Order Dispatching and Delivering Decision for A Food Delivery Service

Wasapol Tritanawat and Wipawee Tharmmaphornphilas
Department of Industrial Engineering
Chulalongkorn University
Bangkok, Thailand
6272080421@student.chula.ac.th, wipawee.t@chula.ac.th

Abstract

This paper investigates a dynamic food delivery problem, in which orders arrive dynamically and must be delivered to customers within specified time windows. A fleet of capacitated vehicles is used to deliver the orders. The goal is to minimize the total transportation distances associated with fulfilling customer demands on time. The authors propose a methodology for solving this problem, which involves two steps: 1) Order grouping: the orders are grouped into sets based on their arrival time and delivery time windows. 2) Route optimization: for each set of orders, an optimal delivery route is found using a CVRPTW model. We evaluate the methodology using experimental results. We found that the decision timeframe (the length of time over which orders are grouped) has a significant impact on the performance of the methodology. When the decision timeframe is narrower, it tends to require a higher number of vehicles compared to wider time frames. However, it also results in a shorter average waiting time for customers. With a wider timeframe, more options for orders can be combined in one delivery routing, which can reduce the travel cost/distance. However, too wide a timeframe may lead to increased travel distances due to a small gap between the time of decision making and the guaranteed time of delivery.

Keywords
CVRPTW, Food Delivery, Order Management, Delivering Decision, Order Dispatching.

1. Introduction
Customer experience is the most crucial component in a highly competitive market for food delivery services. Therefore, having a reliable delivery system that guarantees timely and fresh food delivery is essential to ensure customer satisfaction. Consequently, the utilization of efficient transportation and the development of suitable planning methodologies can help companies maintain their competitive edge.

In the aftermath of the COVID-19 incident, a significant number of people have turned to applications, websites, or phone calls to order food, eliminating the need to personally visit restaurants (Zhou He and Guanghua Han 2019). However, customers also expect prompt service and dislike waiting for extended periods. Technological advancements and the emergence of delivery platforms like Grab, UberEATS, Food panda, Shopee Food, and others have played a pivotal role in driving the growth of online food delivery services (Tsan-Ming Choi, Shu Guo, Na Liu, and Xiutian Shi 2020). These platforms empower customers to effortlessly browse through a diverse selection of restaurants, choose their desired dishes, and enjoy swift food delivery. This service provides customers with convenience and a wide range of options, enabling them to order food from numerous restaurants with just a simple tap on their smartphones. Consequently, food delivery services face the fundamental challenge of ensuring efficient delivery in the face of high order volumes, tight timelines, and complex traffic conditions. They are required to make high-quality decisions within limited time frames, simultaneously meeting the demands for both immediacy and quality since the speed and accuracy of order delivery significantly impacts customer satisfaction (Yi Ding, Xing Gao, Chao Huang, Jia Shu, and Donghui Yang 2018).

Order management in food delivery services is the process of receiving, processing, and fulfilling orders. It involves several steps, including: 1) Order intake: this is the process of receiving orders from customers. This can be done through a variety of channels, such as a website, mobile app, or phone call. 2) order verification: this is the process of verifying that the order is complete and accurate. This includes checking the customer's address, the type and quantity of food ordered, and the payment method. 3) order preparation: this is the process of preparing the food for delivery. This includes cooking the food, packing it, and labeling it. 4) order dispatch: this is the process of sending the order out for delivery. This includes assigning a driver to the order and tracking the order's progress. 5) order delivery: this is the process of delivering the food to the customer. This includes handing the food to the customer and collecting payment. Order management is an important part of any food delivery service. It is essential to ensure that orders are received, processed, and fulfilled in a timely and efficient manner. This can help to improve customer satisfaction and reduce distances.

Orders in a restaurant typically arrive dynamically. We cannot predict or know the customer's order in advance. Considering this situation, it is important to explore how we can effectively manage the restaurant with this incoming data. It is important to find the right balance when processing incoming data in the system. Processing the data every time it enters can lead to unnecessary workload, while not processing it promptly may result in delayed orders. Dynamic order arrival is a challenging problem in food delivery. The problem is that orders can arrive at any time, and the arrival time of each order is uncertain. This makes it difficult to plan and to make decisions about how to deliver food to customers on time. One way to address the problem of dynamic order arrivals is to use a rolling horizon approach. In a rolling horizon approach, a decision is made at a given point in time, and then the decision is updated as new information becomes available.

Delivery decision is another important aspect of a food delivery problem. Normally, point-to-point delivery is applied for a food delivery service. However, routing delivery is a more efficient way to deliver goods. This is because routing delivery allows drivers to make multiple deliveries in a single trip, which reduces the amount of time and fuel that is used. Many papers applied a famous vehicle routing problem (VRP) to determine routing of food delivery (Y Zhang and XD Chen 2014) and (BD Song and YD Ko 2016). Some papers also considered time window in delivery food (Ci Hsu, SF Hung, and HC Li 2007) and (Ren Teng, Xu Hong-bo, Jin Kang-ning, Luo Tian-yu, Wang Ling and Xing Li-ning 2021). Most real systems are dynamic and have uncertainties. A two-stage stochastic model for crowd-shipping was proposed to handle uncertainties and dynamics. The model considered uncertain destinations of drivers and introduced route duration constraints to encourage participation through shorter routes. The model was solved using a branch-and-price algorithm and a heuristic method (Fabian Torres, Michel Gendreau, and Walter Rei 2022).

Order management is a complex process that includes many different steps. This paper focuses on the order dispatch and delivery parts of food order management. Specifically, the paper proposes an algorithm for order grouping and delivery route determination in the context of dynamic food delivery. The algorithm uses a rolling horizon approach to make decisions that are updated as new information becomes available. A capacitated vehicle routing model is used to determine routing.

2. Problem Statement

In real life, some food delivery companies can choose the proper kitchen to make a given order based on the customer's location, the availability of kitchens, and the estimated cooking time. However, to simplify the problem, we assume that there is only one restaurant, and the restaurant's kitchen capacity is enough to cook any order. A restaurant receives food orders from customers and is responsible for delivering them on time. Orders arrive dynamically, so the restaurant needs to determine the optimal time periods to combine orders to make delivery decisions. Orders in the same group can be delivered by the same route. We also assume that there is always a vehicle available to deliver the food; however, the capacity of the vehicle is limited.

The goal is to minimize transportation distances/time, and to deliver orders within the guaranteed time. For example, if a customer places an order at 9:00 AM, the order should arrive by 10:30 AM. If a customer places an order at 10:00 AM, the order should arrive by 11:30 AM. In this case, the guaranteed time is 1.5 hours.

3. Methods

The proposed methodology determines the optimal time to make decisions when orders arrive dynamically. Making decisions early can help ensure that orders are delivered on time, but it can also be less efficient. Waiting to make decisions can be more efficient, but it can also lead to orders being delivered late. The proposed methodology balances these two performances. In a rolling horizon approach, decisions are made at regular intervals, and then the decisions are updated as new information becomes available. This allows the methodology to make decisions that are both timely and efficient. Since various length of time horizon may lead to different results, we propose a 2-step methodology including 1) an order grouping based on a length of time horizon, and 2) a methodology to determine delivery routing.

3.1 Order grouping

Since orders must be delivered within a guaranteed time, the simplest way to group incoming orders is based on their arrival times. In this paper, we explore different lengths of time horizons by considering the guaranteed time and the travel time between nodes.

For example, let the guaranteed time be 120 minutes and the maximum travel time between a restaurant and customer node be 30 minutes. In this case, the maximum length of the time horizon can be 90 minutes. This means that we can wait up to 90 minutes to combine orders before making a delivery decision. Otherwise, at least one order from the farthest customer will be late. In this paper, we vary the length of time horizon to explore the results.

3.2 Delivery decisions

Once orders are grouped based upon the time horizon, the delivery routing can be determined. To determine the optimal route for a food delivery service, a capacitated vehicle routing with time window model is applied. The model objective is to minimize the total distance, which consists of the sum of transportation distance between nodes. Model details are as follows.

Parameters

N = {1, 2, 3, …, n} is the set of clients.
V = $\{0\} \cup N$ is the set of nodes, while $\{0\}$ is the location of the depot.
A = $\{(i, j) \mid i, j \in V^2, i \neq j\}$ is the set of arcs connecting different nodes.
$time_{ij}$ = transportation time from node i to j.
d_{ij} = transportation distance from node i to j.
Q = a vehicle capacity.
q = customer order size.
t_end_i = due date of order from customer node i.
t_{frame} = Time horizon to make decision.

Decision Variables

$x_{ij} = \begin{cases} 1 & \text{if travel from node } i \text{ to } j \\ 0 & \text{otherwise} \end{cases}$
t_i = arrival time at node i.
u_i = accumulated demand at node i during the routing process.

Objective

$$min \sum_{(i,j)\in A} d_{ij}\, x_{ij} \qquad (1)$$

Constraints

$$\sum_{j\in V, i\neq j} x_{ij} = 1 \qquad i \in N \qquad (2)$$
$$\sum_{i\in V, i\neq j} x_{ij} = 1 \qquad j \in N \qquad (3)$$
$$If\ X_{ij} = 1 \Longrightarrow u_i + q = u_j \qquad i, j \in N \qquad (4)$$
$$q \leq u_i \leq Q \qquad i \in N \qquad (5)$$
$$If\ X_{ij} = 1 \Longrightarrow t_i + time_{ij} = t_j \qquad i, j \in N \qquad (6)$$
$$t_i \leq \text{t}_{\text{end}_i} \qquad i \in N \qquad (7)$$
$$t_i \geq t_{frame} + time_{0i} \qquad i \in N \qquad (8)$$
$$X_{ij} \in \{0,1\} \qquad i, j \in N \qquad (9)$$
$$t_i, u_i \geq 0 \qquad i \in N \qquad (10)$$

The objective function is to minimize the total transportation distances. Constraints (2) and (3) ensure that all customers are visited exactly once. Constraints (4) and (5) ensure that the accumulated demand at each node is within the capacity limitation and are used to eliminate sub-tour. Constraints (6) are used to compute arrival times at all customer nodes Constraints (7) ensure that the arrival time at each customer node is within the assigned time windows, while constraints (8) ensure that the arrival time of each node from the depot which must be greater than or equal to time to make decision. For the first nodes that arrived from the depot, their arrival times are the time to make decision plus the travelling time from the depot to these nodes. Finally, Constraints (9) and (10) enforce the binary nature of the decision variables and ensure that the arrival times and accumulated demand are valid and realistic in the problem formulation.

This mathematical model is applied to the food delivery problem. The model is written in Python language and run on the Jupyter Notebook (Python 6.4.12). All experiments are run on a computer with AMD Ryzen 5 3600 6-Core Processor 3.59 GHz, RAM 16.0 GB and 64-bit operating system.

4. Results and Discussion

In an example problem, there are 100 customers. Customer locations and order arrival time are generated. We assume that the order size is one for every customer. Figure 1 shows customer locations of an example problem. The red square point represents a restaurant location. The capacity of a vehicle is five so the maximum number of visits per trip is five.

For this example, we set guaranteed times to be 90, 105, and 120 minutes. Lengths of time horizon (Time frame) are 15, 30, 45, and 60 minutes.

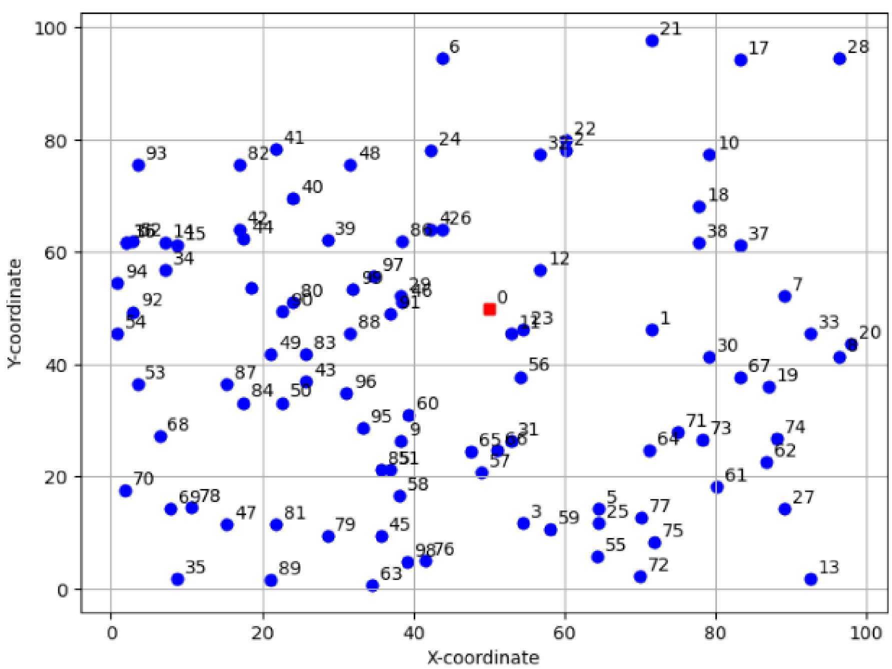


Figure 1. Customer's location (100 customers).

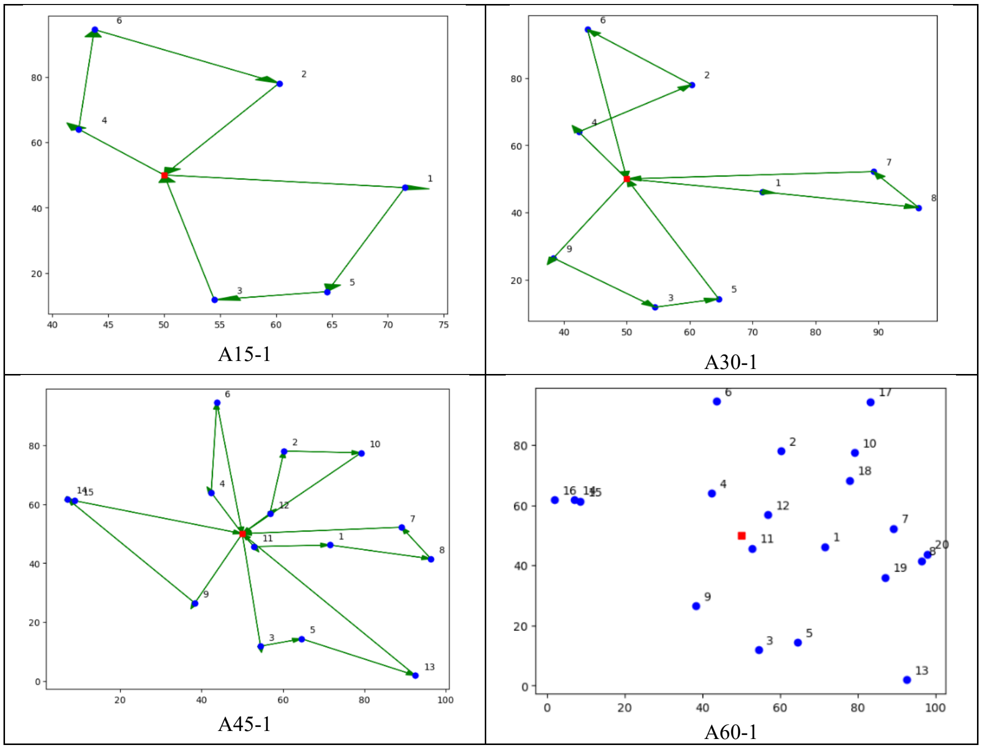


Figure 2. Example of the optimal route for 15, 30, 45, 60-time horizon with guaranteed time 90minutes (A1).

When considering a time horizon of 300 minutes, if decisions are made every 15 minutes, the number of decision periods would be 300/15 = 20 times. Similarly, for 30-minute intervals, there would be 300/30 = 10 decision periods, for 45-minute intervals, there would be 300/45 = 7 decision periods, and for 60-minute intervals, there would be 300/60 = 5 decision points. Figure 2 shows examples of routes from 15-, 30-, 45-, and 60-minutes intervals, with longer intervals, more number of customers nodes are included in decision. Therefore, the number of routes are increased. From A30-1 or a 30-minute interval, a crossing loop appears since an order must be delivered within its guaranteed time. There is no route for A60-1 or 60-minute interval because it is infeasible to deliver within a guaranteed time.

Table 1 shows the results of 2 sample problems (A and B). Problems A and B contain 100 and 110 customer nodes, respectively. Average waiting time is calculated based upon the number of decision periods of each time frame. Distance represents the total distance of all periods. The total number of routings and average number of routings are shown in each scenario.

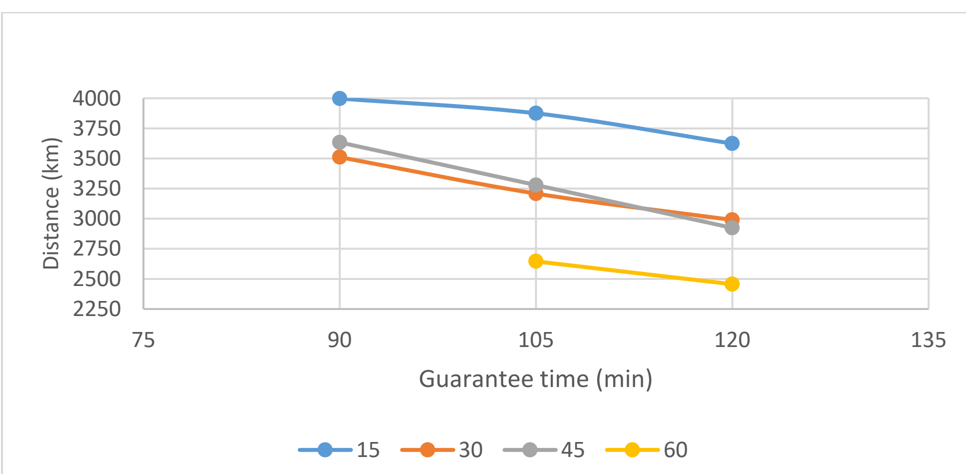
The results show that a narrower time frame leads to lower average waiting time but higher total travel distance and number of routes. On the other hand, when the time frame is increased, the average waiting time is higher, but the travel distance and the number of routes are lower, which are also shown in Figures 3-5. However, it's worth noting that a lower time frame may be more advantageous than a higher time frame in certain cases, as illustrated in Figure 3. In such scenarios, the shorter time frame results in lower travel time. Comparing the case of 30-minute and 45-minute time frames with a guaranteed time of 90 minutes. In the first case, each vehicle has the maximum of 60 minutes to travel while the second case has the maximum of 45 minutes to travel. The 45-minute time frame encounters certain scenarios where more vehicles need to serve specific customers due to the limited 45-minute delivery window. This could result in a less efficient use of vehicles and, in some cases, lead to increased travel time or the need for additional vehicles to meet delivery commitments. From figures 3 and 4, in case of a 90-minute guarantee time, comparing 15-minute and 30-minute time frames, the total distance of the 30-minute is a lot lower than the 15-minute time frames, but the waiting time of both case is approximately the same.

Table 1. The optimal distance, average waiting time, total routing, and average routing of each scenario.

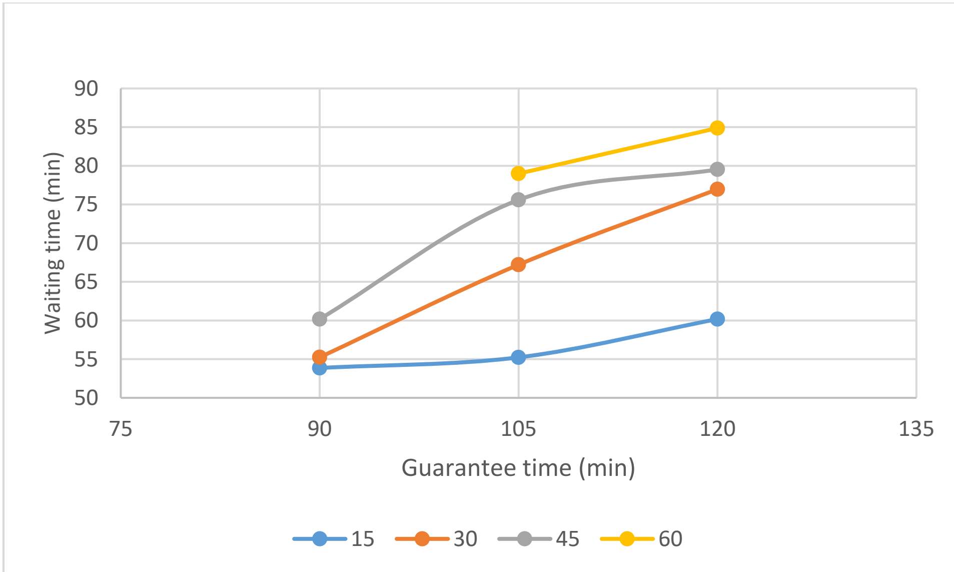
Solution	Time frame (Min)	Guarantee time (Min)	Average Waiting time (Min)	Distance (km)	Routing (Total)	Average Routing
A1	15	90	53.86	3998.05	40	2
A1	30	90	55.24	3511	34	3.4
A1	45	90	60.18	3633.49	35	5
A1	60	90	-	-	-	-
A1	15	105	55.23	3875.27	38	1.9
A1	30	105	67.21	3208.56	29	2.9
A1	45	105	75.59	3279.4	30	4.28
A1	60	105	78.99	2645.62	24	4.8
A1	15	120	60.18	3623.98	33	1.65
A1	30	120	76.97	2990	27	2.7
A1	45	120	79.52	2923.79	25	3.57
A1	60	120	84.88	2455.79	22	4.4
B1	15	90	58.15	6058.14	57	2.85
B1	30	90	65.59	4876.68	46	4.6
B1	45	90	70.9	4548.01	39	5.57
B1	60	90	-	-	-	-
B1	15	105	61.04	5693.26	48	2.4
B1	30	105	71.15	4479.7	39	3.9
B1	45	105	79.71	4016.99	34	4.85
B1	60	105	78.73	3912.73	35	7
B1	15	120	63.05	5572.23	47	2.35
B1	30	120	77.18	4222.77	33	3.3
B1	45	120	86.59	3686.15	29	6.42
B1	60	120	88.21	3363.59	28	5.6

(-) represents infeasible solution.

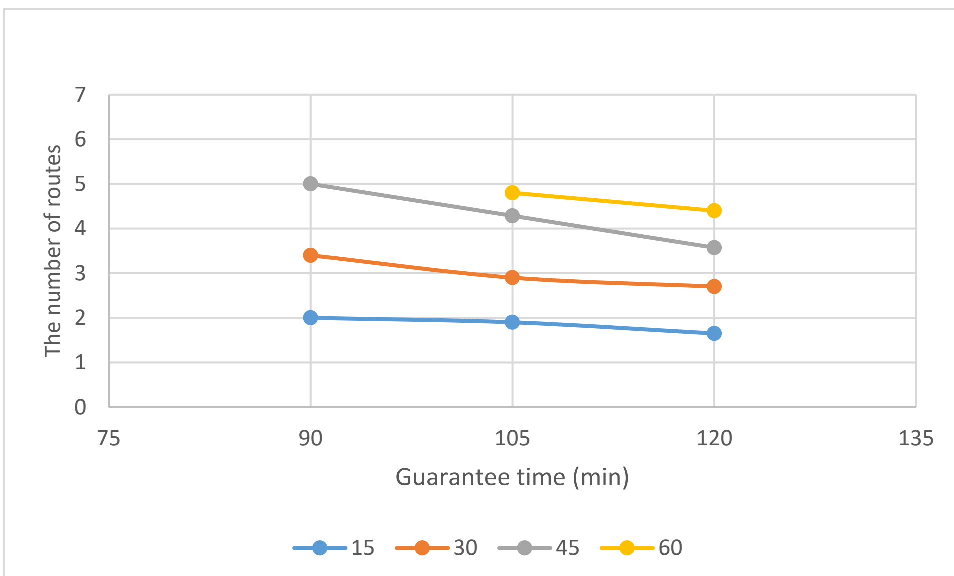
In summary, the choice of time frame can significantly impact the delivery decision. For this specific problem a 30-minute time frame with a 90-minute guarantee provides more flexibility for vehicle routing and can efficiently serve more customers than 15-, 45-, and 60 minute. The 30-minute time frame should be the length of decision plan.



Non-estimable means are not plotted.
Figure 3. Total distance of problem A.



Non-estimable means are not plotted.
Figure 4. Average waiting time of problem A.



Non-estimable means are not plotted.
Figure 5. Average number of routes of problem A.

5. Conclusion

In food delivery management, effective decision-making plays a crucial role in achieving desirable outcomes. The challenge lies in creating an optimal delivery route that strikes a balance between transportation distances and customer satisfaction. The algorithm proposed in the paper is a promising approach for solving the problem with dynamic order arrivals in food delivery. The algorithm can make decisions in real time, and it is able to adapt to changes in the environment. This makes it a good candidate for use in real-world applications.

The paper's findings can be used to inform the development of more sophisticated algorithms for food delivery. By understanding the optimal length of time for grouping orders, food delivery companies can minimize transportation distances and time, and improve the delivery experience for their customers. As the guaranteed time increases, the maximum length of the time horizon can be increased. This is because there is more time available to combine orders and ensure that they are delivered on time. However, travel time also affects the maximum length of the time horizon. If the travel time is longer, then the maximum length of the time horizon must be shorter to ensure that orders are delivered on time.

The assumption that there is only one restaurant simplifies the problem, but it also makes it less realistic. In the real world, food delivery companies need to consider a variety of factors when determining the proper kitchen to make a given order. These factors include the customer's location, the availability of kitchens, the estimated cooking time, and the cost of delivery. This assumption should be relaxed in future study.

In exploring the complexities of food delivery management, the paper introduces a robust algorithm for order dispatching and delivery decisions. However, to enhance its practical value, a deeper examination of real-time constraints and economic factors could be beneficial. Real-time constraints, inherent in dynamic order arrivals and varying delivery windows, could be further investigated to reveal how the algorithm effectively adapts to these uncertainties. Analyzing its responsiveness to sudden demand spikes, unforeseen delays, and changing traffic conditions would underscore its real-world applicability. Additionally, delving into economic implications would offer a broader perspective. While the paper outlines the algorithm's impact on distances and waiting times, a comprehensive economic analysis could highlight potential cost savings and revenue growth. Evaluating aspects like fuel expenses, labor costs, and enhanced customer satisfaction could underscore the algorithm's tangible benefits for food delivery companies. By exploring scenarios of economic uncertainty and demonstrating how the algorithm optimally allocates resources under varying conditions, Examining the total economic distance from the reference point to point 7322.07 unveils an interesting comparison when juxtaposed against the illustrative example of a 30-minute time frame with a 90-minute delivery guarantee.

In this context, the calculated economic distance of 7322.07 units represents a distinctive route's efficiency from a cost perspective. Contrasting this with the total distance of 3511 units in the illustrative scenario further highlights the economic implications of altering delivery parameters. The comparison accentuates the intricate interplay between time constraints and economic considerations in the realm of food delivery operations. It sheds light on the intricate balance that businesses must navigate – maximizing efficiency while upholding delivery commitments. This analysis contributes to the broader discourse on optimizing logistics and underscores the significance of factoring in economic considerations when designing delivery routes within specific time parameters. The paper could provide actionable insights for real-world implementations. This integration of real-time adaptability and economic considerations would amplify the algorithm's relevance and value, catering to the nuanced needs of food delivery operations. The paper could have offered a more holistic guide for decision-makers in the food delivery landscape.

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Biography

Wasapol Tritanawat graduated from Thammasat University with a bachelor's degree in industrial engineering. Currently, he is pursuing a master's degree in industrial engineering at Chulalongkorn University. His research interests primarily revolve around optimization in the areas of CVRP (Capacitated Vehicle Routing Problem) and food delivery**.**

Assoc. Prof. Wipawee Tharmmaphornphilas, Ph.D., is an accomplished academic with expertise in the field of Industrial Engineering. She has an impressive educational background and extensive experience in various areas related to Operations Research and Engineering. Her academic journey began at Chulalongkorn University, where she earned a Bachelor of Engineering (B.Eng.) in Industrial Engineering in 1996. Continuing her pursuit of knowledge, she completed her Master of Science (M.S.) in Industrial Engineering at the University of Pittsburgh in 1998 and a Doctor of Philosophy (Ph.D.) in Industrial Engineering from the same university in 2001.