparation time affects delivery efficiency but has little effect on the results of the Pareto optimization for the two objectives. When driving speed kept at 300m/min in order bundling situation, the optimal balance between delivery efficiency and safe driving speed is maintained.

Table 5.1: *The range of time used per order in the Pareto optimal solutions*

Food preparing time	**Standard /Linear**	**Order bundling**
Original	22.50 - 55.20 min	42.44 -70.32 min
1.25 times	22.70 - 57.32 min	43.39 - 72.53 min

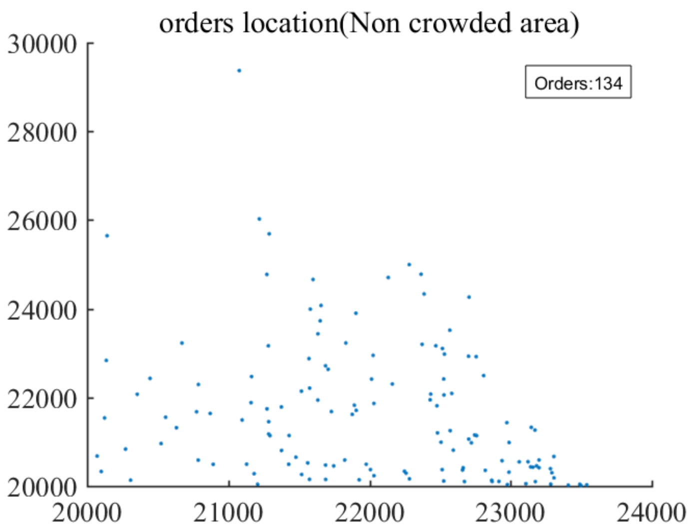
The information of time used per order was summarized in the Table 5.1. The optimization results are in the speed range of 200-500m/min. While the trends in the optimization curves are similar, there is one thing that is worth noting. The average order time increased by 5.33 minutes, but the time spent per order did not increase that much, ranging from 0.20 to 2.12 minutes. The slower the driving speed, the smallest difference in delivery efficiency, the Linear Allocation Model difference of 0.2min, while the bundling case increased by nearly one minute. And when the fastest speed of 500m/min, both models take about two minutes more per order.

There is an effect of food preparation time on delivery efficiency but it's weakened. When the food preparation time increases and driving speed decreases, the Linear Allocation Model receives less impact than the Order Bundle Allocation Model. While maintaining a high driving speed, the delivery efficiency is affected to a similar extent for both models.

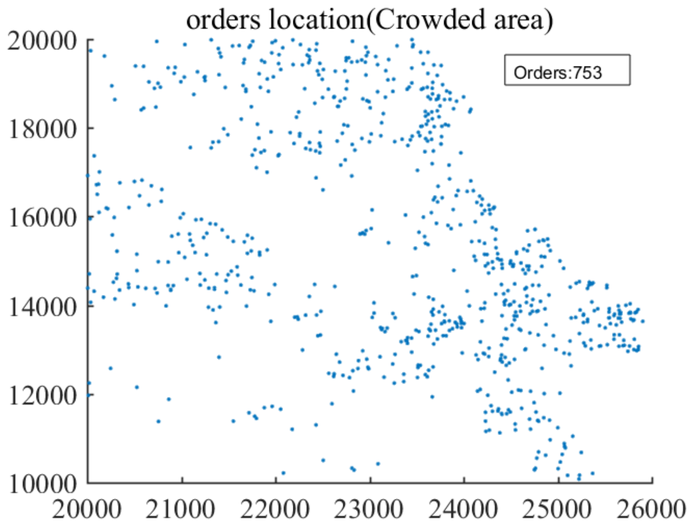
5.3.2 Different Order Density

In this section, we will explore how the two model be optimized in different areas with different order density. The instance we used for this experiment is the instance of 8o50t75s1p100. There are 134 orders in the non-crowded area, while crowded area have 753 orders.

The layout of the orders' locations are visualised in the Figure 5.3, which come from the data analysis of the instance itself. For the non-crowded area, orders are few and relatively evenly dispersed. But for the crowded area, most orders are concentrated in a specific area, with some scattered around.



(a) Non-crowded area



(b) Crowded area

Figure 5.3: *Orders location layouts of non-crowded and crowded area*

We obtained the Pareto frontiers of the the two areas, respectively. As shown in the Figure 5.4, there is the results of non-crowded area, the Pareto frontiers of the two models is relatively closed. The difference in their delivery efficiency was greatest when the slowest driving speed was 200m/min. Each order assigned linearly took on average ten minutes more than the orders assigned in bundles.

The faster the speed, the flatter the blue Pareto frontier and the smaller the optimization effect of the Order Bundle Allocation Model. And when the driving speed keeps increasing, the delivery efficiencies of the two models keep approaching and are close to the same when the speed reaches 500m/min.

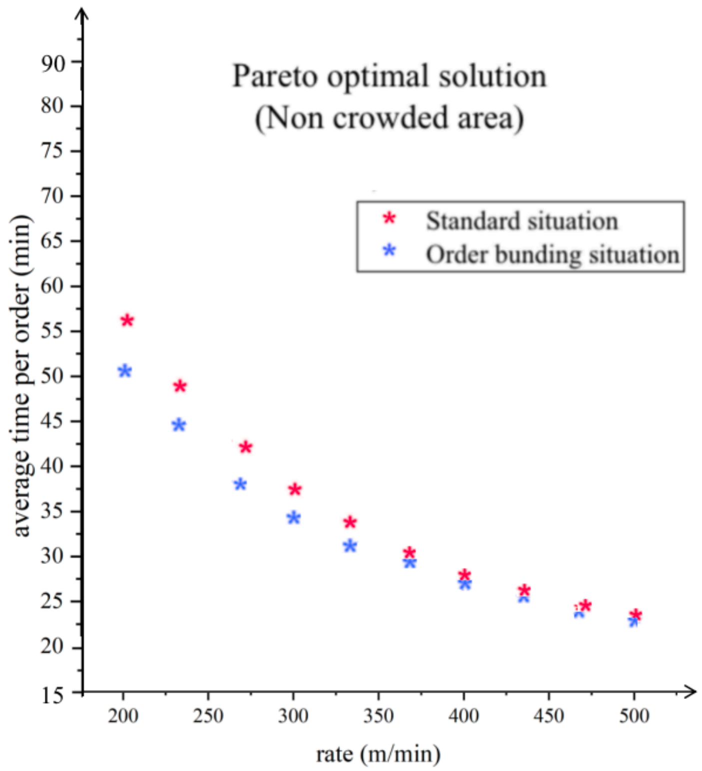


Figure 5.4: *Pareto optimal solutions of non-crowded area*

The Figure 5.5 shows the Pareto solutions of the two models in the crowded area. The blue Pareto frontier of the Order Bundle Allocation Model have a better performance than the red one at any driving speed. The trends and arcs of the two curves are roughly the same, and the difference between them is basically constant. After the speed exceeds 400m/min, the red Pareto frontier gradually flattens out.

The Order Bundle Allocation Model probably improves delivery efficiency per order by roughly 20 min over the Linear Allocation Model at any speed.

By speeding up, The delivery efficiency of the two models can be increased by approximately 33 min.

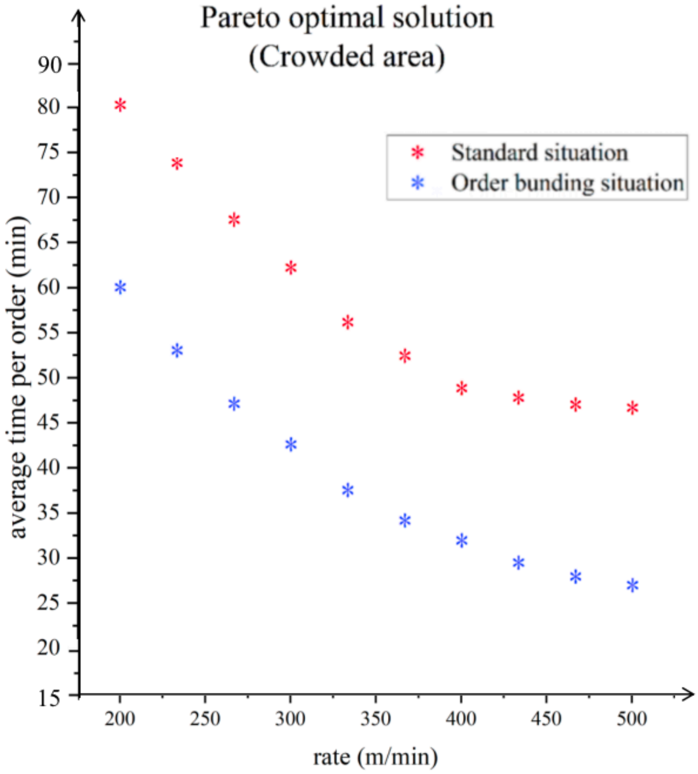
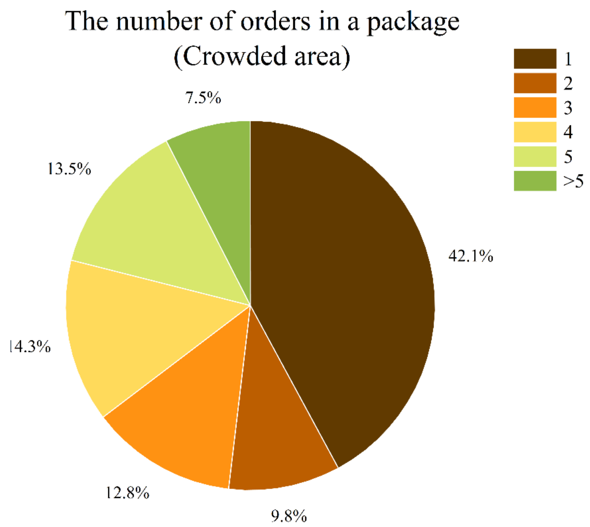


Figure 5.5: *Pareto optimal solutions of crowded area*

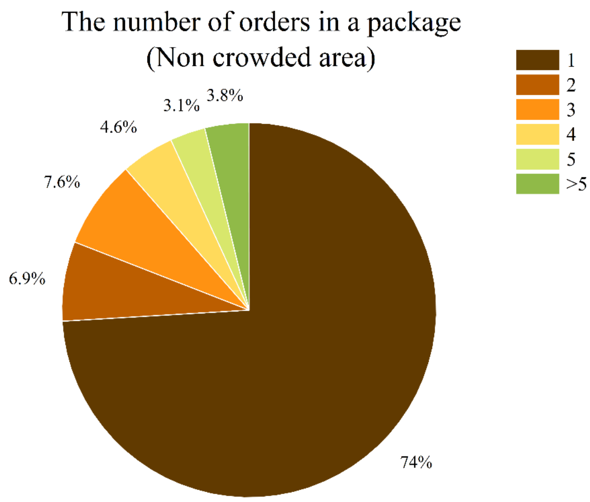
Comparing the optimization results of the two areas, the optimal Pareto equilibrium points for both distribution efficiency and driving speed are in the speed range of 300-350 m/min. In the crowded area, the delivery efficiency per order is 55 min for the Linear Allocation Model and 43 min for the Order Bundle Allocation Model; while the non-crowded area is 33 min and 35 min, respectively. The delivery efficiency in crowded areas is relatively lower than uncrowded area, and requires optimization.

For exploring the factors affecting the optimization results of the Order Bundle Allocation Model, we counted the percentage of different bundle sizes of the optimization results in the Figure 5.6. Bundles of more than 5 orders are relatively few, and we divide the percentage of 1-5 and more than 5 orders in the same bundle. The above figure Fig(a) is the data belonging to the crowded area, and the following figure is the non-crowded area.

As shown in the pie charts, orders in crowded areas are more bundled, which means the number of orders assigned at once exceeds 1, with more than half accounting for 57.9%. In contrast, orders in non-crowded area are less often bundled, accounting for only 26.0% of the total order allocation. In the same interval, there are more orders can be bundle together in the crowded areas..



(a) Crowded area



(b) Non-crowded area

Figure 5.6: *Orders bundle size of non-crowded and crowded area*

Considering that in the order bundle allocation model, orders within a time interval are allocated together, there is a need for earlier generated orders to wait for other orders. In the non-crowded area, there is not many orders can be bundled. The Linear Allocation Model is sufficient when the optimization effect of Order Bundle Allocation Model is not obvious. The order volume is high in crowded areas, and the data instance used in this simulation test is 5.6 times higher than in uncrowded areas. The Order Bundle Allocation Model performs better on the two objectives than the Linear Allocation Model. Drivers can use safer driving speeds while guaranteeing the same delivery efficiency. Compared to non-crowded area, The Order Bundle Allocation Model is more valuable in crowded areas.

5.4 Order Bundle Allocation Model

The order bundle allocation model have a better result than the linear allocation model. In this section, we focused on exploring the performance of the Order Bundle Allocation Model influence the multi-objectives optimization results in different scenarios.

The data of the seven examples was actually collected and is completely different, roughly simulating the different regions and different scenarios. The basic data of the 7 instances are summarized in the Table 5.2.

Table 5.2: *The data analysis of the seven instances*

Instances	Orders	Couriers	Restaurants	Working time
1o50t75s1p100	269	53	90	128.70h
2o50t75s1p100	354	104	126	273.08h
3o50t75s1p100	483	117	131	302.55h
4o50t75s1p100	592	98	134	250.98h
5o50t75s1p100	1362	173	213	561.80h
6o50t75s1p100	835	124	211	393.73h
7o50t75s1p100	1606	212	230	702.43h

And the Pareto solutions for the 7 instances are shown in the Figure 5.7. When the slowest driving speed is 200m/min, the delivery efficiency per order ranges from 47.85 to 61.95 minutes, with an average time of 55.17 minutes. However, when the speed increases to 500m/min, the efficiency per order ranges from 11.45 to 29.44 minutes, with a much larger range of nearly 18 minutes.

There are some similarities between the seven curves, like the optimal equilibrium of the two objectives is at driving speed of 300-350m/min. The purple and red shows a similar trend, and differ with the other Pareto frontiers, which are much flatter, meaning that the increase in driving speed does not significantly improve the efficiency of order delivery for this instance.

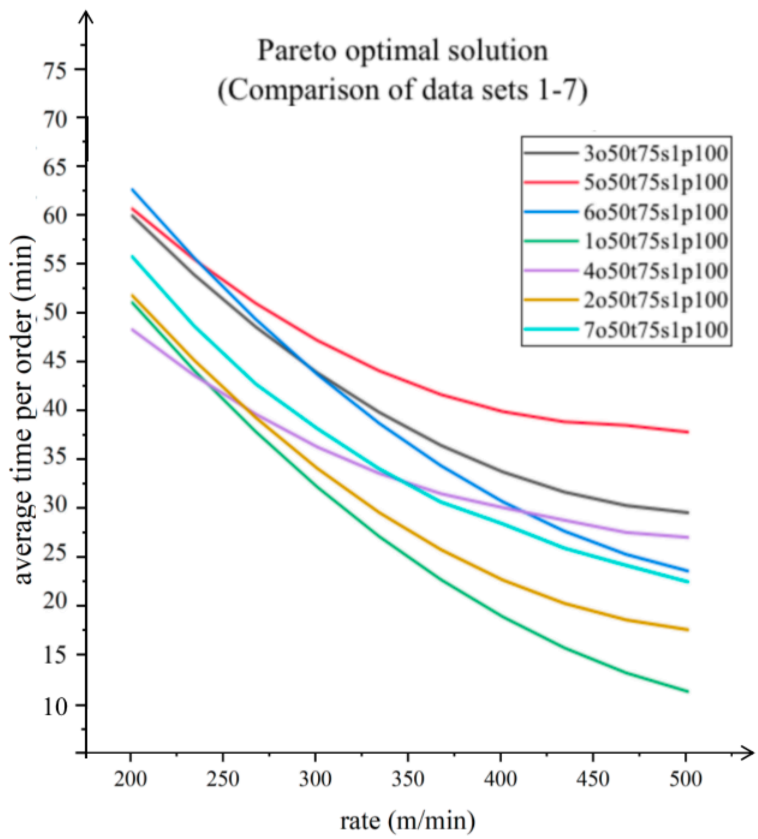


Figure 5.7: *Pareto optimal solutions for the order bundling model*

On the other hand, all curves are different. however, each data is different and it is difficult to analyze the reason for the difference of Pareto curves, so we will use the control variables method to explore the performance of the Order Bundle Allocation Model under the different target beams, number of drivers and their working time.

5.4.1 Different Target Beam Size

In this section, we explore how the bundle size changed with the target beam size, and how the Pareto optimal solutions differ with the different target beam.

The similarity coefficient is defined as the Euclidean distance after the order coordinates have been denormalized. We firstly calculate the similarity factor of orders, which has already shown in the Figure 5.8. Based on the set order similarity, orders will be bundled before assigning.

The target beam size determines the similarity requirement for the target bundle. The larger the target bundle the lower requirement for order similarities, and the more orders are allowed to be bundled into a bundle. In this experiment, we set three target beam sizes: 0.5x size, original size, and 1.5x size, as the Figure 5.8. The horizontal axis is the order number and the vertical axis is the similarity calculated from the destination position of orders.

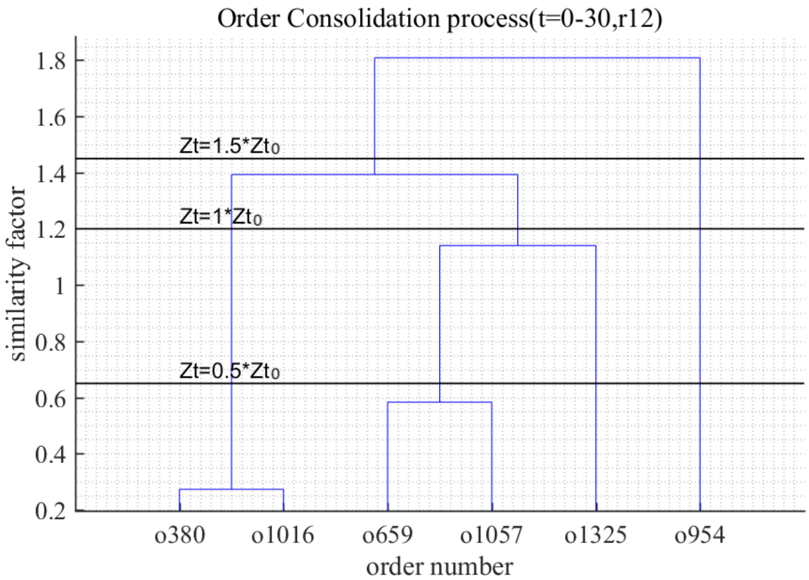


Figure 5.8: *Order consolidation process based on similarity factor*

The Pareto optimal frontiers are shown in the Figure 5.9. Among the three target beam sizes, the difference of the Pareto frontiers between original and 1.5 times is insignificant, but they are better than 0.5 time target beam size.

The original target beam is a dynamic value that is calculated based on the restaurant's real-time workload. When the target bundle is larger, the upper limit of the target bundle size increases, making little difference when the restaurant order volume is low; when the order volume is higher, the bundle size increases as well. In the results of this experiment, the bundle size being allowed to be larger, it's still slight weaker than the original bundle size.

For the green line, the delivery efficiency is the worst of the three outcomes at any driving speed. Even as the speed increases, the curve slows down for the part where the speed exceeds about 350m/min and the delivery efficiency improves at a slower rate. When the target bundle is only half the size, the bundled orders will be required to be more similar, fewer orders will be bundled, and the bundle size will be reduced. The original beam size is the most appropriate one and get the best optimization performance as the blue Pareto frontier.

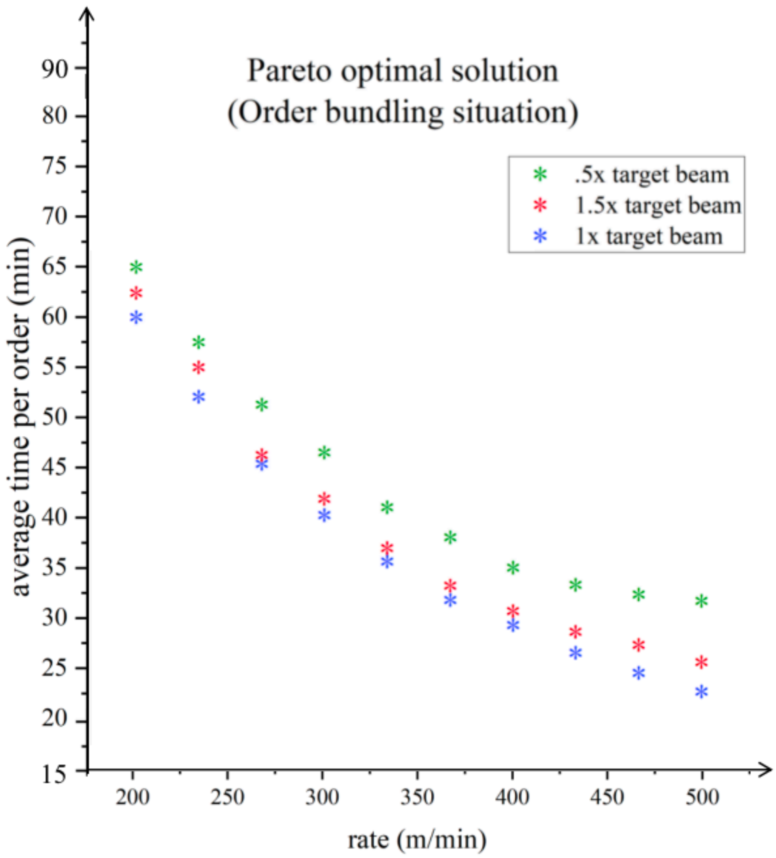


Figure 5.9: *Pareto optimal solution for three kind of target beams*

5.4.2 Different Number of Drivers

In this section, we explore how the number of drivers influence the optimization results. The demand of the drivers also changes with the number of orders generated in real-time.

The instance of 7o50t75s1p100 used as an example, and there are 53 drivers in total. The number of drivers working during the time period counted in this instance example itself. During the peak hours, drivers can receive and fulfill more orders quickly, and the number of working drivers will increase. During the peak period of orders, each courier may need to be burdened with more orders and the demand for the increases of drivers.

A specified amount of random numbers are generated based on the courier number range and deleted with the corresponding serial numbers from the array. There are four groups in total, with no reduction in the number of drivers, 10% reduction, 20% reduction, and 30% reduction. As shown in the Figure 5.10, some drivers were randomly removed according to the specified ratio, and the approximate layout of their initial positions.

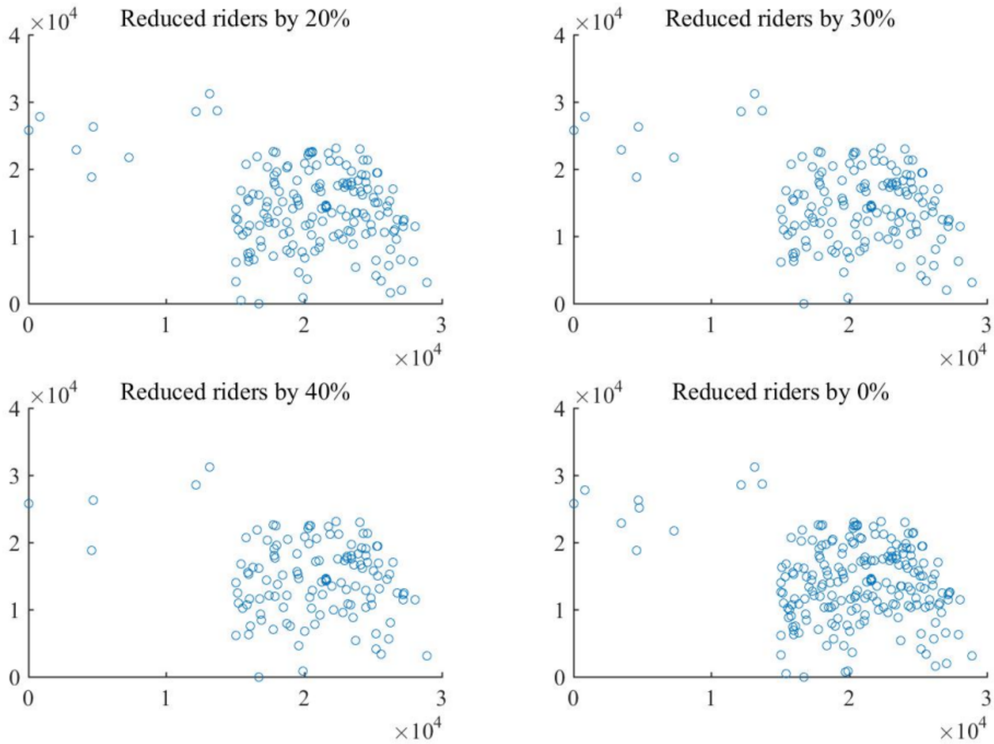


Figure 5.10: *The layout of the riders after reduction*

As shown in the Figure 5.11, Overall, the more drivers, the better the optimization results of the model. The more drivers there are, the more pronounced the arc of the Pareto optimization curve is, and the more pronounced the improvement in delivery efficiency as the speed increases.

Conversely, the lower the number of drivers, the lower the driving speed of the optimal equilibrium point. If a significant improvement in delivery efficiency is needed, it is not obvious by simply increasing the speed.

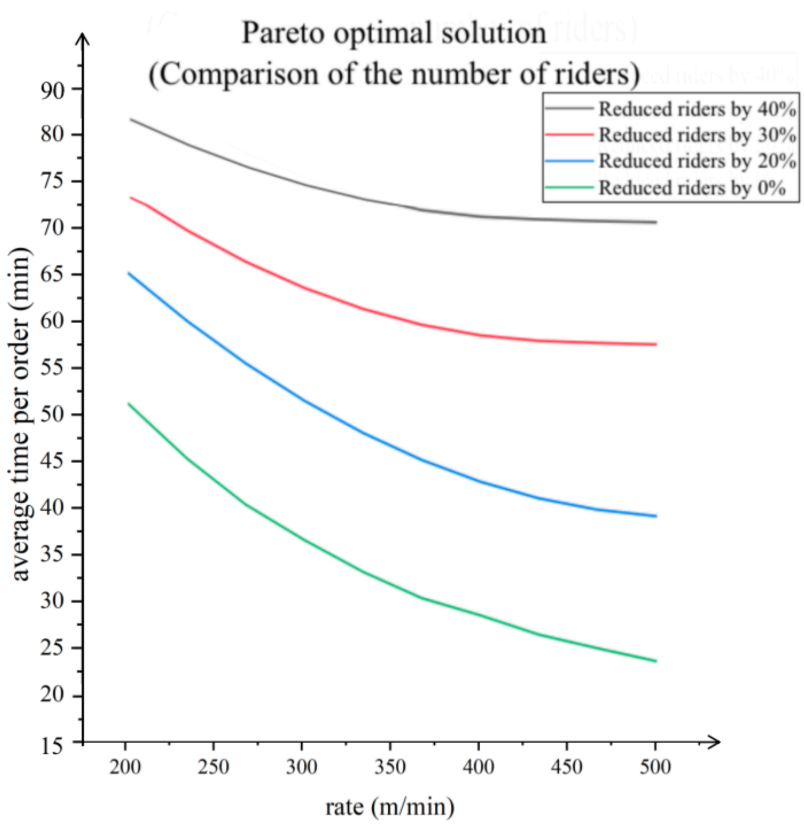


Figure 5.11: *Pareto optimal solution for different number of drivers*

5.4.3 Different Working time

In this section, we explore the optimization results with different working time of drivers. As mentioned in the previous section, the delivery staff includes dedicated and crowdsourcing drivers. There is no required time for the crowdsourcing drivers, and they can start and stop at any time. The number of drivers is changing over time. The main business of takeaway is still food delivery. Orders may be generated at any time but are mainly concentrated at meal times. Only drivers on duty can be assigned an order.

In the data instance, the driver's data contains the time drivers start to work on_time, which is indicated as t_on, and the time finish working off_time is indicated as t_off. The working time is the difference between on_time and off_time. The instance we used in this experiment is the instance example of 7o50t75s1p100. The recorded time interval is 0-810min and the drivers' average working time is 123min.

For exploring the effect of longer drivers' working hours on the optimization results, we increase the on_time and off_time based on the original instance data by a% each. The drivers' working hours by 2a% and obtain the new on_time and off_time as t'_on and t'_off, respectively.

$$\begin{cases} t'\_on = t\_on + \frac{(t\_off - t\_on)*(1+a\%)}{2} \\ t'\_off = t\_off - \frac{(t\_off - t\_on)*(1+a\%)}{2} \end{cases}$$

As the Figure 5.12, there are three control groups, except for the original parameter group, the other two groups are 5% and 10% earlier and later respectively in the commuting time of all couriers, which means the total working hours become 110% and 120% of the original working hours.

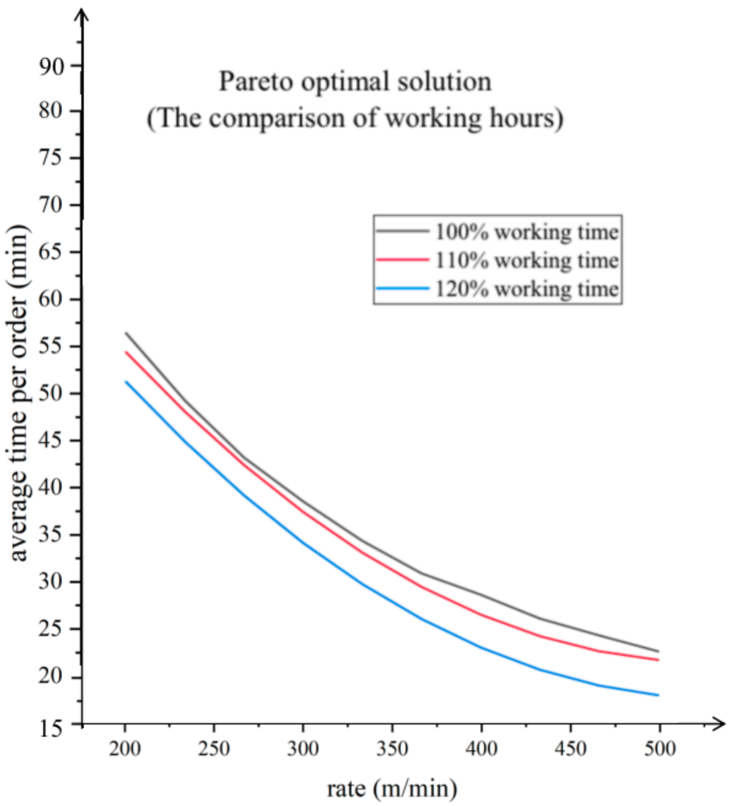


Figure 5.12: *Pareto optimal solutions for different working time*

Overall, the longer the overall working hours of the employees, the better the optimization results of the model. And the arc of Pareto frontiers stays approximately the same for all three cases. One interesting finding here is that a 20% increase in work hours is significantly more effective than a 10% increase in optimization.

5.5 Summary

In this section, we will summarize all the findings of the simulation experiments. On the premise of ensuring delivery efficiency, reducing the accident rate as much as possible, and ensuring driver safety issues, the analysis of simulation tests leads to the following results:

(1)The Order Bundle Allocation Model performs significantly better than the Linear Allocation Model. Orders bundled before assigning with similar order distances can improve delivery efficiency at any driving speed.

(2)The food preparation time takes up delivery time and affects delivery efficiency but it's weakened. The food preparation time range from as fast as 1min to as slow as two hours. After an increase of 5.33 minutes in food preparation time, the delivery time per order increased by only 0.2 to 2.12 minutes. While maintaining a high driving speed, the delivery efficiency is affected to a similar extent for both models. But when the food preparation time increases and driving speed decreases, the Linear Allocation Model receives less impact than the Order Bundle Allocation Model. Some orders with particularly slow preparation times have a high possibility of delaying the delivery of other orders in the bundle. If the expected arrival time remains the same, drivers may choose to speed up to save time because of time constraints.

(3)In non-crowded areas, the optimization results of the two models do not differ much, and the faster the driving speed, the smaller the differences. The Order Bundle Allocation model show a much better optimization results and it's more demanding in crowded areas.

(4)For the Order Bundle Allocation Model, As the optimization results, when the average delivery efficiency of each order is less than half an hour, the driving speed has basically exceeded the safe driving speed. And the original beam size, which is calculated based on the volume of orders to be delivered by the restaurant in real time, gets the best performance in the optimization results. The original beam size is most appropriate one for the Order Bundle Allocation Model.

(5)Increasing driving speed cannot be used as an alternative to a driver shortage. When the number of drivers is insufficient, the delivery efficiency will not be significantly improved by increasing the speed, and the improvement will be lower and lower. And at the same time, driving too fast can cause safety hazards.

(6)Increasing the drivers' working hours contributes to the improvement of the delivery efficiency and the slow down drivers. The more drivers are added, the more effective the optimization gets.

Chapter 6

Limitations and Future Work

In this chapter, we will discuss the implementation of the Linear Allocation Model and Order Bundle Allocation Model, how the NSGA-II algorithm works in obtaining the optimal Pareto frontiers for the two optimization objectives of improving delivery efficiency and drivers' safety, and how the two models perform in the corresponding simulation tests. However, drivers may encounter a variety of situations in the actual delivery process, involving more influencing factors, and the considerations in this paper may not be perfect, and the shortcomings and further research directions of this paper include the following aspects.

(1)The calculating time we counted in the simulation testing is a little bit long, and range from 22.4 to 67.3 min. In the actual case, orders are continuously generated and added, and we allocate them in stages by time period at once, which will sacrifice the efficiency of some orders to some extent. When new orders are added, the system recalculates and plans the paths according to the current driver status and existing orders. The algorithm performance can be improved, the final result can be called approximate or relative optimal solution. The algorithm can be improved or combined with other algorithms in the future research. The path selection can be incorporated into the optimization model in future research to provide more reasonable real-time planning for drivers.

(2)Data is hard to be collected. The order volume collected in current instances are still small and the time span of order generation is large. Nowadays, the takeaway industry is changing rapidly, and the actual order volume should be larger and more frequent. If we can collect more updated and complete data information, the optimization results will be more valuable and some other interesting research directions can be explored.

For example, the delivery path optimization can be carried out considering the order priority, and the high priority orders are delivered first to ensure the delivery within the desired time. In addition, the system can also plan the delivery path according to the food category, such as giving priority to the pasta category under the same time requirement.

(3)The order allocation models we introduced mainly contributes to order allocation planning. The bundle rules of the Order Bundle Allocation Model we used in this article, only consider orders from the same restaurant. And similarity analysis is performed for the order target locations. Different bundling principles can be tried in future research, for example, considering orders from different restaurants for bundling, which can provide a bundling model that can be adapted to more scenarios

Statistics and analysis of food preparation times could be attempted in future studies. The average food preparation time of the restaurant can be estimated and can be included in the calculation of the estimated arrival time. On the other hand, orders that require a lot of time should give alerts to users who are ready to place orders and those who have already placed orders to prevent rushing the drivers.

(4)Other research methods can be blended. Takeaway platform can be based on a fixed time window, through online solicitation of the latest delivery time that customers can accept beyond the time window and the inclusion of whether they are willing to delay delivery options for five minutes. Under the premise of safe speed driving, improve delivery staff earnings, motivation and platform competitiveness, the number of drivers and their working hours, can improve delivery efficiency. If consumers choose to agree to wait five more minutes, the platform needs to ensure that drivers have more time to reduce their driving speed and not ride non-motorized bikes illegally, so that drivers' safe driving gets an additional layer of protection.

Chapter 7

Conclusion

The rapid development of smartphones and "Internet+" brings opportunities for the development of the takeaway industry, and the scale of the takeaway market continues to expand. The delivery time is compressed. This paper starts with the high traffic accident rate of delivery drivers and focuses on exploring the factors that affect their safety. The traditional VRP problem has been studied a lot, and we extend the study of delivery services regarding order allocation and resource management.

There are two order allocation models, the Linear Allocation Model(LAM) and Order Bundle Allocation Model(OBAM), were introduced in this paper. The OBAM was proposed to improve delivery efficiency. Orders of the same restaurant with near destination bundled and assigned to one driver. The OBAM performs better than the LAM under various scenarios and different parameter settings. Especially in crowded areas where orders are generated in large quantities, the LAM does not meet the actual demand and the orders assigned in a bundle are very useful and necessary. The optimized OBAM can reasonably allocate orders and guarantee delivery efficiency while ensuring the drivers slow down. The OBAM is an applicable and reasonable solution for delivery platforms.

Slower driving speed and higher delivery efficiency as a pair of mutually exclusive and conflicting objectives that cannot be maintained at the same time. The NSGA-II algorithm is introduced and finally derives the corresponding Pareto optimal frontiers of driving speed and delivery efficiency, which provides a different perspective of optimization methods and perspectives to complement the study of order allocation in the O2O delivery industry.

For the drivers, a range of driving speeds that is safe and ensures efficient delivery was identified for drivers. The optimal Pareto equilibrium point in almost all scenarios is a driving speed in the range of 300-350m/min. If only the highest delivery efficiency is pursued, all drivers need to reach a speed of 500m/min, which is obviously completely beyond the speed limit of 417m/min and carries a high safety risk. Drivers should be alerted to reduce their driving speed on their own.

With guaranteed efficiency, more reasonable proposals to reduce the pressure on drivers to meet estimated arrival times are explored and ideas provided. More time can be given to drivers, and the improvement of delivery efficiency needs to be based on drivers' own safety.

For takeaway platforms, we found increasing driving speed cannot be used as an alternative to a driver shortage. When the number of drivers is insufficient, the delivery efficiency will not be significantly improved by increasing the speed, and the improvement will be lower and lower. Appropriately extending the working hours of drivers can improve the problem of courier shortage and increase delivery efficiency at a safe driving speed. Improving the welfare, earnings and motivation of drivers will be one of the ways worth considering to improve the delivery efficiency and drivers' safety rights. On the other hand, in addition to considering their costs and customer satisfaction, adding a reasonable, safe and effective time and order planning that considers drivers' safety can attract more drivers to join, helping to improve the competitiveness of the platform and expand the market scale.

This study extends the research on multi-objective optimization in the field of takeaway delivery by exploring explore trading-off between the two objectives of higher delivery efficiency and lower driving speed. The optimization results can expand the ideas of order allocation patterns and strategy selection for takeaway delivery platforms..

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