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***Abstract*—This paper studies a same-day crowd-sourced delivery setting where in-store customers deliver online orders on their way home. This environment is dynamic and uncertain, characterized by fluctuating numbers of in-store customers and online orders throughout the day, and unpredictable customer decisions to accept or reject delivery tasks. To address these challenges, we develop a two-stage event-driven dynamic matching framework. The first stage leverages short-term predictions about future arrivals of in-store customers and online orders, allowing us to postpone matching decisions for certain drivers and orders, thus optimizing immediate outcomes to maximize order satisfaction over a future time interval. In response to these initial outcomes, the second stage computes the probability of in-store customers accepting matched orders and introduces two compensation models. These models are designed to tailor compensation for each customer, aiming to minimize expected delivery costs at the current decision-making point. Experimental results demonstrate that our framework reduces delivery costs by approximately 15% compared to baseline methods, highlighting its potential to improve the efficiency of crowd-sourced delivery systems in a constantly changing market.**

***Index Terms*—Crowd-sourced delivery, dynamic, uncertainty, human factor, prediction, matching**

I. Introduction

Riding on the wave of urbanization and advancements in communication technology, B2C e-commerce sales have reached an astonishing figure of $907.9 billion in 2022 worldwide [1]. In such a fiercely competitive environment, these major retailers are on the constant lookout for efficient, high-quality, and low-cost delivery solutions. Crowd-sourced delivery service (CDS) is an emerging urban logistics solution. Its core philosophy originates from the sharing economy model and is defined as ordinary individuals, such as commuters, taxi drivers, and travelers, sharing available space in their vehicles for parcels and deviating slightly from their original routes in exchange for various forms of compensation. Due to this mode of transportation maximizes the utilization of existing transportation resources, significant economic, social, and environmental benefits are realized [9]. Currently, it is garnering increasing attention by many large-scale retailers such as Walmart with its "Spark" program [2], e-commerce giants like Amazon Flex [3], Jingdong crowdsourcing [4], they have successfully implemented crowd-sourced delivery. Additionally, several startups, such as PiggyBee[5], Postmate[6], and others, have also managed to achieve profitability.

Diverging from traditional freight transport, CDS systems are characterized by a greater degree of inherent uncertainty, such as the uncertainties of delivery request volumes, driver availability, and drivers' order acceptance behaviors. How to achieve effective and efficient matching while accounting for these uncertainties has attracted widely focus of interest. Specifically, in academia, the uncertainty on the demand side of CDS is typically relaxed through assuming demand distributions or addressed by employing data-driven predictive analysis [17]. Regarding the unknown availability of drivers, as highlighted by [10], a significant portion of current literature tends to solve matching problems by requiring crowd-sourced drivers to declare their available period in advance [11]–[13]. Another uncertainty arises from the freedom of crowd-sourced drivers, they may not accept system assigned orders. While some studies attempt to restrict the freedom by setting service areas [14] [5] or limiting detour distances [15] [16], the assumption of drivers automatically accepting orders is unrealistic in real-world scenarios. To address the issues [4] [2] quantify the order acceptance behavior of crowd-sourced drivers and, through compensation mechanisms, incentivize drivers to accept system-assigned orders. In summary, although various studies have addressed the matching problems in uncertain and stochastic environments at different levels, research that simultaneously considers uncertainties on both the supply and demand sides remains a gap.

Meanwhile, some studies employ such as event-driven [5], [6], [8] and time-driven [7] rolling horizon approaches to achieve effective matching through cyclically executing

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[1] https://www.oberlo.com/statistics/global-ecommerce-sales-growth

[2] https://drive4spark.walmart.com/
[3] https://flex.amazon.ca/
[4] https://ir.jd.com
[5] https://www.piggybee.com/
[6] https://postmates.com/

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	Dynamic		Stochastic	
Studies	Event-driven	Time-driven	Demand uncertainty	Supply uncertainty
[17]			✓	
[5], [11]–[16]				✓
[2], [4]	✓			✓
[5], [6], [8]	✓			
[7]		✓		
[5]	✓		✓	
This paper	✓		✓	✓

TABLE I: The differences between this paper and the most relevant literature

the proposed algorithms in dynamic environments. Specially, Dayarian et al. [5] take into account the dynamic variations in transport capacity, as well as the potential for improved dynamic matching outcomes through the postponement of delivery orders. However, as the main actors in CDS, crowd-sourced drivers' dynamic behaviors, such as logging into the system, logging out, accepting, or rejecting orders, significantly affect the system's matching efficiency. Researches, focusing on dynamic decision-making grounded in individual behaviors, is relatively rare. Our work focuses on the development of an event-driven dynamic system considering the uncertainties of both supply and demand sides. Table. I summarize the differences between this paper and most relevant state-of-the-art works.

In this paper, we consider a classic CDS system that utilizes in-store customers to deliver orders, the main contributions include the following three aspects: first, we propose an event-driven dynamic matching framework that considers the uncertainties in both sides of demand and supply. Based on the prediction of supply-demand relation over a certain future time interval, by postponing the matching processes of certain orders and in-store customers, this framework computes optimal matching outcomes throughout a day. Additionally, two compensation models are introduced to generate customized compensation schemes. Based on the probability information of each in-store customer's order acceptance behavior, the customized compensation motivates each in-store customer to accept the system-assigned matching outcome, thereby enhancing the reliability of the matching results; second, we propose a discrete event system simulation (DES) model to validate the feasibility of the proposed framework; third, a comparative study is presented to evaluate the performance of the proposed framework against benchmark methods under two compensation policies.

The rest of this paper is organized as follows. Section II describes the CDS problem and formulates the dynamics of order matching by using a discrete-event system model. Section III presents the designed matching and compensation optimization models. The performance of the proposed approach is evaluated through a computational study in Section IV. Finally, Section V concludes the paper and states future research directions.

II. Problem description

In this section, initially, we present a comprehensive overview of a CDS platform. Subsequently, a DES simulation model is developed to capture the system dynamics and assess the performance of the proposed framework (present in Sec. III). Moreover, some major events that have significant impacts on the system are introduced in details.

A. Overview

The CDS platform is a typical two-sided market, consisting of three components: the platform operators (retailers), the in-store customers, and the online orders. Their interrelationships among each other is presented in Fig. 1

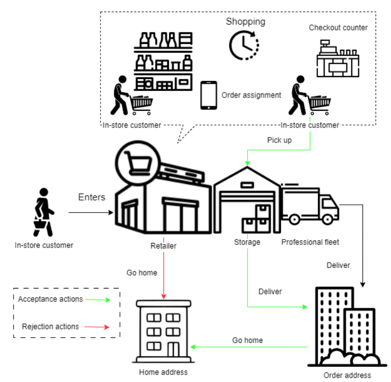

Fig. 1: Overview of the crowd-sourced delivery system

1) Retailer: A retailer provides both in-store and online shopping and delivery services for the residents of surrounding communities. The retailer undertakes the responsibility of managing registered in-store customers, assigning them appropriate orders, and offering monetary compensation in exchange for their delivery capabilities. To ensure the delivery service quality, the retailer equips itself with a professional fleet (PF), guaranteeing the punctual delivery of orders not handled by in-store customers. The objective for the retailer is to minimize delivery costs and reduce the employment of professional drivers. Moreover, the retailer documents the number of online orders and in-store customers from diverse communities within various intervals throughout a day.

2) In-store customers: In-store customers refer to shoppers willing to share spare space within their vehicles to participate in order deliveries. These individuals enlist, via mobile applications, as potential crowd-sourced drivers, voluntarily disclosing details such as their home addresses and anticipated arrival time to the store. Furthermore, each in-store customer is expected to specify their maximum permissible shopping duration (or waiting time) to the retailer. This provides the retailer with a window of opportunity to allocate orders to them. Specifically, upon receipt of orders assigned to them by the retailer, in-store customers will decide either

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accept or reject these assignments. Upon acceptance, they pick up the parcels and undertake its delivery prior to reaching their designated destinations. Conversely, they proceed directly to their residences.

3) Online orders: Online orders refer to those generated by online customers within neighboring communities engaging in digital shopping. Their addresses are transmitted to the retailer via mobile applications. Furthermore, each online order is stipulated with a definitive latest delivery time, mandating that the retailer's delivery for that order must not exceed this temporal constraint. For simplification, we assume that the latest delivery time for an order is a fixed interval post the order placement.

B. Dynamic system modeling

We construct a discrete-event system model, considering each in-store customer within the CDS platform as an individual entity. Key events influencing the state transitions of in-store customers includes: e^a, e^r, e^d, e^n, e^l, and e_g. Let Y be the state space which consists of the set of possible values of the vector $\boldsymbol{y}(k) = [y_1(k)\ ...\ y_i(k)\ ...\ y_{|I|}(k)]^T$, where $y_i(k)$ represents the state of the in-store customer i after the occurrence of the k^{th} event. The value of the state variable $y_i(k)$ indicates if the in-store customer i:

- is unavailable: $y_i(k) = y_0$;
- is available to be matched at the retailer: $y_i(k) = y_1$;
- is evaluating a delivery request: $y_i(k) = y_2$;
- is delivering a parcel: $y_i(k) = y_3$;

The state transitions diagram of a in-store customer i is shown in Fig.2.

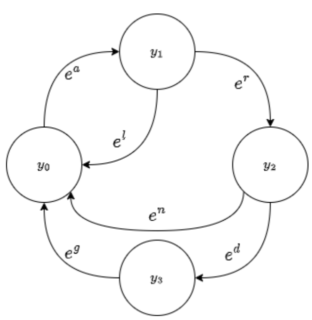

Fig. 2: Events transition diagram

1) In-store customer arrival event and departure event: An arrival event of an in-store customer e_i^a means a transition in its state, subsequently notifying the system of the shift from an "unavailable" y_0 to an "available" y_1 state for that in-store customer. Additionally, this event, occurring at time τ, triggers the solution of the proposed strategy depicted in Sec. III. And, the arrival rate of in-store customers is time-variant. For convenience and without loss of generality, we assume that over a fixed time interval T, the distribution of arrival events for in-store customers of which destination $z \in Z$ follows a Poisson distribution with parameter λ_z^I (similar to the order distribution λ_z^J). Hence, for each locations $z \in Z$, the cumulative anticipated quantities of drivers and orders over an imminent period $[\tau, \tau + T]$ are represented as Eq. (1).

$$|\hat{J}_z(\tau)| = (\tau_{h+1} - \tau)\lambda_z^J(\tau_h) + (\tau + T - \tau_{h+1})\lambda_z^J(\tau_{h+1}) \quad (1)$$

where $|\hat{J}_z(\tau)|$ denotes the estimated number of online orders of which destinations are z in a near future $[\tau, \tau + T]$. τ_h denotes the sequences of the time when the demand/supply is updated (every time interval T). $\lambda_z^J(\tau_h)$ denotes the near future demand rate of zone z in the interval $[\tau_h, \tau_{h+1}]$. Additionally, a graphic representation illustrating a time-weighted amount of future demand is presented in Fig. 3. With respect to the computation of estimated number $|\hat{I}_z(\tau)|$ of in-store customers destined for location z in a near future $[\tau, \tau + T]$, it is analogous to the one described in Fig. 3 as well.

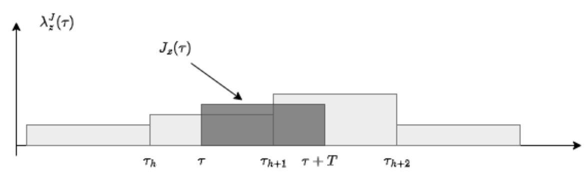

Fig. 3: Time dependence of the order arrival rate

Additionally, the departure event of an in-store customer e_i^l is assumed to occur at $\pi_i = \tau + \delta_i$, being $\delta_i \sim \mathcal{N}(\mu, \sigma^2)$, a Gaussian stochastic variable with expectation μ equal to the average waiting time of in-store customers.

2) In-store customer order receive, acceptance, and rejection events: The occurrence of the "order receive" event e^r results in a delivery request being presented to the in-store customer. The in-store customer is then asked to determine whether they are willing to accept or reject the assigned order, given a calculated compensation. Moreover, each in-store customer operates as an autonomous entity, is free to determine whether to accept an assigned order $j \in \mathcal{J}$. The occurrence of receipt event e_i^r transits the state from y_1 to y_2. And let $P_{i,j}$ be the acceptance probability of in-store customer, meanwhile the rejection probability is defined as $1 - P_{i,j}$, scheduling the occurrence of event e_i^n.

III. Dynamic predictive matching framework

In this section, we propose a dynamic predictive matching framework (DP-MF). In the first stage, we determine the postponed orders and drivers, and the present matching solution to achieve maximizing order satisfaction during a look-ahead time interval. In the second phase, given the present matching solution, with the objective of minimizing

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system expected delivery costs, we compute the customized compensation scheme for in-store customers. The matching and compensation optimization procedures are triggered by the event e^r, occurring at τ, defined in Sec. II-B. Table. II lists the notations used in this paper.

A. Matching and postponement model (MP-OPT)

Given sets I and J of available in-store customers and orders, respectively, of which the in-store customers' states are y_1, the optimization objective at this phase is to maximize the satisfaction of both current orders and estimated future orders that are delivered by in-store customers. Let $x_{i,j}$ serve as the decision variable, representing the matching between in-store customer i and order j. Let $\iota_{i,z}$ be the decision variable whether in-store customer i's matching decision is delayed and reserved for the next decision epoch, let ϱ_j denote the postponement of the order j. The objective function can be represented as follows Eq.(2), where the first term Eq. (3) denotes the satisfaction of estimated future orders plus the satisfaction of current orders; and the second term Eq. (4) represent the detour distance.

$$\min_{\boldsymbol{x},\boldsymbol{\iota},\boldsymbol{\varrho}} G_1(\boldsymbol{x},\boldsymbol{\iota},\boldsymbol{\varrho}) + G_2(\boldsymbol{x}) \tag{2}$$

$$G_1(\boldsymbol{x},\boldsymbol{\iota},\boldsymbol{\varrho}) = \sum_{\forall z\in Z} |\hat{J}_z(\tau)||\boldsymbol{\nu}_z - \boldsymbol{\eta}_z| + |J|(|J| - \sum_{\forall i\in I}\sum_{\forall j\in J} x_{i,j}) \tag{3}$$

$$G_2(\boldsymbol{x}) = \sum_{\forall i\in I} x_{i,j}\mathcal{D}_{i,j} \tag{4}$$

subject to:

$$\boldsymbol{\eta}_z = \sum_{\forall i\in I} \iota_{i,z}, \quad \forall z\in Z \tag{5}$$

$$\boldsymbol{\nu}_z = |\hat{J}_z(\tau)| + \sum_{\forall j\in J_z} \varrho_j, \quad \forall z\in Z \tag{6}$$

$$\mathcal{D}_{i,j} = D_{o,d_j} + D_{d_i,d_j} - D_{o,d_i} \tag{7}$$

$$\pi_j = \rho_j - \frac{D_{o,d_j}}{V_0} \tag{8}$$

$$\tau - \pi_j < M(1-\varrho_j), \quad \forall j\in J \tag{9}$$

$$\tau - \pi_i < M(1 - \sum_{\forall z\in Z} \iota_{i,z}), \quad \forall i\in I \tag{10}$$

$$\sum_{\forall j\in J} x_{i,j} + \sum_{\forall z\in Z} \iota_{i,z} \le 1, \quad \forall i\in I \tag{11}$$

$$\sum_{\forall i\in I} x_{i,j} + \varrho_j = 1, \quad \forall j\in J \tag{12}$$

$$x_{i,j} = \{0,1\}, \quad \forall i\in I, \forall j\in J \tag{13}$$

$$\iota_{i,z} = \{0,1\}, \quad \forall i\in I, \forall z\in Z \tag{14}$$

$$\varrho_j = \{0,1\}, \quad \forall j\in J_z, \forall z\in Z \tag{15}$$

In this model, Eq. (3) equalizes, as much as possible, the number of in-store customers in each zone with respect to the estimated number of orders in the near future. Zones with a higher estimated number of orders are assigned a higher weight. Moreover, the latter term of Eq. (3) allocates a larger proportion of orders to in-store customers. The second term of the objective function, expressed by Eq. (4), minimize the total detour distances. Eq. (5) defines the number of deferred matching in-store customers, reserved for each zone, in the near future. Eq. (6) define the number of orders of each zone in the near future. Eq. (7) define the detour distance of in-store customer i to deliver order j. Eq. (8) defines the latest departure time of order j. Eq. (9) ensure that orders must be matched before their latest departure time. Eq. (10) guarantees that in-store customers must be matched before their latest departure time. Eq. (11) guarantee that each driver can only be deferred to next decision epoch or be matched with at most one order, and Eq. (12) constrains each order can only be postponed to next decision epoch or be matched with at most one driver. Eq. (13), Eq. (14), and Eq. (15) define the decision variables.

Solving the optimization problem determines the optimal customer-order matchings, reported by a mapping $\mu : \tilde{I} \longrightarrow \tilde{J}$, where $\tilde{I} \subseteq \mathcal{I}$ is the set of in-store customer who actually assigned orders. Let $\tilde{J} \subseteq \mathcal{J}$ be the set of the orders to actually be assigned to in-store customers. For example, if an order $j \in \tilde{J}$ is determined to be delivered by an in-store customer $i \in \tilde{I}$, then $\mu(i) = j$. If an in-store customer is not assigned with any online orders, $\mu(i) = \emptyset$.

B. Compensation optimization (C-OPT)

Given matched in-store customers $\tilde{I}$ and online orders $\tilde{J}$, as well as the present matching solution μ, the optimization objective of this phase is to minimize the expected cost for the current decision epoch. Considering that each in-store customer has the freedom to decide whether or not to accept the order allocated to them, we define the probability of each in-store customer accepting the assigned order as $P_{i,j}$, and the probability of rejecting it as $1 - P_{i,j}$. When an order is declined by an in-store customer, it is subsequently assigned to a professional driver for delivery.

$$\min_{\boldsymbol{s}} \sum_{\forall i\in\tilde{I}} [s_i P_{i,j} + c_{\mu(i)}(1 - P_{i,j})] \tag{16}$$

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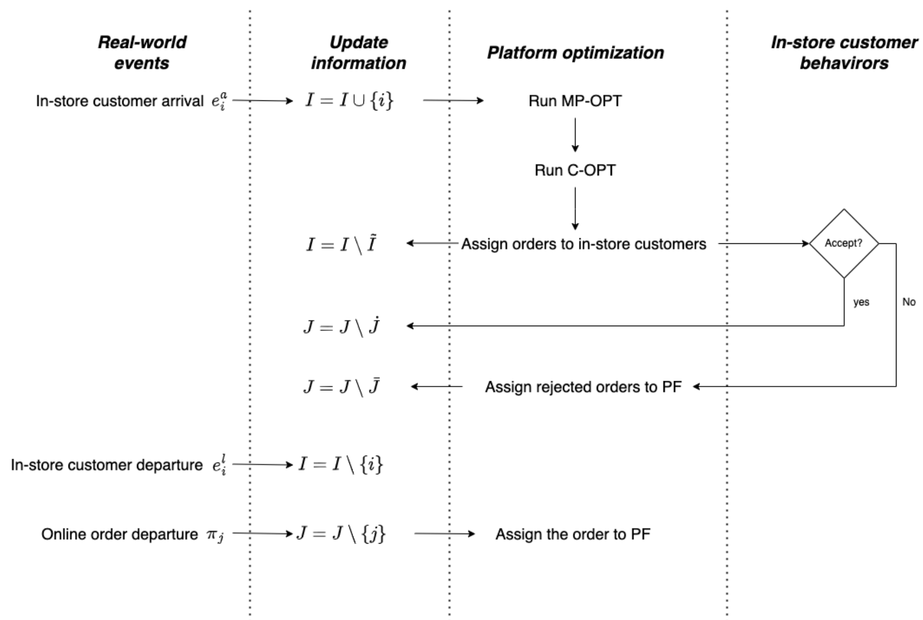
Notation	Description
$\mathcal{I}$	Set of all in-store customers, indexed by i
$\mathcal{J}$	Set of all online orders, indexed by j
I, J	Sets of available in-store customers and online orders
$\lvert\hat{J}_z(\tau)\rvert$	Estimated number of online orders in near future
$\tilde{I}, \tilde{J}$	Sets of matched in-store customers and online orders by CDS platform
$\dot{J}$	Set of accepted online orders
$\bar{J}$	Set of rejected online orders
τ	Decision epoch time point
π_i, π_j	Latest departure time of in-store customer i, and online order j
ρ_j	Latest delivery time of order j
$D_{a,b}$	Distance between two locations a and b
$\mathcal{D}_{i,j}$	Detour distance of in-store customer i to deliver online order j
V_0	Constant indicating the velocity of drivers
c_j	Original delivery costs of online order j by PF
$P_{i,j}$	Probability that an in-store customer i accepts to deliver online order j
M	A larger number
$x_{i,j}$	Decision variable, indicating the matching between in-store customer i and online order j
$\iota_{i,z}$	Decision variable, indicating the deferred matching of in-store customer i to next decision epoch
ϱ_j	Decision variable, indicating the postpone of online order j to next decision epoch
s_i	Decision variable, indicating the compensation paid to in-store custoemr i
M	A large number

TABLE II: Notation and description



(a) Event-driven dynamic matching framework

Fig. 4: An illustration of the dynamic predictive matching framework

subject to:

$$c_{\mu(i)} = c_0 + \alpha_0 D_{o,\mu(i)}, \quad \forall i \in \tilde{I} \tag{17}$$

$$\sum_{\forall i \in \tilde{I}} s_i \leq \omega \sum_{\forall i \in \tilde{I}} c_{\mu(i)} \tag{18}$$

$$s_i \leq \omega_3 c_{\mu(i)}, \quad \forall i \in \tilde{I} \tag{19}$$

$$s_i \geq 0, \quad \forall i \in \tilde{I} \tag{20}$$

In the formulation, expressed by Eq. (16), the objective is to minimize the expected total delivery costs. Eq. (17) defines the delivery costs of professional drivers. The constraints in Eq. 18 and Eq. 19 define two different compensation policies, *Group decision policy* (DP-MF_GDP) and *Single decision policy* (DP-MF_SDP). The difference lies in that the Eq. (18) constrains the compensation amount allocated to each single in-store customer to not exceed a certain percentage ω of

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the original delivery cost, whereas Eq. (19) restricts the total compensation amount to not surpass a specific percentage ω of the cumulative original delivery cost. While Constraint (20) defines the decision variables.

C. Dynamic optimization framework

As what we mentioned, the occurrence of event e^a triggers the solution of our proposed optimization models. After running MP-OPT and C-OPT, we obtain the set of matched in-store customers $\tilde{I}$ and orders $\tilde{J}$, along with their corresponding compensation schemes S. Subsequently, these in-store customers are removed from the available in-store customer set I. Thereafter, we assign the orders $\tilde{J}$ to in-customers $\tilde{I}$. Accepted orders $\dot{J}$ are removed from the available order set I and are delivered by these in-store customers $\dot{I}$. Conversely, orders rejected by the in-store customers were transferred to PF for delivery fulfillment. Additionally, should the wait time of an in-store customer surpass the stipulated latest departure time π_i, they are removed from the available set I and leave the retailer. Similarly, if an order reaches its latest departure time π_j without assignment, it is mandatorily dispatched by PF, and is removed from J. It is worth noting that due to the deferred matching of the in-store customers and the postponement of orders, there is no alteration in the available in-store customer and order sets. Consequently, we do not showcase these changes in the update information module.

IV. Computational study

In this section, we conduct a numerical study to verify the performance of the proposed dynamic predictive matching framework in terms of the cost reduction rate, order rejection rate, and order successfully matched rate. First we present the simulated dataset used to conduct the experiment. Then, we evaluate the proposed DP-MF, varied by two compensation policies (namely DP-MF_GDP, and DP-MF_SDP), by comparing its performance with an alternative optimization approaches, proposed by [2], named *Myopic_GDP* and *Myopic_SDP* respectively, which re-executes the matching and compensation models upon the occurrence of an in-store customer arrival event e^a. The experiment were executed on a computer with an Intel Core i7 6-core CPU with 16 GB of RAM, running at 2.6 GHz, using Mac OS X version 12.0.1. The two-stage optimization models were implemented in Gurobi 10.0.

A. Parameter settings and scenarios generations

For the sake of generality, we randomly generate a central retailer and ten distinct zones within a 10km radius utilizing the Google Maps API,. Moreover, drawing upon the work of [2], we assume that the decision-making behavior of in-store customers is predominantly influenced by the compensation price and the detour distance. The probability function is represented as Eq.(21).

$$P_{i,j} = \frac{1}{1 + e^{-(\beta_0 + \beta_{comp} s_i + \beta_{detour} \mathcal{D}_{i,j})}} \tag{21}$$

where $P_{i,j}$ denotes the probability that an in-store customer accepts the assigned order j. β_0 denotes the alternative specific constant (ASC), β_{comp}, and β_{detour} are suitable coefficients to be estimated. s_i and $\mathcal{D}_{i,j}$ denote the customized compensation paid to in-store customer i and detour distance of in-store customer i to deliver order j, respectively. For additional details regarding the parameters mentioned in previous sections, kindly refer to Table III.

Parameter	Description	Value
ω	Weight of order satisfaction	10
c_0	Base delivery cost of professional fleet	5$
α_0	Delivery cost of professional fleet per kilometer	1$
β_0	Intercept of utility function	-4.8359
β_{comp}	Coefficient of attribute “Compensation”	0.7337
β_{detour}	Coefficient of attribute “Detour distance ”	-0.8522
μ	Mean waiting time of in-store customers	30
σ	Standard deviation of waiting time	10

TABLE III: Parameter values

Moreover, we conclude three different scenarios as follows.

- **Scenarios 1:** Within a unit of time, the arrival rate of in-store customers and online orders with different destinations is the same. This scenario simulates a general supply-demand distribution.
- **Scenarios 2:** Within the same unit of time, some destinations have a higher arrival rate for in-store customers and online orders, while other destinations have a lower rate. This situation simulates the difference in regional consumption capacity.
- **Scenarios 3:** Within the same unit of time, some destinations have an in-store customer arrival rate greater than the online order rate, whereas in other destinations, the in-store customer arrival rate is less than the online order rate. This situation simulates the difference in online and in-store shopping behaviors.

Next, we will compare the performance of two different approaches under various scenarios, varied by the mean driver and order arrival rate and different evaluation metrics.

B. Cost reduction rate (CR) comparison in three scenarios

Cost reduction rate (CR) directly responses to the feasibility and effectiveness of proposed approach, which is defined as:

$$CR = \frac{\sum_{\forall j \in \mathcal{J}} c_j - (\sum_{\forall j \in \dot{\mathcal{J}}} s_j + \sum_{\forall j \in \bar{\mathcal{J}}} c_j)}{\sum_{\forall j \in \mathcal{J}} c_j} \tag{22}$$

Where c_j denotes the original cost of order j delivered by PFs. s_j denotes the computed compensation paid to in-store

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customer $\mu(i)$ to deliver order j. And $\mathcal{J}$, $\dot{J}$, and $\bar{J}$ denote the set of all online orders throughout a day, the accepted set of orders, and the rejected set of orders by in-store customers respectively.

Refer to Fig. 5, we can observe that the value of CR increases with the growth of the average order and driver arrival rate for each sample time interval. The performance of the two methods of DP-MF is superior to the Myopic method under three different scenarios. However, the advantage of the SDP over the GDP is not very pronounced under the CR metric. Furthermore, the CR of these four methods is not significantly affected by scenario changes. To be specific, the DP-MF method generally outperforms the Myopic method by approximately 15 percentage points.

C. Order rejection rate in three scenarios

Order rejection rate (OR) reflects the feasibility of the CDS platform and the quality of service on the supply side. If OR is too high, it indicates a low matching quality; customers who arrive at the store are unwilling to accept the orders allocated to them. Its calculation formula is as follows:

$$OR = \frac{|\bar{\mathcal{J}}|}{|\tilde{\mathcal{J}}|} \tag{23}$$

where $|\tilde{\mathcal{J}}|$ and $|\bar{\mathcal{J}}|$ denote the number of matched orders and set of rejected orders by in-store customers.

From the Fig. 6, we can observe that the OR trends for Scenario 1 and Scenario 3 are roughly the same, decreasing as the average arrival rate increases. In contrast, Scenario 2 shows a superior OR performance compared to the other two scenarios. Furthermore, we find that the DP-MF method consistently outperforms the Myopic method. Notably, the GDP compensation mechanism has evidently reduced the OR by approximately 5 to 10 percentage points.

D. Order successfully matched rate comparison in three scenarios

The Order Successful Matching Rate refers to the proportion of orders delivered by in-store customers to all orders. This metric reveals some hidden attributes of the system, namely, how many orders can be completed by in-store customers rather than hired professional delivery personnel. On another level, it can save hidden costs similar to maintenance and hiring. Its calculation formula is as follows:

$$OM = \frac{|\dot{\mathcal{J}}|}{|\mathcal{J}|} \tag{24}$$

where $|\mathcal{J}|$ and $|\dot{\mathcal{J}}|$ denote the number of all online orders throughout a day and the number of accepted orders by in-store customers.

The experimental results (Fig. 7) show that the growth trends of the four methods under the three scenarios are essentially consistent. OM increases with the growth of the average arrival rate per unit time. The DP-MF method is significantly superior to the Myopic method, allowing more orders to be handed over to in-store customers for delivery, with an increase of up to nearly 15%. Furthermore, the GDP method still outperforms the SDP method on this front.

V. Conclusion and Future Works

This paper introduces a dynamic predictive matching framework designed to address the matching problems in a crowd-sourced delivery system under stochastic environment. The innovation of this paper lies in considering the uncertainties from both the supply and demand sides simultaneously. Firstly, taking into account the variability in arrival rates of orders and drivers, the goal of optimality in subsequent matches is achieved through deferring matching for some orders and drivers. Furthermore, the uncertainty in the behavior of in-store customers is relaxed through a customized compensation incentive strategy. In the future, data-driven predictive analysis of supply and demand sides, as well as the dynamic acceptance behavior of in-store customers, such as the impact of waiting time on their behavior, are also worthwhile directions for exploration.

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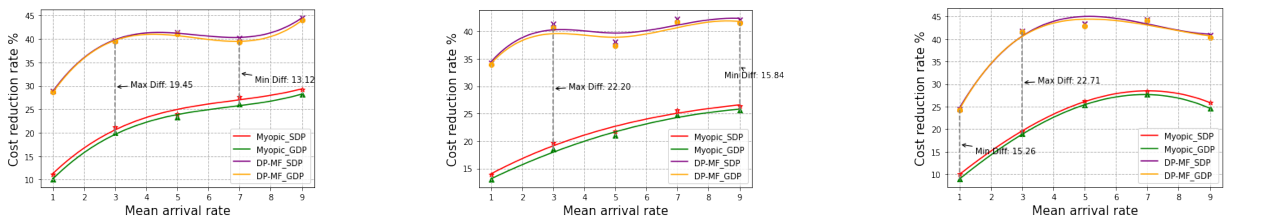
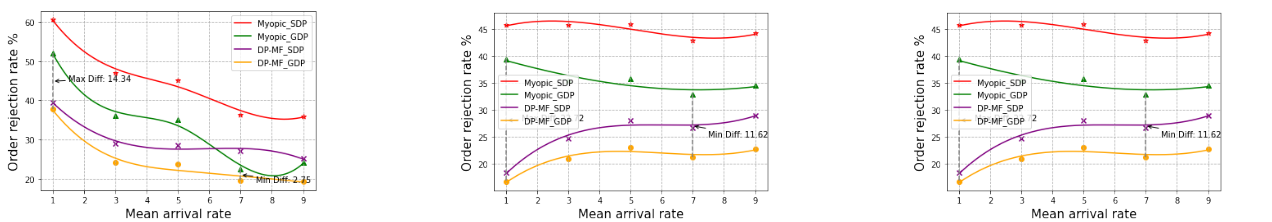


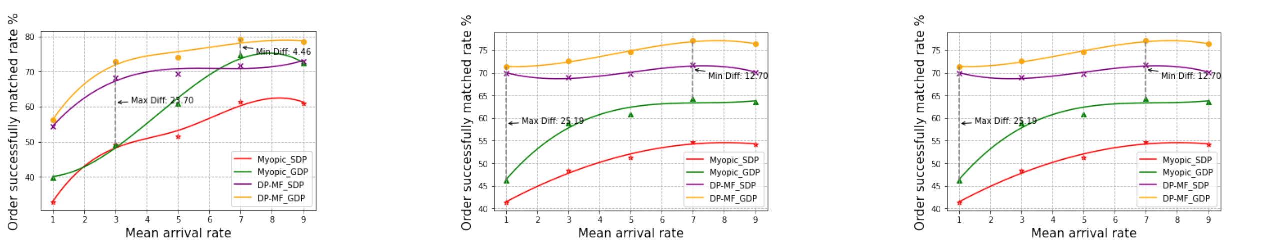
(a) Scenario 1 (b) Scenario 2 (c) Scenario 3

Fig. 5: Comparative analysis of Cost Reduction Rate by DP-MF_GDP, DP-MF_SDP, Myopic_GDP and Myopic_SDP approaches as a function of the mean arrival rate of drivers orders ($= [1, 3, 5, 7, 9]$ per 15 minutes) in three scenarios



(a) Scenario 1 (b) Scenario 2 (c) Scenario 3

Fig. 6: Comparative analysis of Order Rejection Rate by DP-MF_GDP, DP-MF_SDP, Myopic_GDP and Myopic_SDP approaches as a function of the mean arrival rate of orders ($= [1, 3, 5, 7, 9]$ per 15 minutes) in three scenarios



(a) Scenario 1 (b) Scenario 2 (c) Scenario 3

Fig. 7: Comparative analysis of Order Successfully Matched Rate by DP-MF_GDP, DP-MF_SDP, Myopic_GDP and Myopic_SDP approaches as a function of the mean arrival rate of orders ($= [1, 3, 5, 7, 9]$ per 15 minutes) in three scenarios

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