ONLINE FOOD ORDERING SERVICE WITH CROWDSOURCED COURIERS

BY

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عمادة الدراسات العليا
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To my immediate family

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ABSTRACT

Full Name : Ibrahim Abdulaziz Alrajeh

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In this thesis, the online food ordering service problem is studied by considering crowdsourced couriers as the only source of supply for the platform's capacity. The problem is defined to be dynamic and stochastic in terms of the placement of orders and the availability of couriers along with their acceptance behavior. It is modeled as a mixed-integer linear programming that is designed to be the basis for a rolling horizon technique. This rolling technique is developed to be the solution procedure. A computational study is determined to examine the problem results and the sensitivity of the main input parameters for key insights.

ملخص الرسالة

الاسم الكامل: ابراهيم بن عبدالعزيز الراجح

عنوان الرسالة: دراسة خدمة طلب الطعام عبر الإنترنت اعتماداً على السائقين المستقلين

التخصص: الهندسة الصناعية والنظم

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في هذه الأطروحة، تتم دراسة مشكلة خدمة طلب الطعام عبر الإنترنت مع اعتبار السائقين المستقلين المصدر الوحيد للإمداد لقدرة النظام الأساسي. يتم تعريف المشكلة على أنها ديناميكية وعشوائية من حيث استلام الطلبات وتوافر السائقين المستقلين وأيضاً مع اعتبار سلوكهما من حيث قبول الطلب أو رفضه. تم تصميم المشكلة على أنها برمجة خطية ذات عدد صحيح وتم تصميمها لتكون أساساً لأسلوب الأفق المتداول. وتم تطوير هذا الأسلوب ليكون إجراء الحل للمشكلة. ومن ثم تم تحديد دراسة حسابية لفحص نتائج المشكلة ومدى حساسية معلومات الإدخال الرئيسية وذلك من أجل الحصول على رؤى ذو أهمية.

CHAPTER 1

INTRODUCTION

The increase in the demand for online food ordering services has given rise to the spread of platforms that deliver restaurant meals to customers. Examples of countrywide platforms in the Kingdom include HungerStation and Jahez, whereas several regional and local services exist. However, in the academic literature, the analysis of such a system is still growing and somewhat partial.

In such a platform, customers are offered the chance to place an order (through either an internet website or a mobile application) and choose items from a specific list of participating restaurants. Once the customer places an order, the platform matches the order to an available courier, after which the communication to the selected restaurant takes place. Then, the assigned courier's location, contact, and expected delivery time are displayed to the customer. Also, the customer can track the courier on the map and monitor the order progress.

Each courier is considered available for delivery as long as his/her online status is turned on in the platform. The couriers are ordinary drivers (independent contractors) who are willing to carry out the delivery from a selected restaurant (pickup location) to an ordering customer (delivery location) with their resources (time and vehicle). In return, the drivers are compensated per delivery. This concept is known in the literature as crowdsourced delivery. The platform success depends on how couriers are treated and its ability to satisfy the customers requirement.

In this segment, to be competitive, a platform must satisfy the key stakeholders involved in the meal delivery order process. The first key stakeholder is couriers who want to deliver enough orders to earn a decent reward. The second one is partnering with restaurants that require their product to be served fresh to grow their customer base ultimately. The third one is ordering customers who need fast and reliable service. Therefore, fulfilling them is essential to have a reliable platform that eventually grows and competes in the market.

The study of crowdsourced delivery in the segment of the online food ordering service is still new and requires further consideration. Since several research opportunities exist in this direction, the objective of this research is to focus on the modeling of such a problem that reflects the most recent operational challenges. In addition, according to the features of the problem, a rolling horizon method is proposed to obtain faster solutions. Furthermore, a computational study is developed to analyze the problem and provide insights into the platform's operations.

The remainder of the report is organized as follows. In Chapter 2, a literature review is provided. In Chapter 3, the problem definition (including the problem description, assumptions, model, and remarks) is presented. In Chapter 4, the solution approach used is outlined. In Chapter 5, a computational study is defined, and its results are analyzed. In Chapter 6, the study is concluded with final remarks.

CHAPTER 2

LITERATURE REVIEW

The vehicle routing problem (VRP) generalizes the well-known problem, the traveling salesman problem (TSP), which assumes a single vehicle and finds the shortest route to deliver for a given set of demands (customers). That is, the VRP considers a fleet of vehicles and finds the optimal set of routes to fulfill a given group of customers. In the literature, it was first developed by Dantzig and Ramser [5]. In a similar manner, the pickup and delivery problem (PDP) extends the VRP. Instead of a customer only associating with a delivery location, a customer is characterized by pickup and delivery locations. In a general context, Figure 1 visualizes the three problems.

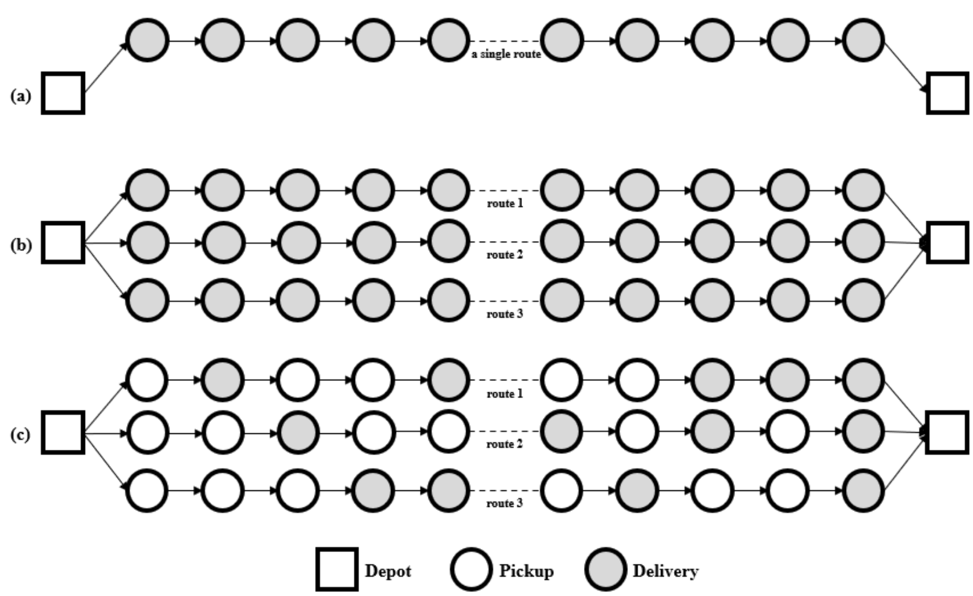

Figure 1 (a) TSP, (b) VRP, and (c) PDP

According to Pillac et al. [10], besides the classical formulation of the VRP, two important dimensions (information evolution and quality) are often considered in real-world applications. Quality of information shows possible uncertainty on the available data, such as in the case of considering future demand. Evolution of information means that the availability of information may change during the execution of the plan (the routes), for instance, with a new customer request arrival. Consequently, four categories of the VRP are identified in Figure 2.

Information Quality	**Information Evolution**	
	Input is known in advance	Input changes over time
Input is deterministic	Static and Deterministic **VRP**	Dynamic and Deterministic **VRP**
Input is stochastic	Static and Stochastic **VRP**	Dynamic and Stochastic **VRP**

Figure 2 Classification of the VRP by the Two Dimensions (Information Quality and Evolution)

In the static and deterministic VRP, all input is known beforehand, and it does not change during the execution of the routes. Due to the stochasticity nature, the static and stochastic VRP is featured by the input that is partially known (as random variables). The real values are realized during the execution phase. Furthermore, the routes are designed in advance. Then, minor changes are accepted during the execution of the routes. In the dynamic and deterministic VRP, all or part of the information is unknown, and it is realized dynamically during the route design or execution. The dynamic and stochastic VRP is similar to the latter category, but there is at least one variable that is described as a random variable.

The most relevant papers are reviewed in the subsequent two sections: Section 2.1 and Section 2.2.

2.1 Dynamic VRP and Restaurant Meal Delivery

A recent paper developed by Rios et al. [13] surveys the literature on dynamic vehicle routing problems published recently (from 2015 to 2021). Mainly, the survey focuses on the problem applications and the related solution methods. It mentions that both heuristics and metaheuristics stand out compared to the other solution methods. According to the problem applications, the survey remarks that crowdsourced delivery plays a vital role in recent business models of logistical operations, such as online food ordering and ride-sharing services. Some of the highlighted future directions are recognizing the dynamism and stochasticity of information (e.g., delivery orders and couriers' availability) and considering proper objective functions that ensure a reliable system.

The paper provided by Steever et al. [17] addresses the problem of dynamic vehicle routing in the segment of online food delivery service. The problem in this paper is called (the virtual food court delivery problem) due to the use of a virtual node in the defined network. The optimization model is based on simulation. The orders are assumed to be dynamic, arriving over time. It considers multiple restaurants that can be included in a customer order. Three objective functions are modeled. The first one focuses on the delivery time to be fast, and the other two concern the food freshness. As part of the solution method, each time a new order arrives, a mixed-integer programming problem is solved to assign both customers and routes to the fleet of couriers. The problem assumes that the fleet size of couriers is known in advance. Delivery time is considered as a soft constraint by including a penalty for lateness. Besides, a vehicle capacity constraint is included.

Ulmer et al. [20] consider the stochastic dynamic vehicle routing problem where a fleet of couriers delivers restaurant meals to customers. The sources of stochasticity in the problem are the arrivals of orders and the food ready-time at the restaurant. The problem objective is to minimize the delays with respect to the customers deadlines (expected delivery time) to control the fleet of couriers dynamically. A policy is introduced to handle stochasticity called (anticipatory customer assignment). Also, a time buffer is used as a strategy to reduce delays. The geographical location considered in this study shows clustering of the locations of the restaurants, encouraging the authors to use a bundling strategy for the customers' orders.

2.2 Crowdsourced Delivery System

A review paper by Alnaggar et al. [1] focuses on crowdsourced delivery systems in the industry and academia. The paper aims to classify the key elements of such systems that differentiate them from other transportation systems. Furthermore, Savelsbergh and Ulmer [15] emphasize the challenges and opportunities in crowdsourced delivery planning and operations. The uncertainty in the demand and delivery capacity differentiates the crowdsourced delivery system from the conventional one. Although the crowdsourced delivery system brings uncertainty and complexity to the system, it adds advantages to the system in terms of cost-saving and flexibility.

Archetti et al. [2] develop the first paper to consider crowdsourced couriers by modeling the vehicle routing problem with occasional couriers in addition to the company's existing fleet. Simply, it extends the classical vehicle routing problem by outsourcing part of the demand to be fulfilled by in-store customers (occasional couriers) willing to make a delivery on their way back home. Macrina et al. [9] extend this idea by considering delivery time windows and suggesting two mixed-integer programming models. The first one allows for multiple deliveries per occasional courier, while the second allows for split deliveries.

Following the paper developed by Archetti et al. [2], Gdowaka et al. [7] define the same problem, but they consider one more decision that occasional couriers have the option to accept or reject possible assignments. Accordingly, the paper models the problem as a bi-level stochastic problem. Similarly, the study of Arslan et al. [3] considers the same problem in which the in-store customers support the fleet by contributing partially to the demand fulfillment. However, it assumes that their arrival and the arrival of the customer orders are dynamic. Also, the paper of Dayarian and Savelsbergh [6] considers the crowd-sourced delivery problem by including dynamism and stochasticity natures for both arrivals: In-store customers and customer orders. A maximum weighted matching problem is solved to determine optimal matches (orders to couriers). A higher weight is given to long-distance and urgent orders. All of these studies assume deterministic transportation duration. As a result, Zhang et al. [22] extend this assumption to be uncertain instead with the aim of studying its impact on the performance of the system.

The paper shared by Soto Setzke et al. [18] discusses a crowd-sourced delivery system where the matches between couriers and customer orders are based on couriers' already planned routes. The problem is modeled as a max-flow min-cost problem. In a similar direction, Sampaio et al. [14] study a crowdsourced system in which couriers show their availability to perform deliveries for a given time. Then, the platform communicates a schedule with customer orders to be served. Besides, the paper introduces the option of order transfer to support courier activities and investigates the potential benefits of such a consideration. The problem is modeled as a multi-depot pickup and delivery problem with transfers and delivery time windows. An adaptive large neighborhood search algorithm is proposed to solve the problem. The results show that such a problem setting can significantly reduce system-wide travel distance. Moreover, the number of couriers required to serve a given set of orders can be reduced, especially when orders have high service requirements and couriers have short availability.

Following the surveys developed by Savelsbergh and Ulmer [15], Alnaggar et al. [1], and Rios et al. [13], all of the above studies contribute to the pickup and delivery problem and the crowdsourced delivery systems. However, the academic literature still requires further consideration of the subject. As a result, this paper aims to continue in this direction. Table 1 shows the literature classification for the abovementioned studies, and this paper highlights three main dimensions: Application, type of couriers, and elements of uncertainty. The first dimension, application, represents the context of the paper if it is specific to restaurant meal delivery or not. The second dimension, type of couriers, distinguishes three types: Fully Committed couriers, Committed couriers, and Occasional couriers. A fully committed courier means that the system controls a courier's availability and behavior. In contrast, a committed courier's behavior is uncertain while his/her availability is known to the system. An occasional courier's availability and behavior are uncertain. Both committed and occasional couriers are known as crowdsourced couriers.

The third dimension, elements of uncertainty, focuses on three uncertain elements: Travel time, delivery orders, and couriers.

Table 1 Literature Classification

Reference	Application		Type of Couriers			Uncertain Elements		
	Restaurant Meal Delivery	Goods Delivery	Fully Committed	Committed	Occasional	Travel Time	Order	Courier
Archetti et al. [2]		*	*		*			
Arslan et al. [3]		*	*		*			
Dayarian and Savelsbergh [6]		*	*		*		*	*
Gdowska et al. [7]		*	*		*			
Macrina et al. [9]		*	*		*			
Sampaio et al. [14]		*		*				
Soto Setzke et al. [18]		*		*				
Steever et al. [17]	*			*			*	
Ulmer et al. [20]	*			*			*	
Zhang et al. [22]		*	*		*	*		
This paper	*	**	**	**	*	*	*	*

Note: “**” indicates that this paper also considers the generalization of the problem model, which is discussed in Section 3.4.

CHAPTER 3

PROBLEM DEFINITION

This chapter is split into four parts. The first one describes the problem of online food ordering services with crowdsourced couriers, including the required notations. The second part is about the problem assumptions. The third one explains the model formulation, and the fourth one highlights the remarks that concern the generalization of the problem model.

3.1 Problem Description

In this thesis, the main focus is on online food delivery platforms' operations. The problem is modeled as a one-to-one matching rolling horizon framework where the key decision is to match an order to a courier on time. Table 2 and Table 3 summarize the list of required problem notations.

The problem is defined on a service area $\mathcal{A} = (\mathcal{L}, \mathcal{D})$ that is already known to the platform, where $\mathcal{L}$ represents the node set for locations and $\mathcal{D}$ represents the arc set connecting the locations in unit distance. Let $\mathcal{L} = \mathcal{L}^R \cup \mathcal{L}^O \cup \mathcal{L}^C$ with $\mathcal{L}^R$ the set of restaurant locations, $\mathcal{L}^O$ the set of potential online order locations, and $\mathcal{L}^C$ the set of potential courier locations. Potential means that each location on the network may represent the delivery location for several placed orders and courier location for several available couriers. The travel time τ_{uv} between two locations $u, v \in \mathcal{L}$ is assumed to be deterministic. The service time at a restaurant is denoted by τ^R, while the service time at a customer is denoted by τ^O. The placement of online orders and the couriers joining time to the platform are assumed to follow Poisson processes with rate λ^O and λ^C, respectively. Let $\mathcal{N}^O$ and $\mathcal{N}^C$ represent the sets of actual online orders placed and available couriers (willing to deliver the orders) that arrive during the (planning) time horizon of length $|T|$.

Now, consider a time point t at every minute during the platform's operations T, where $t \in \{0, 1, 2, \dots, |T|\}$. At each decision point t^d, there are $m = |\mathcal{N}^C|$ couriers who are available to perform the deliveries and $n = |\mathcal{N}^O|$ orders placed by customers. For $i \in \{0, 1, 2, \dots, m\}$ and $j \in \{0, 1, 2, \dots, n\}$, the location of courier i is denoted by $u_i^C \in \mathcal{L}^C$, whereas order j is associated with both restaurant location (pickup location) $v_j^R \in \mathcal{L}^R$ and customer location (delivery location) $v_j^O \in \mathcal{L}^O$. For the sake of simplicity, the time index is not included in the notations although they are dependent on the decision point t^d. As of now, let τ_{ij} denote the total travel time between the locations associated with courier $i \in \mathcal{N}^C$ and online order $j \in \mathcal{N}^O$, including the time to a pickup location and from the pickup to the delivery location. Similarly, let d_{ij} represent the total distance between the locations related to the courier $i \in \mathcal{N}^C$ and the order $j \in \mathcal{N}^O$. The placement time of online order $j \in \mathcal{N}^O$ and the time at which courier $i \in \mathcal{N}^C$ joins the platform are denoted by t_j^O and t_i^C, respectively.

The delivery time promised by the platform is expressed by δ, which represents the maximum time between the time an order is placed and the time the order is delivered to the customer's location. Thus, online order $j \in \mathcal{N}^O$ has to be delivered by courier $i \in \mathcal{N}^C$ no later than $\rho_j^O = t_j^O + \delta$. Let $s_{ij} = t^d + \left(t^d - t_j^O\right) + \tau^R + \tau^O + \tau_{ij}$ denote the time at which order $j \in \mathcal{N}^O$ is delivered by courier $i \in \mathcal{N}^C$ and assigned at time t^d, referred to as service time. If $s_{ij} > \rho_j^O$, the customer experiences a delay.

Let θ represent the maximum time the courier is willing to wait for delivery assignment before leaving the platform. In addition, the willingness of courier $i \in \mathcal{N}^C$ to accept or reject order $j \in \mathcal{N}^O$ is captured by ω_{ij} that is a randomly generated number (takes either 0 or 1) and used as constraints in the model.

For the mode of transportation, it is assumed that cars are the only option that couriers can use. Therefore, the capacity of a courier's vehicle should not be a restriction since the problem only deals with restaurant meals, typically of small size. In other words, the courier's vehicle capacity restriction is assumed to be of less importance than the time restrictions.

Table 2 Sets and Parameters

$\mathcal{A}$	Service area with $\mathcal{L}$ set of locations and $\mathcal{D}$ set of arcs, $\mathcal{A} = (\mathcal{L}, \mathcal{D})$
$\mathcal{L}^R$	Set of restaurant locations, $\mathcal{L}^R \subseteq \mathcal{L}$
$\mathcal{L}^O$	Set of potential online order locations, $\mathcal{L}^O \subseteq \mathcal{L}$
$\mathcal{L}^C$	Set of potential courier locations, $\mathcal{L}^C \subseteq \mathcal{L}$
τ^R	Service time at a restaurant
τ^O	Service time at a customer
λ^O	Placement rate of online orders per minute
λ^C	Availability rate of couriers per minute
T	Platform's (service time) planning time, $T = \{0, 1, 2, \dots, \|T\|\}$
t	Time points during T
t^d	Decision point in time
φ	Time between two consecutive decision points t^d
m	Number of available couriers at time t^d, $m = \|\mathcal{N}^C\|$

n	Number of placed orders at time t^d, $n = \lvert\mathcal{N}^O\rvert$
u_i^C	Location of courier i, $i \in \{0, 1, 2, \dots, m\}$ and $u_i^C \in \mathcal{L}^C$
v_j^R	Pickup location of order j, $j \in \{0, 1, 2, \dots, n\}$ and $v_j^R \in \mathcal{L}^R$
v_j^O	Delivery location of order j, $j \in \{0, 1, 2, \dots, n\}$ and $v_j^O \in \mathcal{L}^O$
τ_{ij}	Total travel time between locations related to courier $i \in \mathcal{N}^C$ and online order $j \in \mathcal{N}^O$
d_{ij}	Total distance between locations related to courier $i \in \mathcal{N}^C$ and online order $j \in \mathcal{N}^O$
t_j^O	Placement time of online order $j \in \mathcal{N}^O$
t_i^C	Time at which courier $i \in \mathcal{N}^C$ joins the platform
s_{ij}	Service time for order $j \in \mathcal{N}^O$ delivered by courier $i \in \mathcal{N}^C$ at time t^d, $s_{ij} = t^d + \left(t^d - t_j^O\right) + \tau^R + \tau^O + \tau_{ij}$
δ	Promised service window time by the platform
ρ_j^O	Promised delivery time by the platform for order $j \in \mathcal{N}^O$, $\rho_j^O = t_j^O + \delta$
θ	Courier's maximum time to wait for a delivery order
ω_{ij}	Willingness of courier $i \in \mathcal{N}^C$ to accept order $j \in \mathcal{N}^O$ (binary parameter)
d_{ij}^{MP}	Travel distance for the meal pickup stage
d_j^{MD}	Travel distance for the meal delivery stage
τ_{ij}^{MP}	Travel time for the meal pickup stage
τ_j^{MD}	Travel time for the meal delivery stage
c^F	Fixed compensation paid to courier $i \in \mathcal{N}^C$ for delivering order $j \in \mathcal{N}^O$
c^V	Variable compensation per unit distance
c_{ij}	Total compensation for order $j \in \mathcal{N}^O$ delivered by courier $i \in \mathcal{N}^C$
p	Penalty per unit time
ε^{max}	Upper bound of the allowable delay time ε_{ij}

Table 3 Decision Variables

x_{ij}	Decision variable for the matching of courier $i \in \mathcal{N}^C$ to order $j \in \mathcal{N}^O$ at time t^d
ε_{ij}	Decision variable for the allowable delay time experienced by the customer of order $j \in \mathcal{N}^O$ delivered by courier $i \in \mathcal{N}^C$ at time t^d

3.2 Assumptions

The problem entails the following assumptions:

- The service area $\mathcal{A}$ is known to the platform;
- Each potential location in the service area may represent the delivery location for several placed orders and courier location for several available couriers;
- The travel time τ_{ij} is assumed to be deterministic (the uncertain travel time is analyzed in the computational study);
- The service time at a restaurant τ^R and the service time at a customer τ^O are assumed to be known;
- The placement of online orders and the availability of couriers are assumed to follow Poisson processes with rate λ^O and λ^C, respectively;
- The decision point is considered to be greater than or equal to the placement time of the online order $j \in \mathcal{N}^O$ $\left(t^d \geq t_j^O\right)$;
- The decision point is considered to be greater than or equal to the joint time of courier $i \in \mathcal{N}^C$ $\left(t^d \geq t_i^C\right)$;
- The willingness of courier $i \in \mathcal{N}^C$ to accept or reject order $j \in \mathcal{N}^O$ is assumed to be uncertain and captured by ω_{ij};

- The joint couriers are considered to be able to wait for a certain time θ while the placed orders are assumed to be expired by the decision point t^d;
- The delivery time promised by the platform δ is global for all customers;
- The capacity of a courier's vehicle is not a restriction since cars are the only option that couriers can use;
- The function of the delivery cost c_{ij}, Equation (1), depends on the served orders and does not penalize the unserved ones.

3.3 Model

Given the courier input information $\left(t_i^C, u_i^C\right)$ and delivery order inputs $\left(t_j^O, v_j^R, v_j^O\right)$, for $i \in \{0, 1, 2, \dots, m\}$ and $j \in \{0, 1, 2, \dots, n\}$, at the decision point t^d, the problem becomes how to best determine the matching between couriers and orders. The model objective is to minimize the total delivery cost, which is proportional to the distance traveled by the couriers for the orders. Besides, the model minimizes the total delay time that is allowable to be experienced by the customers for the delivered orders. Before solving the model, the delivery cost is first determined. There are two possible position relationships between the locations of couriers and delivery orders, as illustrated in Figure 3.

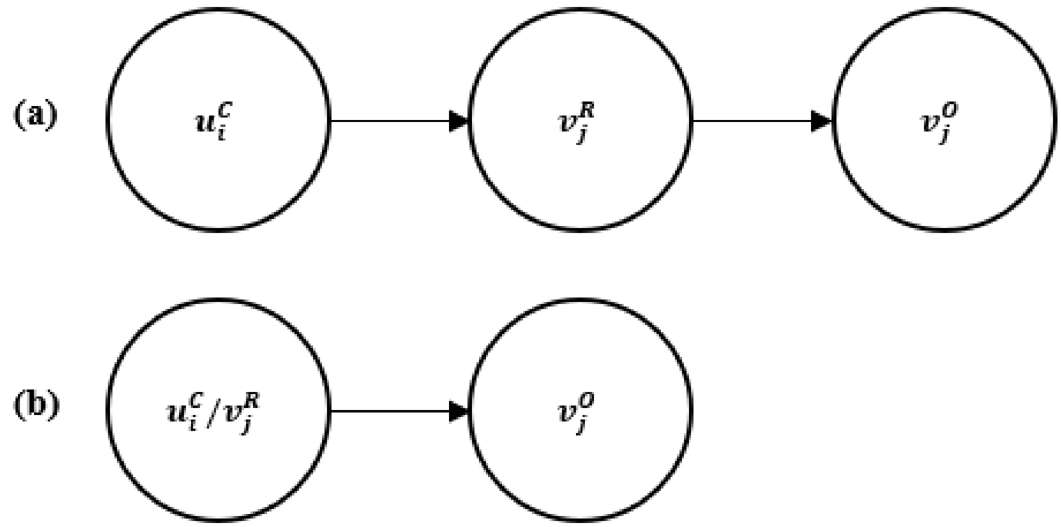

Figure 3 (a) Different Locations for the Courier and Order Pickup Point and (b) Same Location for the Courier and Order Pickup Point

In Figure 3 (a), the courier should first arrive at the location of the delivery order (restaurant) and pick it up. Then, the order should be delivered to the customer. Figure 3 (b) shows that the courier picks up the order from the same location and delivers it to the customer.

Accordingly, these two possibilities show that the process of meal delivery orders performed by the crowdsourced couriers can be split into two transportation stages. The first one is the pickup stage, from the courier's location to the order pickup (restaurant) location. The second stage is the delivery stage, from the pickup order's location to the customer's location. After completing the assigned order, a courier will either receive a new order to deliver or exit the platform.

In each transportation stage, the distance of each courier completing each delivery order can be obtained. Let d_{ij}^{MP} and d_j^{MD} represent the transportation distances that courier $i \in \mathcal{N}^C$ preforms for delivery order $j \in \mathcal{N}^O$ in the two transportation stages: The meal pickup and the meal delivery, respectively. Thus, the total distance between locations related to the courier and the order $d_{ij} = d_{ij}^{MP} + d_j^{MD}$. From the distance, the total travel time between locations associated with the courier and the order can be calculated as follows: $\tau_{ij} = \tau_{ij}^{MP} + \tau_j^{MD}$. Explicitly, the total travel time is obtained through dividing the calculated total distance by the considered speed of vehicles.

The compensation to couriers is assumed to include two components. The first one, denoted by c^F, represents the fixed compensation paid to courier $i \in \mathcal{N}^C$ for delivering order $j \in \mathcal{N}^O$. The second component, denoted by c^V, is the variable compensation that is proportional to the distance unit traveled by courier $i \in \mathcal{N}^C$ for delivering order $j \in \mathcal{N}^O$ (Zhang et al. [22]). Thus, the compensation for order $j \in \mathcal{N}^O$ delivered by courier $i \in \mathcal{N}^C$ is expressed by:

$$c_{ij} = c^F + c^V \left(d_{ij}\right) \tag{1}$$

After determining the delivery cost, the matching model can be developed. Let x_{ij} represent the decision variable for matching courier $i \in \mathcal{N}^C$ and delivery order $j \in \mathcal{N}^O$ at the decision point t^d where $x_{ij} = 1$ means that courier $i \in \mathcal{N}^C$ is matched with the delivery order $j \in \mathcal{N}^O$; otherwise, $x_{ij} = 0$. Let ε_{ij} denote the delay time experienced by the customer of order $j \in \mathcal{N}^O$, which should not exceed ε^{max}. Let p represent the penalty per unit time due to the delay associated with delivering to the customer beyond the promised time ρ_j^O. The model at the time point t^d can be represented as:

$$\text{Min} \qquad \sum_{i=1}^{m}\sum_{j=1}^{n} c_{ij}x_{ij} + p\sum_{i=1}^{m}\sum_{j=1}^{n} \varepsilon_{ij} \tag{2}$$

$$s.t. \qquad \sum_{j=1}^{n} x_{ij} \leq 1, \forall i \in \mathcal{N}^C \tag{3}$$

$$\sum_{i=1}^{m} x_{ij} = 1, \forall j \in \mathcal{N}^O \tag{4}$$

$$\left(t^d + \left(t^d - t_j^O\right) + \tau^R + \tau^O + \tau_{ij}\right)x_{ij} \leq \rho_j^O + \varepsilon_{ij}, \forall i \in \mathcal{N}^C, j \in \mathcal{N}^O \tag{5}$$

$$\varepsilon_{ij} \leq \varepsilon^{max}x_{ij}, \forall i \in \mathcal{N}^C, j \in \mathcal{N}^O \tag{6}$$

$$x_{ij} \leq \omega_{ij}, \forall i \in \mathcal{N}^C, j \in \mathcal{N}^O \tag{7}$$

$$x_{ij} \in \{0,1\}, \forall i \in \mathcal{N}^C, j \in \mathcal{N}^O \tag{8}$$

$$\varepsilon_{ij} \geq 0, \forall i \in \mathcal{N}^C, j \in \mathcal{N}^O \tag{9}$$

Equation (2) is the objective function that minimizes the sum of the delivery costs of the matching between m couriers and n delivery orders at the decision point t^d along with minimizing the total of the penalized delay time. Constraints (3) guarantee that each courier $i \in \mathcal{N}^C$ completes no more than one delivery order. Constraints (4) ensure that each delivery order $j \in \mathcal{N}^O$ is matched with only one of the m couriers. Constraints (5) state that delivery must be delivered before the promised time ρ_j^O (plus a penalized delay time ε_{ij}) if courier $i \in \mathcal{N}^C$ is assigned to deliver online order $j \in \mathcal{N}^O$. Constraints (6) represent the upper bound ε^{max} for the allowable delay time ε_{ij}. Constraints (7) ensure that the willingness ω_{ij} (acceptance behavior) of courier $i \in \mathcal{N}^C$ for order $j \in \mathcal{N}^O$ is captured by the model. Constraints (8) and Constraints (9) define the restriction domains for the decision variables, x_{ij} and ε_{ij}, respectively.

3.4 Remarks

In this research, the model focuses on the online food ordering services (restaurant meal delivery) with crowdsourced couriers (occasional couriers). However, it can be generalized to consider any type of goods delivery and different types of couriers. In the subject model, Constraints (5) and Constraints (6) can be modified to fit the time requirements of the studied goods type (e.g., grocery items). Also, if the capacity of the studied items is significant, a constraint should be added to the model. In addition, if the committed couriers are assumed instead of the occasional couriers, Constraints (7) would not be required due to the certain couriers' acceptance behavior. Similarly, if the fully committed couriers are used by the platform, Constraints (7) would not be required, along with relaxing the uncertainty assumption for the couriers' availability to be deterministic but still dynamic.

CHAPTER 4

SOLUTION APPROACH

The subject problem is clearly NP-hard since it is known to be a version of the PDP, which is an extension of the VRP. Besides that, the problem is defined to be dynamic and stochastic in nature. The survey, developed by Rios et al. [13], shows that heuristics techniques are the solution approach for the majority of the VRPs, feature with dynamism and stochasticity. The main reason for such a preference is that they are computationally fast and provide simple rules, generating solutions of good quality, such as re-optimization techniques.

A rolling horizon method is introduced in this chapter to match crowdsourced couriers to online food orders dynamically based on the model proposed in the previous chapter. Generally, the rolling method is considered an effective technique for decision-making in dynamic settings. By optimizing decisions based on the information at the current time and repeating the process when the information is revealed, the rolling horizon method can successfully diminish the problems' complexity (Rios et al. [13] and Zhang et al. [22]). Therefore, it is selected to be the solution procedure for the problem presented in this research.

Figure 4 clearly explains the main idea of the rolling horizon method. It can be seen from the pseudocode that the procedure is split into four key steps that are repeated at each decision point t^d. A brief description of each one is as follows:

Step 1: Confirm the information of currently available couriers $\left(t_i^C, u_i^C\right)$ and placed delivery orders $\left(t_j^O, v_j^R, v_j^O\right)$, for $i \in \{0, 1, 2, \dots, m\}$ and $j \in \{0, 1, 2, \dots, n\}$;

Step 2: Based on the proposed model, determine the matching decisions between the couriers and the delivery orders;

Step 3: If part of the couriers has not been assigned to the delivery orders and still willing to wait for an assignment (not exceeding the couriers' waiting time θ), then they are kept for the next decision point t^d in Step 1; otherwise, go to Step 4;

Step 4: Delete the assigned couriers and all delivery orders that have been assigned or not (the order not assigned is considered unserved), and go to Step 1 for the next decision point t^d.

According to the proposed rolling procedure, the problem model is solved periodically. Meaning that the procedure repeats at every decision point t^d till the end of the time horizon defined by the platform T.

```
Data: The defined service area (either A1 or A2 or A3) and the interaction rate (either Rate1
      or Rate2 or Rate3)
Result: Delivery Cost, Delay Cost, Total Cost, Served Orders, Unserved Orders, Service
        Level, and Time per Decision Point (as the average of 60 instances)
repeat
    while ϕ = 5 minutes; ϕ <= 960 minutes; ϕ + 5 minutes do
        while i = ϕ - 5; i < ϕ; i + 5 do
            t^d = i + 4
            for t = i; t <= t^d; t + 1 do
                Step 1: Confirm the information of currently available couriers and placed
                  delivery orders
            end
        end
        Step 2: Determine the matching decisions between the couriers and the delivery
          orders (based on the model in Section 3.3)
        Step 3: Capture the unassigned couriers (not exceeding their waiting time θ)
        Step 4: Delete the used information for the next decision point t^d
    end
    return the results for one instance
until 60 instances;
return the Result
```

Figure 4 Pseudocode of the rolling horizon procedure

CHAPTER 5

COMPUTATIONAL STUDY

A series of computational experiments is conducted to show some key insights of the problem. First, a description of how the instances are generated is presented. After that, their results using the solution approach are shown. Then, comparative and complexity analyses are conducted. Finally, a sensitivity analysis of the problem characteristics is provided.

5.1 Problem Instances

A set of instances consisting of several instance classes are generated. Each class of the instances is categorized by a service area and an interaction rate (between couriers' availability and online orders' placement). This section considers three service areas and three interaction rates. For each of the nine instance classes, 60 instances are generated, which results in a total of 540 instances. Given a 95% confidence interval, this number of instances gives the desired level of accuracy within 1%. Before solving each instance, the parameters are set to the following values:

- Platform's service time: $T = 960$ minutes,
- Time between two consecutive decision points t^d: $\varphi = 5$ minutes,
- Promised service time by the platform: $\delta = 30$ minutes,
- Couriers' maximum time to wait for a delivery order: $\theta = 30$ minutes,
- Allowable delay time: $\varepsilon^{max} = 5$ minutes,

- Service time at a restaurant: $\tau^R = 5$ minutes,
- Service time at a customer: $\tau^O = 2$ minutes,
- Fixed compensation paid to a courier: $c^F = \$2$,
- Variable compensation per unit distance (kilometer): $c^V = \$1$,
- Penalty per minute: $p = \$3$, and
- Couriers' acceptance behavior: ω_{ij} is based on 75% ($Pr(\omega_{ij} = 1) = 0.75$).

A service area $\mathcal{A}$ consists of 50 restaurants, 100 potential locations for crowdsourced couriers, and 100 potential locations for online food orders. These locations are located randomly in 10 x 10 square kilometers area. This is true for the three predefined service areas, referred to as $\mathcal{A}1$, $\mathcal{A}2$, and $\mathcal{A}3$. For restaurants, they are randomly located in the area's center to give accessibility to all potential locations for online orders. That is, based on the 10 x 10 grid's center, the restaurants are uniformly located within a disk of 1 kilometer radius. Thus, the orders' potential locations are randomly located with respect to the restaurants, following a normal distribution distance with a mean zero and standard deviation of 2 kilometers (Ulmer et al. [21]), which means the number of customers lessens with the distance to restaurants. This makes sense if the ordering customers' needs (fast delivery and food freshness) are considered. Figure 5, Figure 6, and Figure 7 illustrate the three service areas: $\mathcal{A}1$, $\mathcal{A}2$, and $\mathcal{A}3$, respectively. The circle, in red color, is for restaurants, while the square, in green color, is for customers. The couriers' potential locations are represented by the triangle that is in blue color.

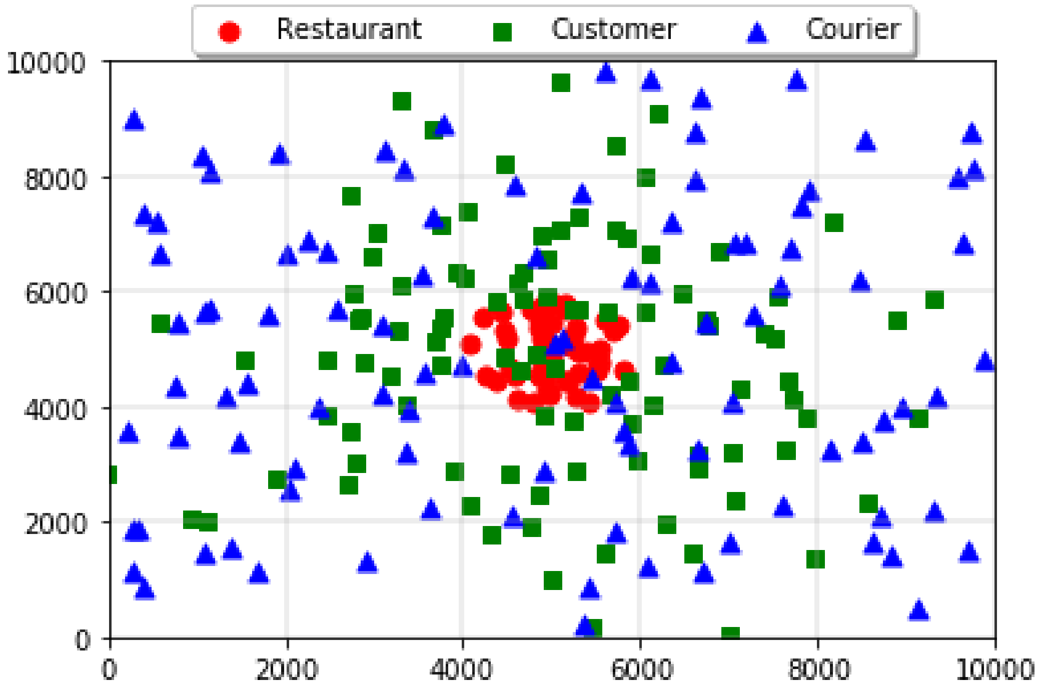

Figure 5 Service Area 1

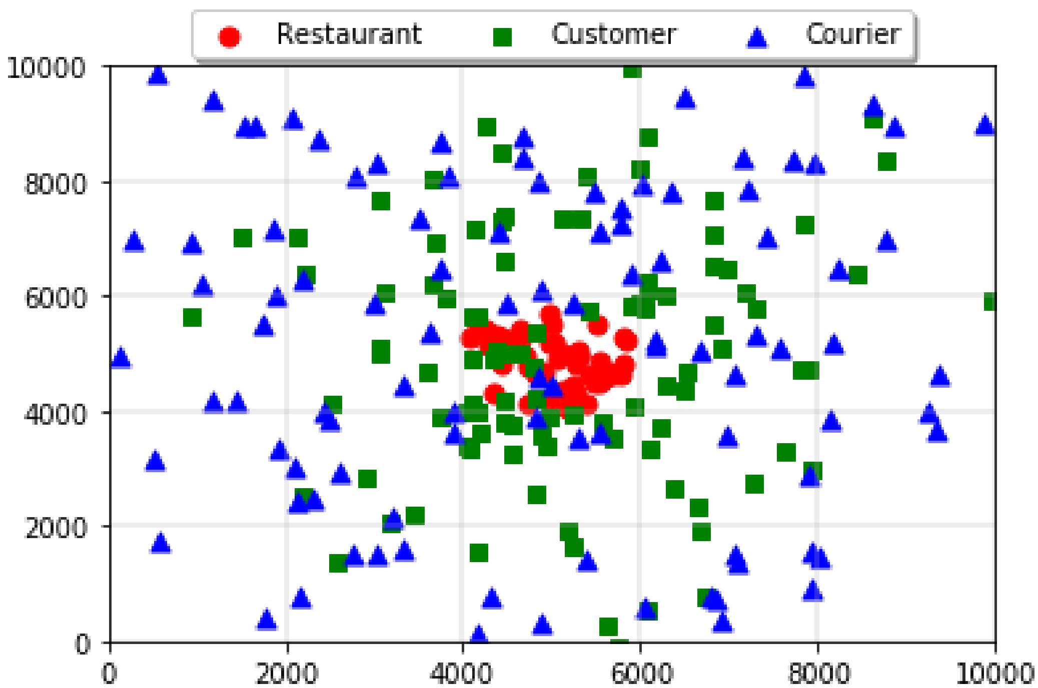

Figure 6 Service Area 2

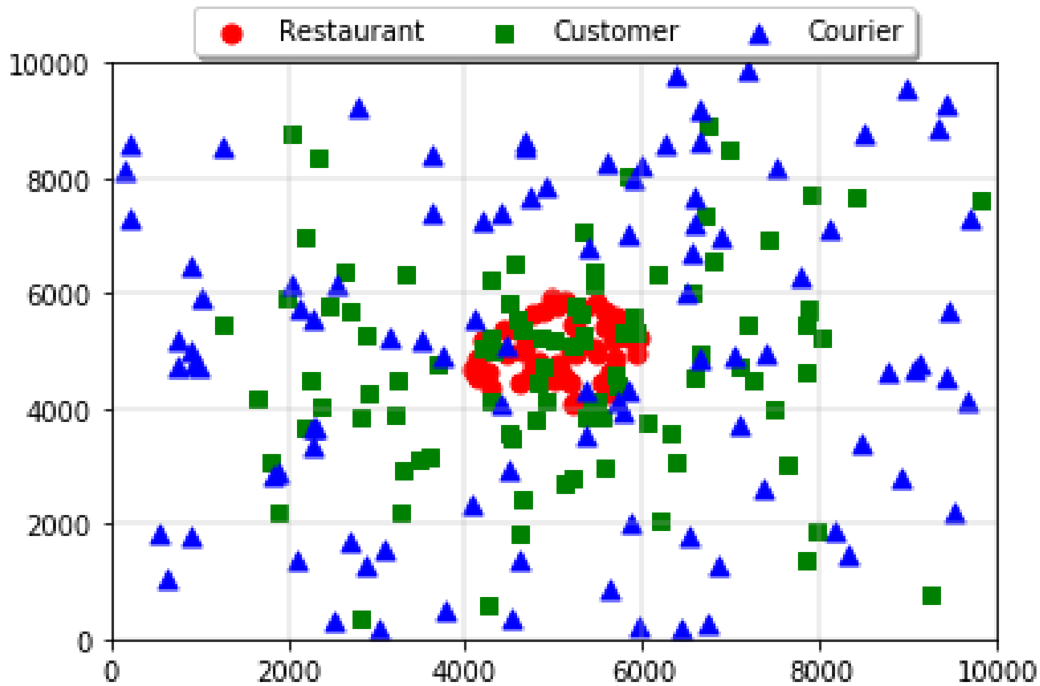

Figure 7 Service Area 3

It should be noted that the distances between locations are obtained by multiplying the Euclidean distances by a delay factor of 1.4 to mimic a street network. For the speed of vehicles, it is assumed to be 25 kilometers per hour (Ulmer et al. [21]).

As mentioned earlier, the couriers' availability rate and the orders' placement rate follow independently Poisson processes with λ^C and λ^O, respectively. The interaction between the rates is considered to study better the platform's behavior (Dayarian and Savelsbergh [6]). That is, an interaction rate is equal to λ^C/λ^O. The three predefined interaction rates are 0.75, 1, and 1.25. They are referred to as*: Rate1*, *Rate2*, and *Rate3*, respectively. Simply, an instance class is a match between one of the three service areas and one of the three interaction rates.

The platform's time horizon T is assumed to be 960 minutes. Following Poisson processes, arrivals of online food orders are modeled as a combination of five arrival streams with different rates. The first and third streams are for 180 minutes with an arrival rate of 1 order per minute. The second and fourth streams are for 240 minutes with an arrival rate of 2 orders per minute (representing lunch and dinner times). The last stream is for 120 minutes with an arrival rate of 1 order per minute. Figure 8 shows the pattern of the daily placed orders.

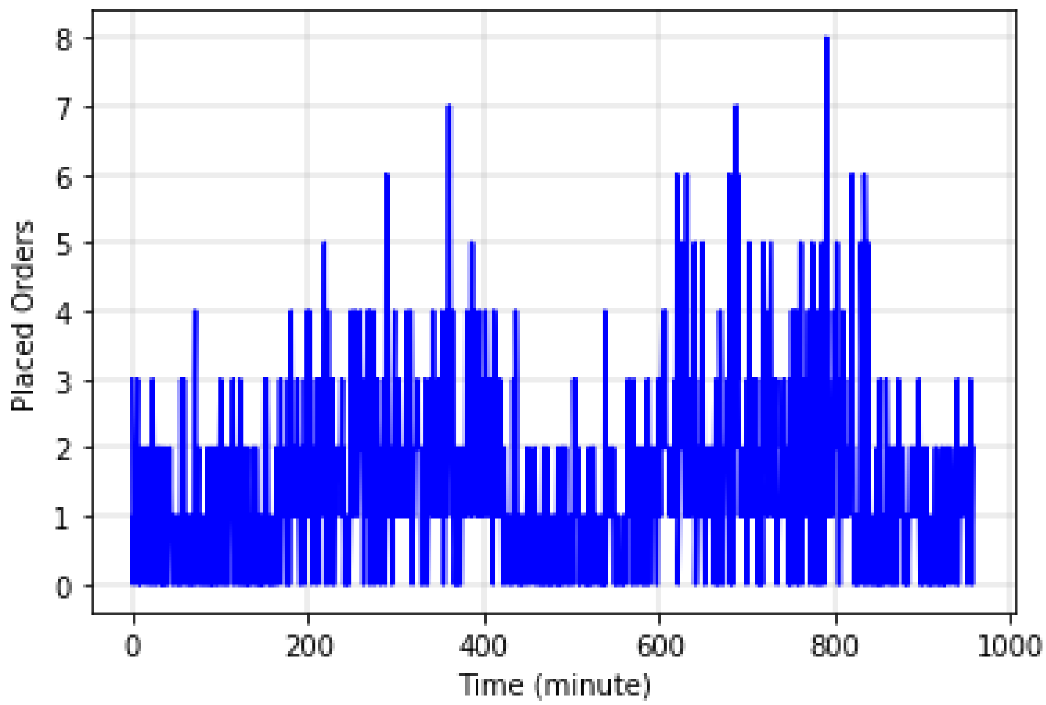

Figure 8 Daily Placed Orders Pattern

Similarly, arrivals of crowdsourced couriers are modeled. Figure 9, Figure 10, and Figure 11 illustrate the pattern of the active daily couriers for the three interaction rates: *Rate1*, *Rate2*, and *Rate3*, respectively.

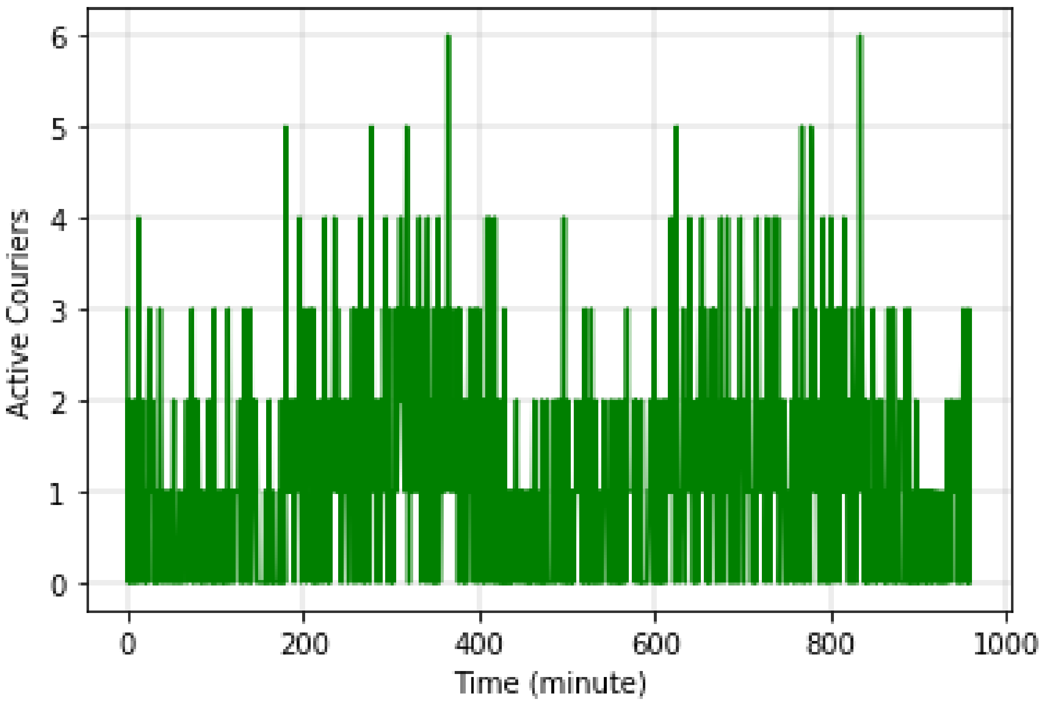

Figure 9 Daily Active Couriers Pattern (for *Rate1*)

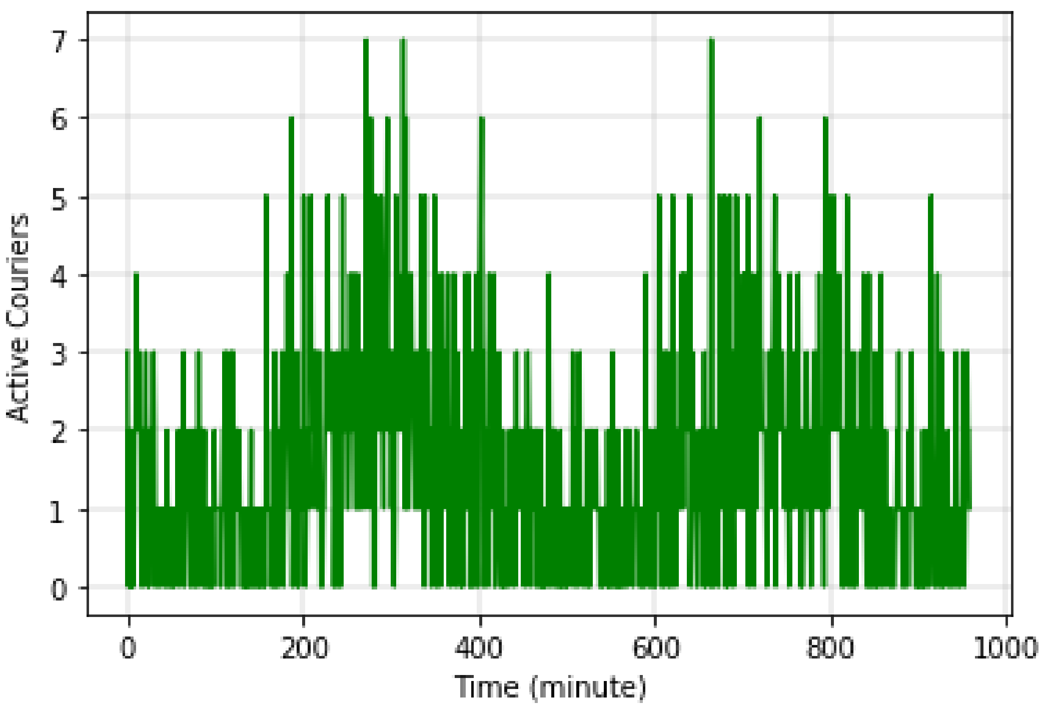

Figure 10 Daily Active Couriers Pattern (for *Rate2*)

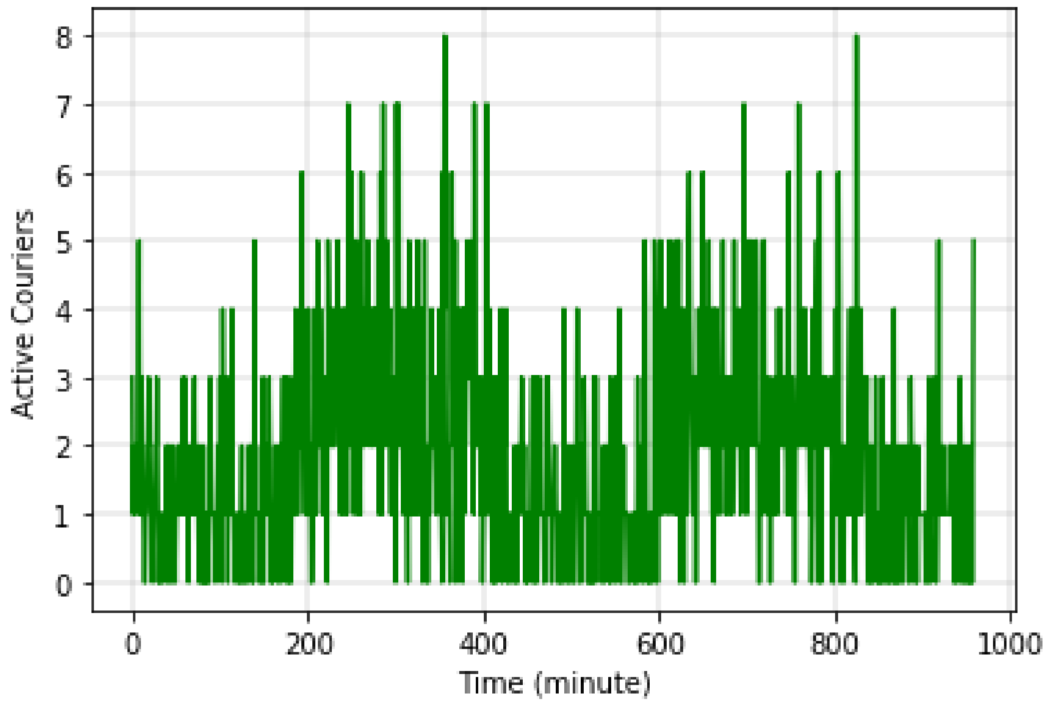

Figure 11 Daily Active Couriers Pattern (for *Rate3*)

5.2 Problem Results

The solution approach is implemented in PYTHON. GUROBI is used as the optimization solver. It is worth mentioning that the model may result in infeasible solutions due to Constraints (4) which dictate the number of crowdsourced couriers must be at least equal to the number of online orders. In such a case, the used optimization solver relaxes the feasibility of the model to avoid receiving infeasible solutions. This was done using $Model.feasRelaxS(\,)$ from GUROBI. This consideration on top reflects what is done in practice since the online orders require instant delivery service.

Table 4 summarizes the results obtained for the different instances for the proposed approach. Each line of the table represents one of the instance classes. It corresponds to the average of over 60 different instances (except the Average lines reflect the average of the three areas for one interaction rate and the overall average). The results are analyzed based on the following performance metrics:

- *Delivery Cost*: The total compensation paid to crowdsourced couriers,
- *Delay Cost*: The total penalized delivery delay experienced by ordering customers,
- *Total Cost*: The sum of the *Delivery Cost* and the *Delay Cost*,
- *Served Orders*: The total number of ordering customers served during the platform's service time,
- *Unserved Orders*: The total number of ordering customers could not be served during the decision epoch φ due to a shortage in the available number of crowdsourced couriers for the whole service time of the platform,
- *Service Level (as a percentage)*: The fraction of ordering customers served during the platform's service time compared to the total ordering customers, and
- *Time per Decision Point (second)*: The average time required per decision point t^d for an instance for the selected approach.

It can be seen from the results that Service Area 1 always indicates higher *Total Cost* compared to the other service areas for all interaction rates. Particularly, the highest increase among the cost metrics comes from the *Delay Cost*. Basically, this reflects an important fact that the random locations in Service Area 1 are more scattered compared to the ones in Service Area 2 and Service Area 3, regardless of crowdsourced couriers' availability. Consequently, this negatively influences its *Served Orders*, which generally leads to less *Service Level* compared to the other service areas.

Table 4 Problem Results

		Delivery Cost	*Delay Cost*	*Total Cost*	*Served Orders*	*Unserved Orders*	*Service Level*	*Time per Decision Point*
Rate1	**$\mathcal{A}$1**	10089.02	3695.12	13784.14	1029.62	364.38	73.86	0.0256
	$\mathcal{A}$2	9842.23	2827.51	12669.74	1040.70	353.30	74.66	0.0264
	$\mathcal{A}$3	9745.14	2759.44	12504.58	1037.07	356.93	74.40	0.0318
	Average	**9892.13**	**3094.02**	**12986.15**	**1035.80**	**358.20**	**74.30**	**0.0279**
Rate2	**$\mathcal{A}$1**	11852.37	4190.03	16042.40	1223.20	170.80	87.75	0.0488
	$\mathcal{A}$2	11713.31	3396.74	15110.05	1247.70	146.30	89.51	0.0458
	$\mathcal{A}$3	11457.98	3242.38	14700.36	1232.15	161.85	88.39	0.0471
	Average	**11674.55**	**3609.72**	**15284.27**	**1234.35**	**159.65**	**88.55**	**0.0472**
Rate3	**$\mathcal{A}$1**	12289.29	3672.54	15961.83	1307.63	86.37	93.80	0.0664
	$\mathcal{A}$2	12137.63	3023.36	15161.00	1331.13	62.87	95.49	0.0640
	$\mathcal{A}$3	11761.39	2864.20	14625.59	1303.67	90.33	93.52	0.0665
	Average	**12062.77**	**3186.70**	**15249.47**	**1314.14**	**79.86**	**94.27**	**0.0656**
Average		**11209.82**	**3296.81**	**14506.63**	**1194.76**	**199.24**	**85.71**	**0.0469**

Moreover, the results show that when more crowdsourced couriers are available during the platform's time horizon, a higher number of ordering customers is served. For example, comparing 1035.80, 1234.35, and 15249.47 for *Rate1*, *Rate2*, and *Rate3*, respectively. Thus, the *Service Level* of the platform gets higher. As expected, with a higher *Service Level*, the *Delivery Cost* gets higher as well since it is proportional to the total number of *Served Orders*.

For the sake of comparison, a static approach is introduced. It assumes that all information required by the platform is known in advance. Meaning that one decision point t^d is required for serving all ordering customers, according to the platform's service time T.

Table 5 reports the results of the static approach. It follows the same framework of Table 4.

Table 5 Static Approach Results

		Delivery Cost	***Delay Cost***	***Total Cost***	***Served Orders***	***Unserved Orders***	***Service Level***	***Time per Decision Point***
Rate1	$\mathcal{A}\mathbf{1}$	10017.15	0.010	10017.16	1087	307	77.98	2539.559
	$\mathcal{A}\mathbf{2}$	9688.47	0	9688.47	1087	307	77.98	1477.624
	$\mathcal{A}\mathbf{3}$	9532.94	0	9532.94	1087	307	77.98	1933.748
	Average	**9746.19**	**0.0033**	**9746.19**	**1087**	**307**	**77.98**	**1983.644**
Rate2	$\mathcal{A}\mathbf{1}$	13689.50	1.79	13691.29	1394	0	100	891.859
	$\mathcal{A}\mathbf{2}$	13220.19	0	13220.19	1394	0	100	1443.282
	$\mathcal{A}\mathbf{3}$	13055.20	40.44	13095.64	1394	0	100	944.015
	Average	**13321.63**	**14.08**	**13335.71**	**1394**	**0**	**100**	**1093.052**
Rate3	$\mathcal{A}\mathbf{1}$	12705.02	3.77	12708.79	1394	0	100	1808.955
	$\mathcal{A}\mathbf{2}$	12498.40	0.01	12498.41	1394	0	100	1381.211
	$\mathcal{A}\mathbf{3}$	12155.30	42.69	12197.99	1394	0	100	1585.995
	Average	**12452.91**	**15.49**	**12468.40**	**1394**	**0**	**100**	**1592.054**
Average		**11840.24**	**9.86**	**11850.10**	**1291.67**	**102.33**	**92.66**	**1556.25**

Comparing the results for the two approaches in Table 4 and Table 5, generally, the static approach shows that all customers can be served without the need of the allowable delay ε_{ij}, designed by the model. This results in 99.70% reduction in the *Delay Cost* while the *Delivery Cost* is almost maintained. Mainly, this is due to the assumption that receives all information required by the platform in advance and only requires one decision point t^d to match orders to couriers. Obviously, this augments the problem's size, which leads to the increase in the difficulty of the problem. It can be seen from the results that the increase in the *Time per Decision Point* is significant compared to the proposed approach. In addition, the static approach does not reflect the context of the subject problem, where the required information arrives over time (dynamically). Accordingly, the proposed approach is much better when it comes to the evolution of information and the quality of decision-making process.

5.3 Complexity Analysis

This section aims to study the complexity of the problem. To start, Service Area 2 and *Rate2* are selected to be the base for this analysis. A one hundred (100) increase is considered for the potential locations for the ordering customers and the crowdsourced couriers. The range is from 100 to 500 potential locations. Consequently, the arrival rates, λ^O and λ^C, are doubled (starting from 1 arrival per minute) for each one of the increments considered for the number of potential locations. For instance, 100, 200, …, and 500 are the number of potential locations. Then, the arrival rates are 1, 2, …, and 16, respectively. The problem size is captured by the average number of variables and constraints per decision point t^d for an instance. Their general formulas can be represented by $2mn$ and $m + n + 5mn$, respectively. Where m is the number of available couriers at time t^d, $m = |\mathcal{N}^C|$, and n is the number of placed orders at time t^d, $n = |\mathcal{N}^O|$.

Table 6 illustrates the results of the problem complexity. The results are summarized in terms of the average runtime, number of variables, and number of constraints (per decision point t^d for an instance). As expected, the outcomes increase as the problem size enlarges due to the nature of the problem. As explained earlier, it is classified as an NP-hard problem.

Table 6 Complexity Results

	Number of Potential Locations				
	100	**200**	**300**	**400**	**500**
Time per Decision Point	0.0458	0.1557	0.5485	2.2366	12.3661
Number of Variables per Decision Point	98	392	1682	6962	28800
Number of Constraints per Decision Point	259	1008	4263	17523	72240

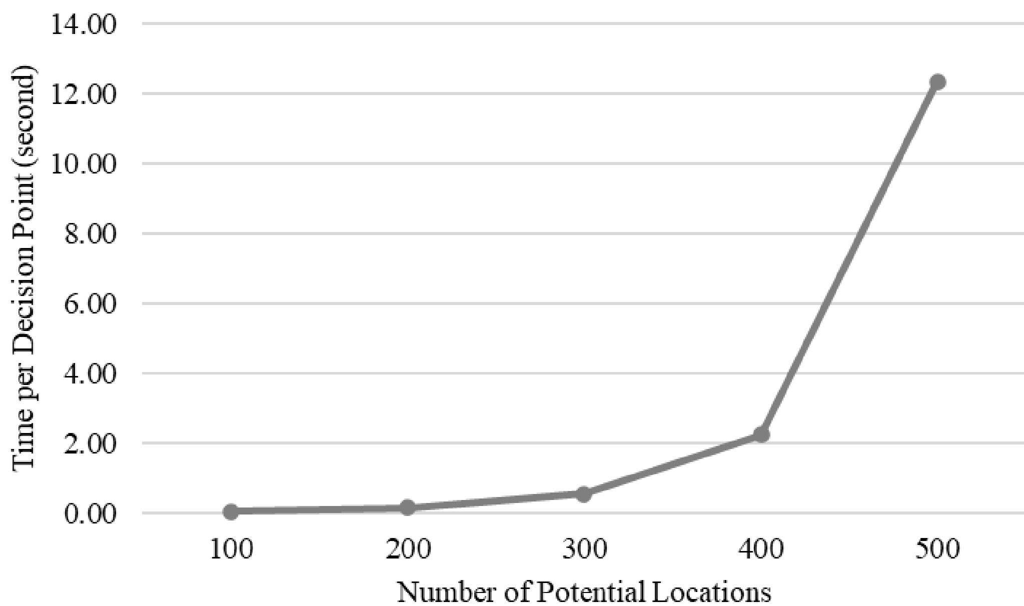

Figure 12 Runtime versus problem's size

Figure 12 demonstrates an exponential increase for the average runtime, *Time per Decision Point*, as function of the number of potential locations and the arrival rates, λ^O and λ^C. To maintain the accuracy and instant delivery service nature of the problem, the average runtime should not exceed one second. Based on our experiments, when the problem size is within 300 potential locations, the proposed solution approach would be more practical. Also, this is in line with the practice if a Service Area is considered to be a zone in a city.

5.4 Sensitivity Analysis to Problem Characteristics

This section aims to provide insights regarding the problem sensitivity to the main input parameters: the acceptance behavior of crowdsourced couriers, the waiting time of crowdsourced couriers, the frequency of decision-making, the promised service time, and the uncertain travel time.

5.4.1 The Impact of Crowdsourced Couriers' Acceptance Behavior ($\boldsymbol{\omega_{ij}}$)

This subsection studies the impact of the acceptance behavior of the crowdsourced couriers on the platform's performance. It considers the outcomes of ω_{ij} for three levels: 100% acceptance, 75% acceptance, and 50% acceptance. Table 7, Table 8, and Table 9 are shown in the Appendix for details. They display the results when the crowdsourced couriers' acceptance behavior changes according to the three levels.

Figure 13 and Figure 14 illustrate the effect of the couriers' acceptance behavior on the platform's performance. Specifically, the *Delay Cost* increases as the uncertainty level of couriers' behavior increases (as demonstrated in Figure 13), whereas the *Service Level* of the platform decreases (as shown in Figure 14). The increase of the *Delay Cost* and the decrease of the *Service Level* are much smaller than the decrease in the couriers' willingness to accept orders for delivery service. The main reason for the increase of the *Delay Cost* and the decrease of the *Service Level* is that the presence of the uncertainty in couriers' acceptance behavior limits the model to best select orders (within the promised service time) and to serve more orders.

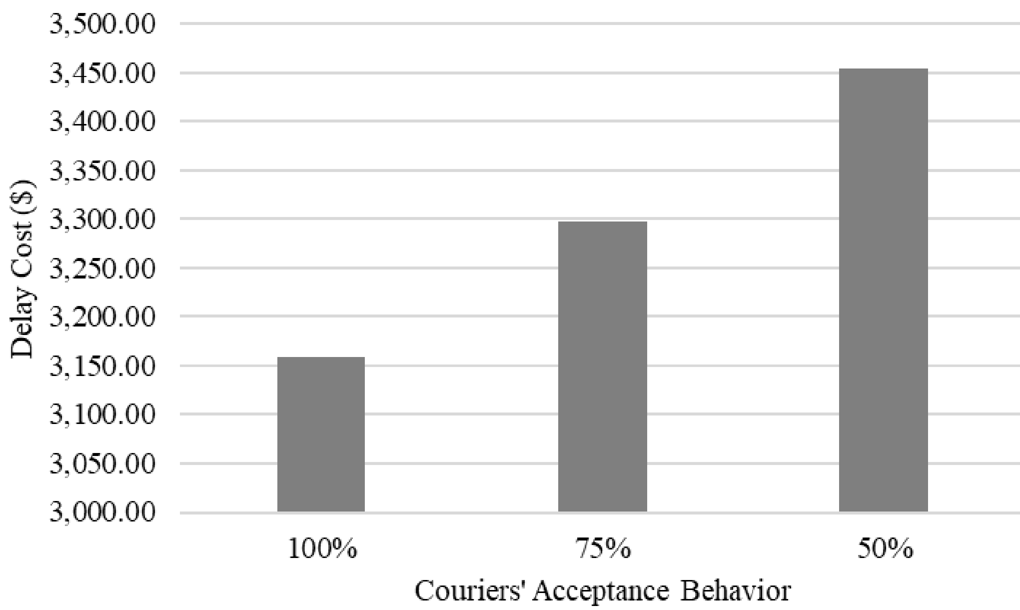

Figure 13 Average Delay Cost as Function of Couriers' Acceptance Behavior

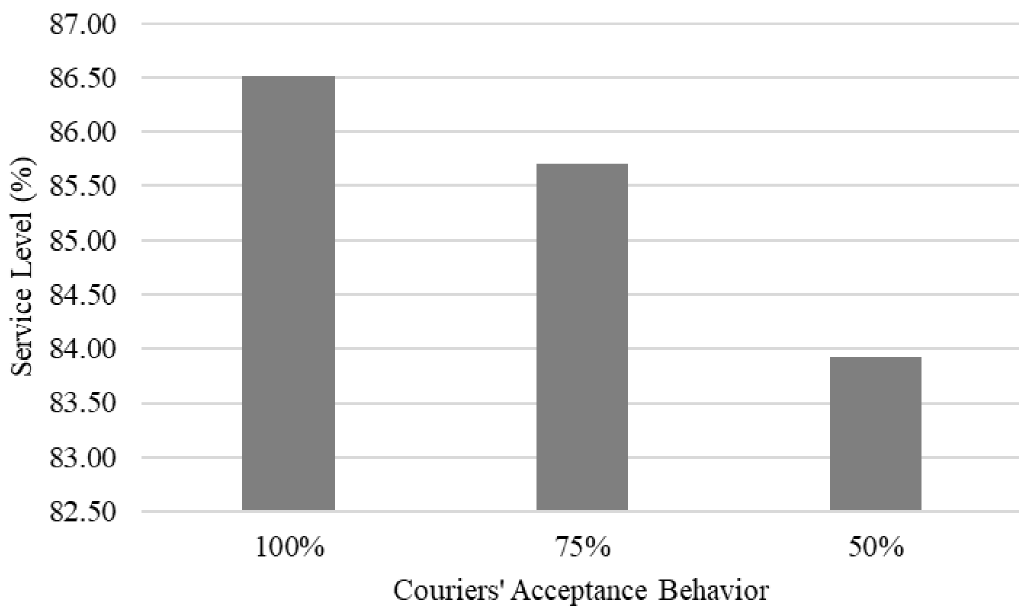

Figure 14 Average Service Level as Function of Couriers' Acceptance Behavior

5.4.2 The Impact of Crowdsourced Couriers' Waiting Time ($\boldsymbol{\theta}$)

The impact of the crowdsourced couriers' waiting time for delivery assignment is analyzed in this subsection. Three value levels of the crowdsourced couriers' waiting time are considered (15 minutes, 30 minutes, and 45 minutes). Table 10, Table 11, and Table 12 are shown in the Appendix for details. They represent the results when the crowdsourced couriers' waiting time varies according to the three levels.

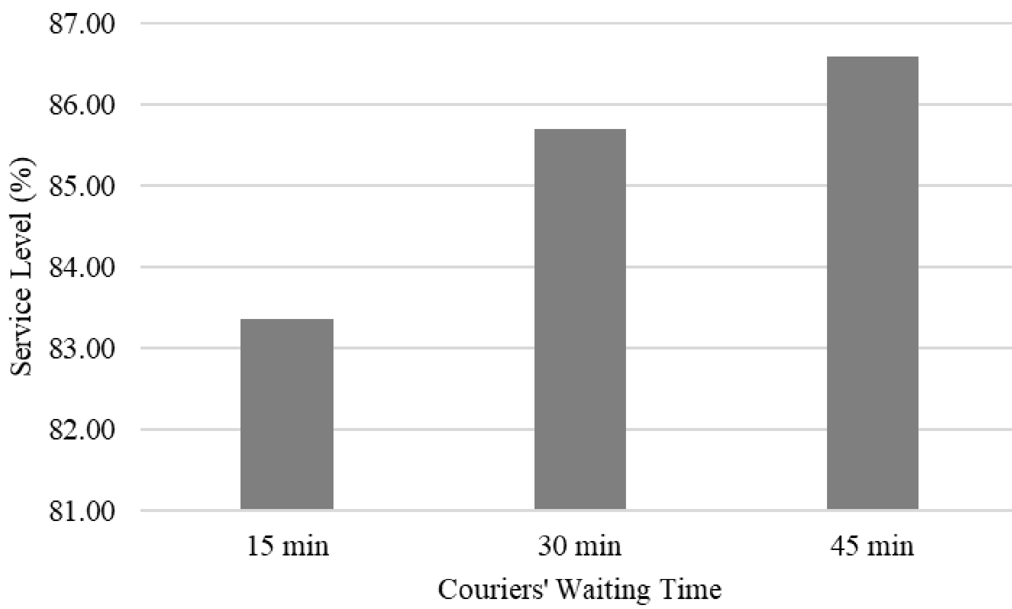

Figure 15 Average Service Level as Function of Couriers' Waiting Time

Figure 15 explains that the *Service Level* of the platform is influenced by the couriers' waiting time. That is, the *Served Orders* become higher as the couriers' willingness to wait for longer time. Similarly, the *Delay Cost* increases as the waiting time of couriers increases (as illustrated in Figure 16). Furthermore, the *Service Level* is increased by 3.90% when the couriers' waiting time is tripled. This shows low sensitivity. In addition, a similar behavior is revealed for the *Delay Cost*. This appears to be counter-intuitive because of the promised service time, which has been designed to be tight enough.

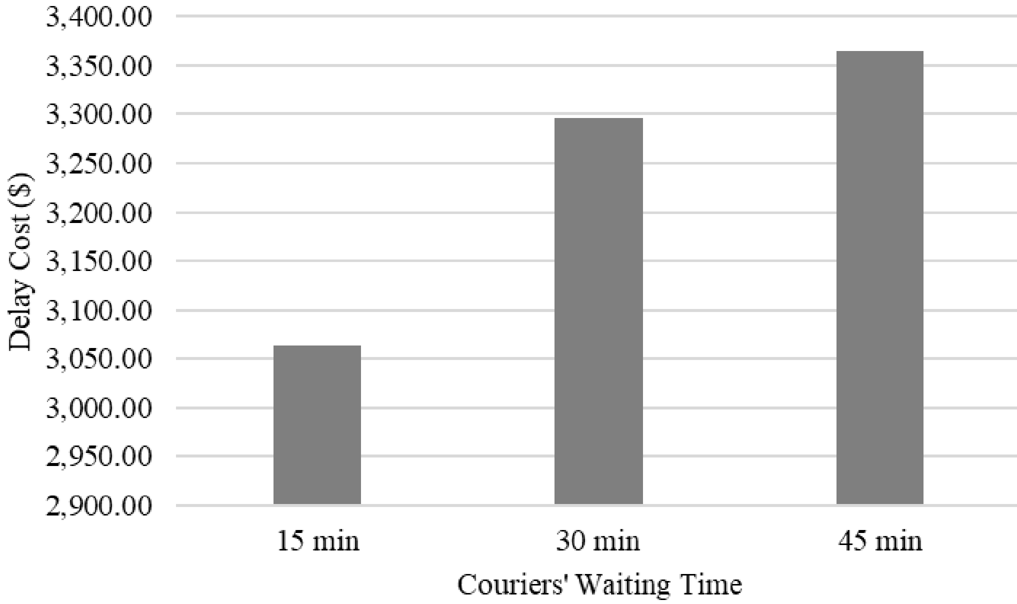

Figure 16 Average Delay Cost as Function of Couriers' Waiting Time

5.4.3 The Impact of Decision-Making Frequency (φ)

This part of sensitivity analysis studies the impact of the decision-making frequency. It assumes five value levels of the decision-making frequency, 1 minute, 2 minutes, 3 minutes, 4 minutes, and 5 minutes. Table 13, Table 14, Table 15, Table 16, and Table 17 are shown in the Appendix for details. They show the results when the decision-making frequency changes according to the five levels.

Generally, with more frequent decision-making, the platform's performance enhances for both the *Delay Cost* and *Service Level*, as demonstrated in Figure 17 and Figure 18, respectively. The *Delay Cost* is increased by 85.86% when the decision-making frequency is altered from 1 minute to 5 minutes. This displays high sensitivity. In the contrast, a low sensitivity is shown for the *Service Level*. The key reason for the significant increase in the *Delay Cost* is that more waiting time for the online orders is required by the platform as the decision-making frequency lessens. Also, the promised service time is considered to be tight, and the more waiting time for the online orders makes it insufficient.

For the *Service Level*, the results illustrate that by forcing the online orders to wait for some time to be matched with crowdsourced couriers is beneficial for the platform performance. For instance, the enhancement happens by changing the decision-making frequency from 1 minute to 2 minutes and to 3 minutes. This phenomenon is because of the need for more crowdsourced couriers for the online orders. However, this is not true all the time, and the balance between the online orders' waiting time and having more crowdsourced couriers for delivery service is essential.

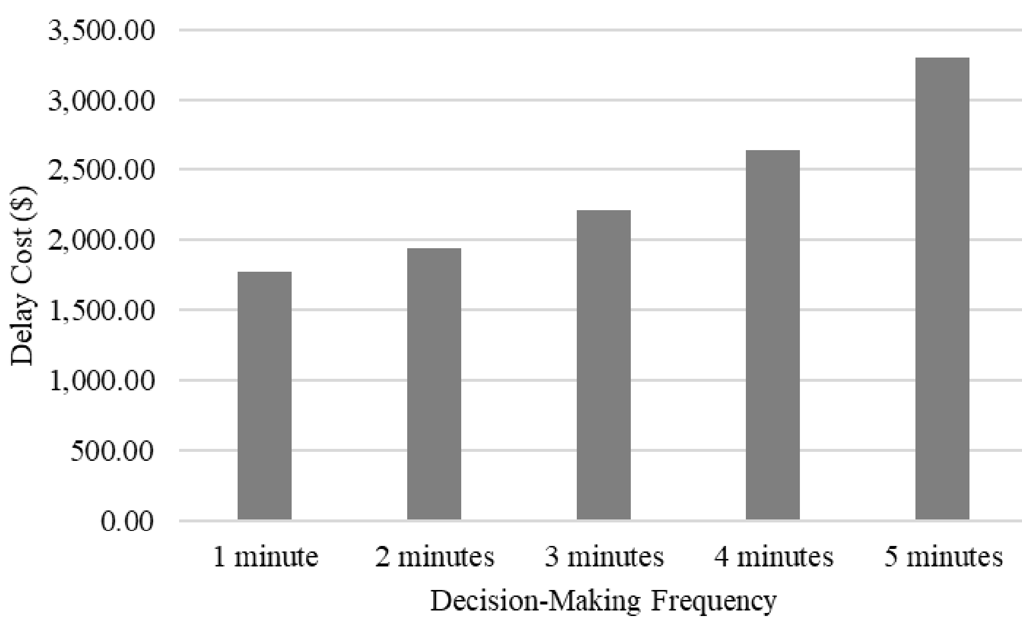

Figure 17 Average Delay Cost as Function of Decision-Making Frequency

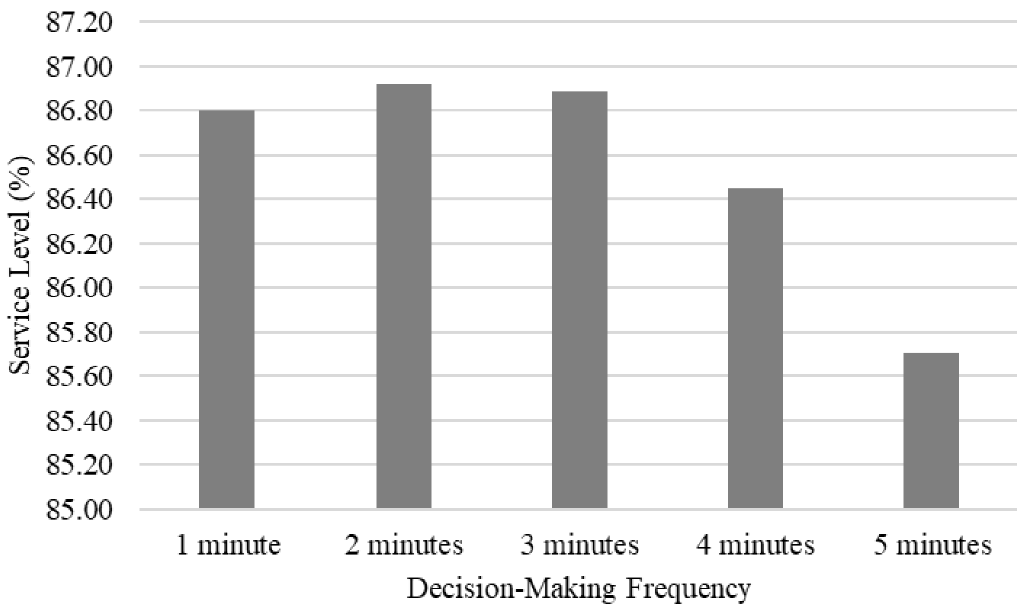

Figure 18 Average Service Level as Function of Decision-Making Frequency

5.4.4 The Impact of Promised Service Time ($\boldsymbol{\delta}$)

This subsection examines the impact of the promised service time. Three value levels of promised service time are assumed (25 minutes, 30 minutes, and 35 minutes). Table 18, Table 19, and Table 20 are shown in the Appendix for details. They illustrate the results when the delivery time promised by the platform varies as per the given three levels.

According to Figure 19, the platform's *Delay Cost* is significantly reduced as the promised service time becomes less strict. Through relaxing the promised service time by only five minutes (e.g., from 30 minutes to 35 minutes), the *Delay Cost* is reduced by 77.85% that demonstrates high sensitivity. Moreover, the results show that by keeping the promised service time more than 35 minutes, the platform can serve most of the online orders, if not all, without using the allowable delay time considered by the problem.

In Figure 20, the *Service Level* of the platform becomes higher as the promised service time gets extended. The modification from 25 minutes to 35 minutes shows 25.92% increase in the *Served Orders*. This proves moderate sensitivity. However, it can be seen that the change from 30 minutes to 35 minutes is less sensitive. As a result, the promised service time is shown to be critical to the platform performance, and it requires a careful consideration.

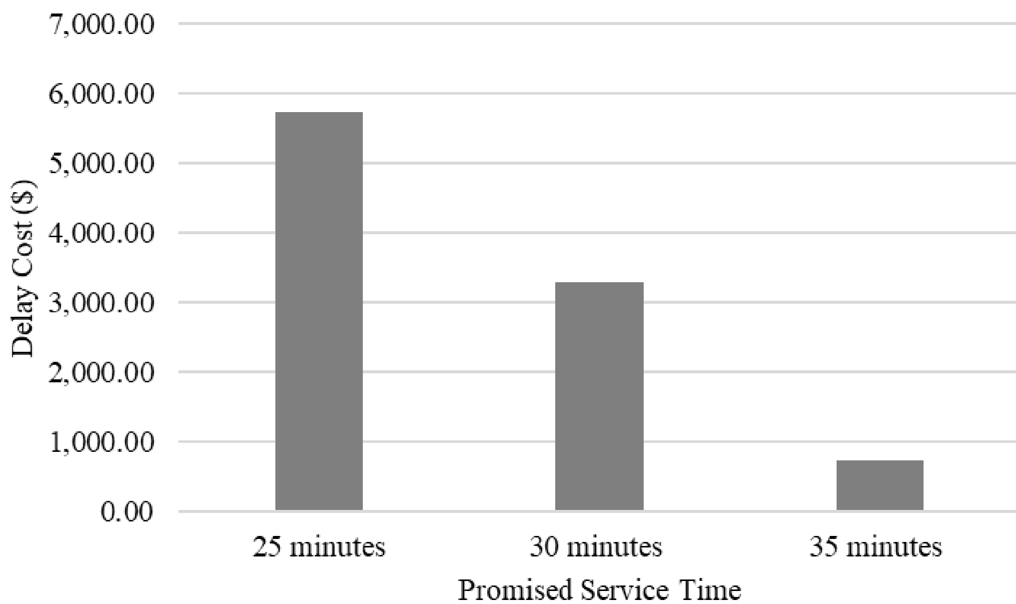

Figure 19 Average Delay Cost as Function of Promised Service Time

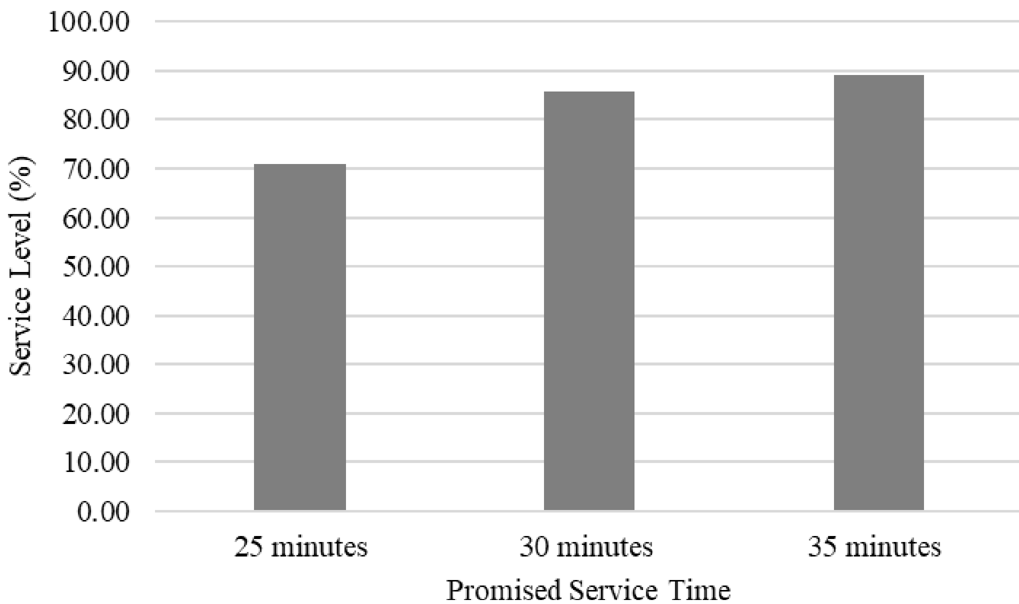

Figure 20 Average Service Level as Function of Promised Service Time

5.4.5 The Impact of Uncertain Travel Time (τ_{ij})

This subsection studies the impact of the travel time if it is considered to be uncertain as opposed to the problem definition. The delay factor (1.4) was introduced in Section 5.1, for simulating a street network. To include the uncertainty, this factor is assumed to be equal to $1 + U,$ where U is normally distributed with considering the 0.4 to be its mean. Its standard deviation is determined based on the mean and coefficient of variation (COV). Six value levels of the COV are defined (0, 0.1, 0.2, 0.3, 0.4, and 0.5) to examine the impact of uncertain travel time. Table 21, Table 22, Table 23, Table 24, Table 25, and Table 26 are shown in the Appendix for details. They demonstrate the results when the COV differs as per the given six value levels.

Figure 21 depicts that when the COV is more than zero, the *Total Cost* of the platform reduces. Moreover, the platform's *Service Level* improves, as shown in Figure 22.

Ultimately, by considering uncertain travel time, the outcomes of the problem are much better than the case that assumes known travel time (COV = 0). By considering the two extreme values of the COV (0 and 0.5), the observed change is 15.10% decrease in the *Total Cost* while it is 2.84% increase in the *Service Level*. This shows moderate sensitivity for the *Total Cost* and low sensitivity for the *Service Level*.

The interesting part is that the reduction in the *Total Cost* comes from its two components: the *Delivery Cost* and the *Delay Cost*, whereas the number of the *Served Orders* increases. The main reason for this occurrence is that the delay factor (1.4) is fixed for all instances for the deterministic case (COV = 0), but for the uncertain cases (COV = 0.1, 0.2, 0.3, 0.4, and 0.5), the delay factor may happen in less values due to the existence of the variation. Therefore, capturing uncertainty in the travel time is very important to get better results and be closer to the reality. That is, the quality of the decision-making of the platform would be better.

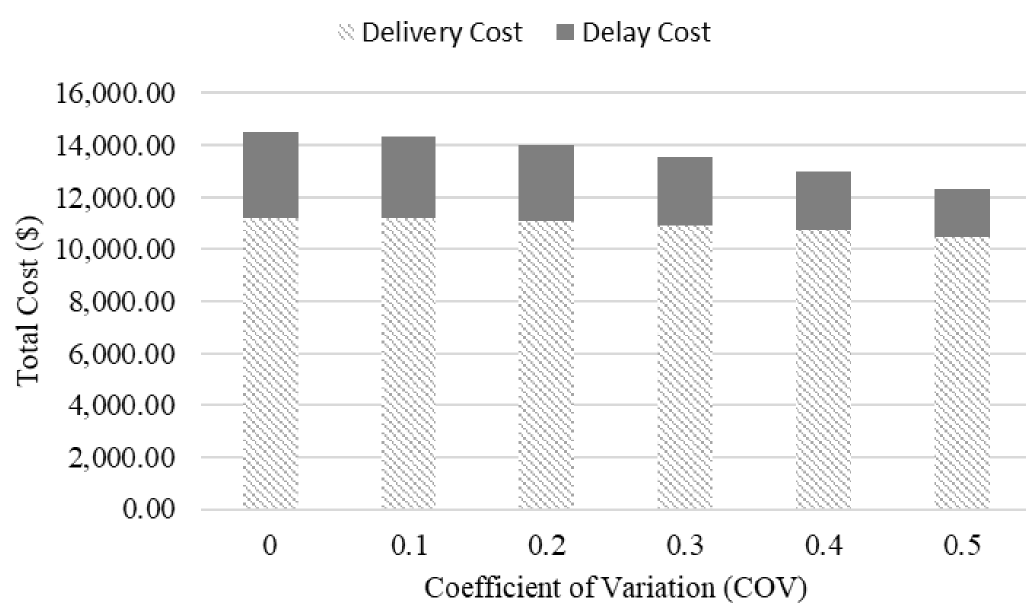

Figure 21 Average Total Cost as Function of COV of Travel Time

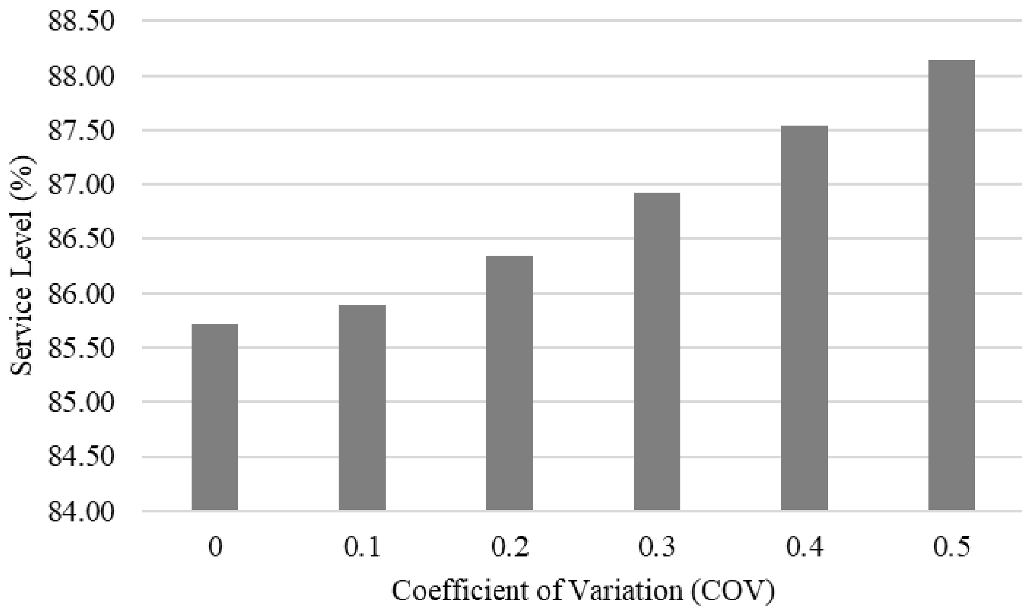

Figure 22 Average Service Level as Function of COV of Travel Time

5.5 Discussion

The problem results show that the proposed approach, the rolling horizon procedure, has the capability in diminishing the complexity of the problem. It can return the optimizing decisions in less than one second if the problem size is considered to be within 300 potential locations, as demonstrated in Figure 12. Furthermore, the results in Table 4 illustrate that the *Rate3* can be the platform's choice if the platform targets the *Service Level* to be 90% and more.

Figure 13 and Figure 14 quantify the impact of the crowdsourced couriers' acceptance behavior, ω_{ij}. If the couriers' acceptance behavior changes from 100% to 75%, the *Delay Cost* rises by 4.35%, whereas the *Service Level* lessens by 0.92%. This shows low sensitivity, but it clearly limits the problem model to best match couriers to orders. Similarly, Figure 15 and Figure 16 show low sensitivity regarding the couriers' waiting time, θ. For the *Delay Cost*, it is expected to be lower as the couriers' waiting time gets higher, but the results indicate that the *Delay Cost* behaves differently. Mainly, this is because of the designed delivery due date, δ.

Regarding the decision-making frequency, φ, Figure 17 and Figure 18 reveal that more frequent decision-making is not necessary to be the best action for the platform. The balance between the online orders' waiting time and having more crowdsourced couriers for delivery service is required. Clearly, it can be seen from the increase in the *Service Level* due to the change of the decision-making frequency from more frequent decisions (1 minute) to less frequent ones (2 minutes and 3 minutes).

Figure 19 and Figure 20 measure the impact of the promised service time, δ. They confirm the criticality of the delivery due date on the performance of the platform and other key input parameters. Therefore, a careful consideration for δ is essential. Likewise, Figure 21 and Figure 22 explain that capturing uncertainty in the travel time, τ_{ij}, leads to better results, and of course that is better in simulating the reality compared to the deterministic case (COV = 0). So, the quality of the optimizing decisions would be superior.

CHAPTER 6

CONCLUSION

This thesis studied the problem of online food ordering services by considering crowdsourced couriers as the only source of supply for the platform's capacity. The problem was defined to be dynamic and stochastic in terms of the placement of orders and the availability of couriers, along with their acceptance behavior. It was modeled as a mixed-integer linear programming (MILP), designed to be the basis for a rolling horizon technique. This rolling technique was developed to be the solution procedure for the subject problem. A computational study was determined to examine the problem results and the sensitivity of the main input parameters for key insights.

The problem results showed that the more crowdsourced couriers are available for delivery service, the higher number of ordering customers is served. Through comparing the results of the three service areas, in particular, the outcomes concerning Service Area 1 continuously indicate higher *Total Cost* and lower *Service Level*. This is because of the dispersion of the area.

The results of the sensitivity analysis indicated that the impact of the promised service time is significant on the *Cost* and *Service level* as compared to the other key input parameters (couriers' acceptance behavior, couriers' waiting time, and decision-making frequency). The changes in the value levels of the couriers' acceptance behavior negatively affect the *Service Level* and the *Delay Cost*. The main reason for this is that the presence of uncertainty in couriers' acceptance behavior limits the model to best assign orders within the promised service time and to serve more orders. Moreover, the changes in the value levels of the couriers' waiting time positively impacts the *Service Level*. However, they negatively affect the *Delay Cost*. This seems to be counter-intuitive due to the promised service time.

Furthermore, the deviations in the value levels of the decision-making frequency positively influence the *Delay Cost* and the *Service Level*. Specifically, the balance between the online orders' waiting time and having more crowdsourced couriers for delivery service is essential. In addition, the outcomes of the sensitivity analysis showed that capturing uncertainty in the travel time positively affects the performance of the platform. Hence, considering uncertain travel time for the subject problem is vital to get better results.

One future research direction may focus on one-to-many matching by assigning more than one order to crowdsourced couriers. There are two possible assignment strategies. The first one is based on time requirements that can be accomplished by calculating the time compatibility for combining any two online orders (Zhang et al. [22]). The second strategy can be done in sequential assignments of two orders to the same courier as an anticipatory way to overcome any shortage of couriers that may occur in the coming decision points. This one is expected to foster the platform's performance.

Second future research direction would be considering the promised service time to be customer-dependent rather than a general one. Meaning that different customers are offered different delivery deadlines (e.g., based on customers' locations). Moreover, the current problem assumes that all customers are eligible to order from all available restaurants on the platform. This leads us to another interesting research direction; different customers are accessible to different restaurants, but not for all available restaurants on the platform. It can be determined based on the locations of the customers (Ulmer et al. [21]). It is worth mentioning that the promised service time and the eligibility of customers for delivery service are strongly related. Therefore, the simultaneous consideration of the last two future directions is highly recommended.

REFERENCES

[1] Alnaggar, A., Gzara, F., & Bookbinder, J. H. (2021). Crowdsourced delivery: A review of platforms and academic literature. *Omega*, 98, 102139.

[2] Archetti, C., Savelsbergh, M., & Speranza, M. G. (2016). The vehicle routing problem with occasional drivers. *European Journal of Operational Research*, 254(2), 472-480.

[3] Arslan, A. M., Agatz, N., Kroon, L., & Zuidwijk, R. (2019). Crowdsourced delivery—a dynamic pickup and delivery problem with ad hoc drivers. *Transportation Science*, 53(1), 222-235.

[4] Boscoe, F. P., Henry, K. A., & Zdeb, M. S. (2012). A nationwide comparison of driving distance versus straight-line distance to hospitals. *The Professional Geographer*, 64(2), 188-196.

[5] Dantzig, G. B., & Ramser, J. H. (1959). The truck dispatching problem. *Management science*, 6(1), 80-91.

[6] Dayarian, I., & Savelsbergh, M. (2020). Crowdshipping and same-day delivery: Employing in-store customers to deliver online orders. *Production and Operations Management*, 29(9), 2153-2174.

[7] Gdowska, K., Viana, A., & Pedroso, J. P. (2018). Stochastic last-mile delivery with crowdshipping. *Transportation research procedia*, 30, 90-100.

[8] Kohar, A., & Jakhar, S. K. (2021). A capacitated multi pickup online food delivery problem with time windows: a branch-and-cut algorithm. *Annals of Operations Research*, 1-22.

[9] Macrina, G., Di Puglia Pugliese, L., Guerriero, F., & Laganà, D. (2017, September). The vehicle routing problem with occasional drivers and time windows. In *International Conference on Optimization and Decision Science* (pp. 577-587). Springer, Cham.

[10] Pillac, V., Gendreau, M., Guéret, C., & Medaglia, A. L. (2013). A review of dynamic vehicle routing problems. *European Journal of Operational Research*, 225(1), 1-11.

[11] Powell, W. B. (2011). Approximate Dynamic Programming: Solving the curses of dimensionality. *John Wiley & Sons*.

[12] Powell, W. B., Simao, H. P., & Bouzaiene-Ayari, B. (2012). Approximate dynamic programming in transportation and logistics: a unified framework. *EURO Journal on Transportation and Logistics*, 1(3), 237-284.

[13] Rios, B. H. O., Xavier, E. C., Miyazawa, F. K., Amorim, P., Curcio, E., & Santos, M. J. (2021). Recent dynamic vehicle routing problems: A survey. *Computers & Industrial Engineering*, 160, 107604.

[14] Sampaio, A., Savelsbergh, M., Veelenturf, L. P., & Van Woensel, T. (2020). Delivery systems with crowd-sourced drivers: A pickup and delivery problem with transfers. *Networks*, 76(2), 232-255.

[15] Savelsbergh, M. W., & Ulmer, M. W. (2022). Challenges and opportunities in crowdsourced delivery planning and operations. *4OR*, 1-21.

[16] Sethi, S., & Sorger, G. (1991). A theory of rolling horizon decision making. *Annals of Operations Research*, 29(1), 387-415.

[17] Steever, Z., Karwan, M., & Murray, C. (2019). Dynamic courier routing for a food delivery service. *Computers & Operations Research*, 107, 173-188.

[18] Soto Setzke, D., Pflügler, C., Schreieck, M., Fröhlich, S., Wiesche, M., & Krcmar, H. (2017). Matching drivers and transportation requests in crowdsourced delivery systems.

[19] Ulmer, M. (2017). Delivery deadlines in same-day delivery. *Logistics Research*, 10(3), 1-15.

[20] Ulmer, M. W., Thomas, B. W., Campbell, A. M., & Woyak, N. (2021). The restaurant meal delivery problem: Dynamic pickup and delivery with deadlines and random ready times. *Transportation Science*, 55(1), 75-100.

[21] Ulmer, M. W., Erera, A., & Savelsbergh, M. (2022). Dynamic service area sizing in urban delivery. *OR Spectrum*, 1-31.

[22] Zhang, Q., Liu, Y., Fan, Z. P., & Li, Z. L. (2021). Model-based rolling matching strategy for crowdsourced drivers and delivery tasks considering uncertain transportation duration. *Transportation Research Record*, 2675(4), 181-200.

APPENDIX

Table 7 The Impact of Crowdsourced Couriers' Acceptance behavior (100% Acceptance)

		Delivery Cost	*Delay Cost*	*Total Cost*	*Served Orders*	*Unserved Orders*	*Service Level*
	$\mathcal{A}1$	10123.66	3495.21	13618.87	1036.43	357.57	74.35
Rate1	$\mathcal{A}2$	9828.42	2607.73	12436.15	1045.55	348.45	75.00
	$\mathcal{A}3$	9726.80	2525.25	12252.05	1043.08	350.92	74.83
	$\mathcal{A}1$	11987.62	4144.91	16132.53	1237.82	156.18	88.80
Rate2	$\mathcal{A}2$	11799.54	3256.76	15056.30	1259.12	134.88	90.32
	$\mathcal{A}3$	11587.64	3166.61	14754.25	1245.85	148.15	89.37
	$\mathcal{A}1$	12424.26	3645.50	16069.76	1322.23	71.77	94.85
Rate3	$\mathcal{A}2$	12205.93	2872.03	15077.96	1341.77	52.23	96.25
	$\mathcal{A}3$	11866.67	2719.54	14586.21	1321.30	72.70	94.78
Average		**11283.39**	**3159.28**	**14442.67**	**1205.91**	**188.09**	**86.51**

Table 8 The Impact of Crowdsourced Couriers' Acceptance behavior (75% Acceptance)

		Delivery Cost	*Delay Cost*	*Total Cost*	*Served Orders*	*Unserved Orders*	*Service Level*
	$\mathcal{A}1$	10089.02	3695.12	13784.14	1029.62	364.38	73.86
Rate1	$\mathcal{A}2$	9842.23	2827.51	12669.74	1040.70	353.30	74.66
	$\mathcal{A}3$	9745.14	2759.44	12504.58	1037.07	356.93	74.40
	$\mathcal{A}1$	11852.37	4190.03	16042.40	1223.20	170.80	87.75
Rate2	$\mathcal{A}2$	11713.31	3396.74	15110.05	1247.70	146.30	89.51
	$\mathcal{A}3$	11457.98	3242.38	14700.36	1232.15	161.85	88.39
	$\mathcal{A}1$	12289.29	3672.54	15961.83	1307.63	86.37	93.80
Rate3	$\mathcal{A}2$	12137.63	3023.36	15161.00	1331.13	62.87	95.49
	$\mathcal{A}3$	11761.39	2864.20	14625.59	1303.67	90.33	93.52
Average		**11209.82**	**3296.81**	**14506.63**	**1194.76**	**199.24**	**85.71**

Table 9 The Impact of Crowdsourced Couriers' Acceptance behavior (50% Acceptance)

		Delivery Cost	*Delay Cost*	*Total Cost*	*Served Orders*	*Unserved Orders*	*Service Level*
	$\mathcal{A}1$	9907.02	3872.43	13779.45	1007.02	386.98	72.24
Rate1	$\mathcal{A}2$	9735.57	3157.96	12893.53	1024.03	369.97	73.46
	$\mathcal{A}3$	9651.62	3046.81	12698.43	1021.77	372.23	73.30
	$\mathcal{A}1$	11533.58	4236.33	15769.91	1191.38	202.62	85.46
Rate2	$\mathcal{A}2$	11499.77	3592.92	15092.69	1224.17	169.83	87.82
	$\mathcal{A}3$	11243.15	3453.25	14696.40	1206.28	187.72	86.53
	$\mathcal{A}1$	11948.07	3706.74	15654.81	1272.88	121.12	91.31
Rate3	$\mathcal{A}2$	11845.92	3070.91	14916.83	1302.42	91.58	93.43
	$\mathcal{A}3$	11514.50	2943.93	14458.43	1278.48	115.52	91.71
Average		**10986.58**	**3453.48**	**14440.06**	**1169.83**	**224.17**	**83.92**

Table 10 The Impact of Crowdsourced Couriers' Waiting Time (15 minutes)

		Delivery Cost	*Delay Cost*	*Total Cost*	*Served Orders*	*Unserved Orders*	*Service Level*
	$\mathcal{A}1$	9629.74	3328.09	12957.83	990.95	403.05	71.09
Rate1	$\mathcal{A}2$	9400.57	2503.88	11904.45	1004.57	389.43	72.06
	$\mathcal{A}3$	9337.15	2504.59	11841.74	1001.92	392.08	71.87
	$\mathcal{A}1$	11425.97	3872.18	15298.15	1184.42	209.58	84.97
Rate2	$\mathcal{A}2$	11217.44	3025.34	14242.78	1204.82	189.18	86.43
	$\mathcal{A}3$	11023.00	2953.98	13976.98	1192.08	201.92	85.52
	$\mathcal{A}1$	12140.34	3695.88	15836.22	1287.42	106.58	92.35
Rate3	$\mathcal{A}2$	11910.18	2917.81	14827.99	1305.92	88.08	93.68
	$\mathcal{A}3$	11605.09	2772.95	14378.04	1285.03	108.97	92.18
Average		**10854.39**	**3063.86**	**13918.25**	**1161.90**	**232.10**	**83.35**

Table 11 The Impact of Crowdsourced Couriers' Waiting Time (30 minutes)

		Delivery Cost	*Delay Cost*	*Total Cost*	*Served Orders*	*Unserved Orders*	*Service Level*
	$\mathcal{A}$**1**	10089.02	3695.12	13784.14	1029.62	364.38	73.86
Rate1	$\mathcal{A}$**2**	9842.23	2827.51	12669.74	1040.70	353.30	74.66
	$\mathcal{A}$**3**	9745.14	2759.44	12504.58	1037.07	356.93	74.40
	$\mathcal{A}$**1**	11852.37	4190.03	16042.40	1223.20	170.80	87.75
Rate2	$\mathcal{A}$**2**	11713.31	3396.74	15110.05	1247.70	146.30	89.51
	$\mathcal{A}$**3**	11457.98	3242.38	14700.36	1232.15	161.85	88.39
	$\mathcal{A}$**1**	12289.29	3672.54	15961.83	1307.63	86.37	93.80
Rate3	$\mathcal{A}$**2**	12137.63	3023.36	15161.00	1331.13	62.87	95.49
	$\mathcal{A}$**3**	11761.39	2864.20	14625.59	1303.67	90.33	93.52
Average		**11209.82**	**3296.81**	**14506.63**	**1194.76**	**199.24**	**85.71**

Table 12 The Impact of Crowdsourced Couriers' Waiting Time (45 minutes)

		Delivery Cost	*Delay Cost*	*Total Cost*	*Served Orders*	*Unserved Orders*	*Service Level*
	$\mathcal{A}$**1**	10328.35	3937.31	14265.66	1046.17	347.83	75.05
Rate1	$\mathcal{A}$**2**	10029.11	2969.53	12998.64	1056.63	337.37	75.80
	$\mathcal{A}$**3**	9937.41	2916.56	12853.97	1052.98	341.02	75.54
	$\mathcal{A}$**1**	12058.73	4341.72	16400.45	1241.83	152.17	89.08
Rate2	$\mathcal{A}$**2**	11885.07	3488.11	15373.18	1264.08	129.92	90.68
	$\mathcal{A}$**3**	11644.20	3380.88	15025.08	1249.72	144.28	89.65
	$\mathcal{A}$**1**	12292.78	3581.57	15874.35	1312.47	81.53	94.15
Rate3	$\mathcal{A}$**2**	12095.62	2891.48	14987.10	1333.13	60.87	95.63
	$\mathcal{A}$**3**	11738.79	2772.56	14511.35	1308.27	85.73	93.85
Average		**11334.45**	**3364.41**	**14698.86**	**1207.25**	**186.75**	**86.60**

Table 13 The Impact of Decision-Making Frequency (1 minute)

		Delivery Cost	*Delay Cost*	*Total Cost*	*Served Orders*	*Unserved Orders*	*Service Level*
	$\mathcal{A}1$	10579.47	2212.81	12792.28	1036.60	357.40	74.36
Rate1	$\mathcal{A}2$	10264.06	1726.76	11990.82	1043.20	350.80	74.84
	$\mathcal{A}3$	10195.07	1730.96	11926.03	1038.73	355.27	74.51
	$\mathcal{A}1$	12416.22	2190.66	14606.88	1242.65	151.35	89.14
Rate2	$\mathcal{A}2$	12114.88	1727.56	13842.44	1254.92	139.08	90.02
	$\mathcal{A}3$	11903.78	1724.84	13628.62	1241.47	152.53	89.06
	$\mathcal{A}1$	12996.15	1815.78	14811.93	1341.57	52.43	96.24
Rate3	$\mathcal{A}2$	12670.21	1395.60	14065.81	1354.98	39.02	97.20
	$\mathcal{A}3$	12399.63	1439.77	13839.40	1335.47	58.53	95.80
Average		**11726.61**	**1773.86**	**13500.47**	**1209.95**	**184.05**	**86.80**

Table 14 The Impact of Decision-Making Frequency (2 minutes)

		Delivery Cost	*Delay Cost*	*Total Cost*	*Served Orders*	*Unserved Orders*	*Service Level*
	$\mathcal{A}1$	10487.77	2411.33	12899.10	1040.30	353.70	74.63
Rate1	$\mathcal{A}2$	10159.46	1817.03	11976.49	1045.02	348.98	74.97
	$\mathcal{A}3$	10088.49	1811.69	11900.18	1041.85	352.15	74.74
	$\mathcal{A}1$	12339.22	2431.42	14770.64	1245.53	148.47	89.35
Rate2	$\mathcal{A}2$	12023.18	1869.23	13892.41	1257.35	136.65	90.20
	$\mathcal{A}3$	11808.34	1830.87	13639.21	1243.25	150.75	89.19
	$\mathcal{A}1$	12935.19	2065.45	15000.64	1342.77	51.23	96.32
Rate3	$\mathcal{A}2$	12582.53	1584.62	14167.15	1354.23	39.77	97.15
	$\mathcal{A}3$	12302.35	1617.24	13919.59	1334.32	59.68	95.72
Average		**11636.28**	**1937.65**	**13573.93**	**1211.62**	**182.38**	**86.92**

Table 15 The Impact of Decision-Making Frequency (3 minutes)

		Delivery Cost	***Delay Cost***	***Total Cost***	***Served Orders***	***Unserved Orders***	***Service Level***
	$\mathcal{A}1$	10353.11	2644.55	12997.66	1037.95	356.05	74.46
Rate1	$\mathcal{A}2$	10028.61	1984.60	12013.21	1044.82	349.18	74.95
	$\mathcal{A}3$	9981.21	2033.87	12015.08	1040.72	353.28	74.66
	$\mathcal{A}1$	12291.09	2821.87	15112.96	1247.68	146.32	89.50
Rate2	$\mathcal{A}2$	12012.73	2159.60	14172.33	1260.87	133.13	90.45
	$\mathcal{A}3$	11778.88	2173.90	13952.78	1245.23	148.77	89.33
	$\mathcal{A}1$	12814.33	2397.62	15211.95	1339.32	54.68	96.08
Rate3	$\mathcal{A}2$	12499.60	1834.77	14334.37	1352.73	41.27	97.04
	$\mathcal{A}3$	12213.81	1871.79	14085.60	1332.23	61.77	95.57
Average		**11552.60**	**2213.62**	**13766.22**	**1211.28**	**182.72**	**86.89**

Table 16 The Impact of Decision-Making Frequency (4 minutes)

		Delivery Cost	***Delay Cost***	***Total Cost***	***Served Orders***	***Unserved Orders***	***Service Level***
	$\mathcal{A}1$	10280.34	3132.76	13413.10	1036.18	357.82	74.33
Rate1	$\mathcal{A}2$	10001.82	2359.09	12360.91	1046.98	347.02	75.11
	$\mathcal{A}3$	9893.18	2294.20	12187.38	1042.58	351.42	74.79
	$\mathcal{A}1$	12111.52	3379.46	15490.98	1236.97	157.03	88.74
Rate2	$\mathcal{A}2$	11855.35	2600.35	14455.70	1254.38	139.62	89.98
	$\mathcal{A}3$	11617.07	2540.66	14157.73	1238.47	155.53	88.84
	$\mathcal{A}1$	12619.74	2925.47	15545.21	1326.82	67.18	95.18
Rate3	$\mathcal{A}2$	12333.45	2283.94	14617.39	1341.98	52.02	96.27
	$\mathcal{A}3$	12018.39	2239.86	14258.25	1321.93	72.07	94.83
Average		**11414.54**	**2639.53**	**14054.07**	**1205.14**	**188.86**	**86.45**

Table 17 The Impact of Decision-Making Frequency (5 minutes)

		Delivery Cost	*Delay Cost*	*Total Cost*	*Served Orders*	*Unserved Orders*	*Service Level*
	$\mathcal{A}1$	10089.02	3695.12	13784.14	1029.62	364.38	73.86
Rate1	$\mathcal{A}2$	9842.23	2827.51	12669.74	1040.70	353.30	74.66
	$\mathcal{A}3$	9745.14	2759.44	12504.58	1037.07	356.93	74.40
	$\mathcal{A}1$	11852.37	4190.03	16042.40	1223.20	170.80	87.75
Rate2	$\mathcal{A}2$	11713.31	3396.74	15110.05	1247.70	146.30	89.51
	$\mathcal{A}3$	11457.98	3242.38	14700.36	1232.15	161.85	88.39
	$\mathcal{A}1$	12289.29	3672.54	15961.83	1307.63	86.37	93.80
Rate3	$\mathcal{A}2$	12137.63	3023.36	15161.00	1331.13	62.87	95.49
	$\mathcal{A}3$	11761.39	2864.20	14625.59	1303.67	90.33	93.52
Average		**11209.82**	**3296.81**	**14506.63**	**1194.76**	**199.24**	**85.71**

Table 18 The Impact of Promised Service Time (25 minutes)

		Delivery Cost	*Delay Cost*	*Total Cost*	*Served Orders*	*Unserved Orders*	*Service Level*
	$\mathcal{A}1$	7304.18	5513.93	12818.11	822.97	571.03	59.04
Rate1	$\mathcal{A}2$	7777.53	5618.46	13395.99	891.77	502.23	63.97
	$\mathcal{A}3$	7637.15	5339.79	12976.94	883.05	510.95	63.35
	$\mathcal{A}1$	8410.42	6053.86	14464.28	966.83	427.17	69.36
Rate2	$\mathcal{A}2$	8815.20	6009.72	14824.92	1030.27	363.73	73.91
	$\mathcal{A}3$	8607.97	5608.97	14216.94	1019.83	374.17	73.16
	$\mathcal{A}1$	9036.03	6106.25	15142.28	1059.47	334.53	76.00
Rate3	$\mathcal{A}2$	9332.88	5954.67	15287.55	1113.72	280.28	79.89
	$\mathcal{A}3$	9032.64	5382.08	14414.72	1097.50	296.50	78.73
Average		**8439.33**	**5731.97**	**14171.30**	**987.27**	**406.73**	**70.82**

Table 19 The Impact of Promised Service Time (30 minutes)

		Delivery Cost	***Delay Cost***	***Total Cost***	***Served Orders***	***Unserved Orders***	***Service Level***
	$\mathcal{A}$**1**	10089.02	3695.12	13784.14	1029.62	364.38	73.86
Rate1	$\mathcal{A}$**2**	9842.23	2827.51	12669.74	1040.70	353.30	74.66
	$\mathcal{A}$**3**	9745.14	2759.44	12504.58	1037.07	356.93	74.40
	$\mathcal{A}$**1**	11852.37	4190.03	16042.40	1223.20	170.80	87.75
Rate2	$\mathcal{A}$**2**	11713.31	3396.74	15110.05	1247.70	146.30	89.51
	$\mathcal{A}$**3**	11457.98	3242.38	14700.36	1232.15	161.85	88.39
	$\mathcal{A}$**1**	12289.29	3672.54	15961.83	1307.63	86.37	93.80
Rate3	$\mathcal{A}$**2**	12137.63	3023.36	15161.00	1331.13	62.87	95.49
	$\mathcal{A}$**3**	11761.39	2864.20	14625.59	1303.67	90.33	93.52
Average		**11209.82**	**3296.81**	**14506.63**	**1194.76**	**199.24**	**85.71**

Table 20 The Impact of Promised Service Time (35 minutes)

		Delivery Cost	***Delay Cost***	***Total Cost***	***Served Orders***	***Unserved Orders***	***Service Level***
	$\mathcal{A}$**1**	10482.72	775.54	11258.26	1057.45	336.55	75.86
Rate1	$\mathcal{A}$**2**	10052.88	527.06	10579.94	1058.98	335.02	75.97
	$\mathcal{A}$**3**	10215.65	651.24	10866.89	1070.47	323.53	76.79
	$\mathcal{A}$**1**	12777.50	973.99	13751.49	1288.78	105.22	92.45
Rate2	$\mathcal{A}$**2**	12289.55	697.55	12987.10	1290.83	103.17	92.60
	$\mathcal{A}$**3**	12228.14	798.12	13026.26	1285.68	108.32	92.23
	$\mathcal{A}$**1**	13276.52	811.10	14087.62	1379.75	14.25	98.98
Rate3	$\mathcal{A}$**2**	12779.12	570.20	13349.32	1383.00	11.00	99.21
	$\mathcal{A}$**3**	12703.26	767.77	13471.03	1373.60	20.40	98.54
Average		**11867.26**	**730.29**	**12597.55**	**1243.17**	**150.83**	**89.18**

Table 21 The Impact of Uncertain Travel Time (COV = 0)

		Delivery Cost	*Delay Cost*	*Total Cost*	*Served Orders*	*Unserved Orders*	*Service Level*
	$\mathcal{A}1$	10089.02	3695.12	13784.14	1029.62	364.38	73.86
Rate1	$\mathcal{A}2$	9842.23	2827.51	12669.74	1040.70	353.30	74.66
	$\mathcal{A}3$	9745.14	2759.44	12504.58	1037.07	356.93	74.40
	$\mathcal{A}1$	11852.37	4190.03	16042.40	1223.20	170.80	87.75
Rate2	$\mathcal{A}2$	11713.31	3396.74	15110.05	1247.70	146.30	89.51
	$\mathcal{A}3$	11457.98	3242.38	14700.36	1232.15	161.85	88.39
	$\mathcal{A}1$	12289.29	3672.54	15961.83	1307.63	86.37	93.80
Rate3	$\mathcal{A}2$	12137.63	3023.36	15161.00	1331.13	62.87	95.49
	$\mathcal{A}3$	11761.39	2864.20	14625.59	1303.67	90.33	93.52
Average		**11209.82**	**3296.81**	**14506.63**	**1194.76**	**199.24**	**85.71**

Table 22 The Impact of Uncertain Travel Time (COV = 0.1)

		Delivery Cost	*Delay Cost*	*Total Cost*	*Served Orders*	*Unserved Orders*	*Service Level*
	$\mathcal{A}1$	10057.76	3593.12	13650.88	1029.38	364.62	73.84
Rate1	$\mathcal{A}2$	9794.08	2741.36	12535.44	1041.68	352.32	74.73
	$\mathcal{A}3$	9716.06	2696.36	12412.42	1038.78	355.22	74.52
	$\mathcal{A}1$	11826.97	4047.70	15874.67	1226.83	167.17	88.01
Rate2	$\mathcal{A}2$	11670.75	3267.84	14938.59	1250.75	143.25	89.72
	$\mathcal{A}3$	11447.81	3145.06	14592.87	1236.00	158.00	88.67
	$\mathcal{A}1$	12250.45	3550.86	15801.31	1311.62	82.38	94.09
Rate3	$\mathcal{A}2$	12071.97	2893.22	14965.19	1333.68	60.32	95.67
	$\mathcal{A}3$	11695.78	2718.19	14413.97	1307.05	86.95	93.76
Average		**11170.18**	**3183.75**	**14353.93**	**1197.31**	**196.69**	**85.89**

Table 23 The Impact of Uncertain Travel Time (COV = 0.2)

		Delivery Cost	***Delay Cost***	***Total Cost***	***Served Orders***	***Unserved Orders***	***Service Level***
	$\mathcal{A}$**1**	10003.54	3371.83	13375.37	1035.88	358.12	74.31
Rate1	$\mathcal{A}$**2**	9713.29	2520.02	12233.31	1045.35	348.65	74.99
	$\mathcal{A}$**3**	9632.34	2516.12	12148.46	1041.93	352.07	74.74
	$\mathcal{A}$**1**	11787.38	3787.30	15574.68	1237.65	156.35	88.78
Rate2	$\mathcal{A}$**2**	11561.78	2985.89	14547.67	1256.82	137.18	90.16
	$\mathcal{A}$**3**	11369.27	2936.76	14306.03	1243.22	150.78	89.18
	$\mathcal{A}$**1**	12146.46	3225.60	15372.06	1318.97	75.03	94.62
Rate3	$\mathcal{A}$**2**	11897.83	2585.01	14482.84	1338.52	55.48	96.02
	$\mathcal{A}$**3**	11603.00	2526.36	14129.36	1315.08	78.92	94.34
Average		**11079.43**	**2939.43**	**14018.86**	**1203.71**	**190.29**	**86.35**

Table 24 The Impact of Uncertain Travel Time (COV = 0.3)

		Delivery Cost	***Delay Cost***	***Total Cost***	***Served Orders***	***Unserved Orders***	***Service Level***
	$\mathcal{A}$**1**	9878.89	3008.54	12887.43	1040.58	353.42	74.65
Rate1	$\mathcal{A}$**2**	9560.82	2220.57	11781.39	1047.37	346.63	75.13
	$\mathcal{A}$**3**	9498.81	2250.92	11749.73	1044.73	349.27	74.94
	$\mathcal{A}$**1**	11669.07	3401.64	15070.71	1250.07	143.93	89.68
Rate2	$\mathcal{A}$**2**	11413.26	2678.59	14091.85	1264.95	129.05	90.74
	$\mathcal{A}$**3**	11220.38	2648.64	13869.02	1251.37	142.63	89.77
	$\mathcal{A}$**1**	12010.71	2860.52	14871.23	1332.67	61.33	95.60
Rate3	$\mathcal{A}$**2**	11716.80	2237.67	13954.47	1347.87	46.13	96.69
	$\mathcal{A}$**3**	11436.05	2248.04	13684.09	1325.38	68.62	95.08
Average		**10933.87**	**2617.24**	**13551.11**	**1211.67**	**182.33**	**86.92**

Table 25 The Impact of Uncertain Travel Time (COV = 0.4)

		Delivery Cost	*Delay Cost*	*Total Cost*	*Served Orders*	*Unserved Orders*	*Service Level*
	$\mathcal{A}$**1**	9687.20	2597.45	12284.65	1044.87	349.13	74.95
Rate1	$\mathcal{A}$**2**	9380.29	1979.31	11359.60	1051.18	342.82	75.41
	$\mathcal{A}$**3**	9327.06	1977.92	11304.98	1048.38	345.62	75.21
	$\mathcal{A}$**1**	11494.86	2923.51	14418.37	1261.67	132.33	90.51
Rate2	$\mathcal{A}$**2**	11192.27	2266.70	13458.97	1273.72	120.28	91.37
	$\mathcal{A}$**3**	11045.32	2304.20	13349.52	1262.85	131.15	90.59
	$\mathcal{A}$**1**	11748.34	2347.25	14095.59	1344.72	49.28	96.46
Rate3	$\mathcal{A}$**2**	11430.65	1833.53	13264.18	1357.67	36.33	97.39
	$\mathcal{A}$**3**	11227.55	1929.18	13156.73	1337.60	56.40	95.95
Average		**10725.95**	**2239.89**	**12965.84**	**1220.30**	**173.70**	**87.54**

Table 26 The Impact of Uncertain Travel Time (COV = 0.5)

		Delivery Cost	*Delay Cost*	*Total Cost*	*Served Orders*	*Unserved Orders*	*Service Level*
	$\mathcal{A}$**1**	9495.05	2236.54	11731.59	1051.32	342.68	75.42
Rate1	$\mathcal{A}$**2**	9180.16	1675.96	10856.12	1055.20	338.80	75.70
	$\mathcal{A}$**3**	9139.72	1757.47	10897.19	1052.03	341.97	75.47
	$\mathcal{A}$**1**	11197.43	2385.22	13582.65	1271.05	122.95	91.18
Rate2	$\mathcal{A}$**2**	10878.78	1829.33	12708.11	1282.22	111.78	91.98
	$\mathcal{A}$**3**	10809.75	1952.55	12762.30	1272.47	121.53	91.28
	$\mathcal{A}$**1**	11421.22	1890.01	13311.23	1357.30	36.70	97.37
Rate3	$\mathcal{A}$**2**	11072.08	1467.20	12539.28	1366.70	27.30	98.04
	$\mathcal{A}$**3**	10911.99	1538.75	12450.74	1350.08	43.92	96.85
Average		**10456.24**	**1859.23**	**12315.47**	**1228.71**	**165.29**	**88.14**

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