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A multi-depot vehicle routing optimization model for quick commerce last-mile delivery☆

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A R T I C L E I N F O

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A B S T R A C T

Last-mile delivery is a critical and complex element of supply chain network design because ineffective planning can lead to higher customer dissatisfaction, increased operational costs, and greater environmental impacts. These challenges intensify in the context of Quick Commerce (Q-commerce), a retail model characterized by extremely short fulfillment cycles and strict delivery expectations. This study develops a decision support system for multi-depot vehicle routing problems with time windows to optimize last-mile delivery operations in Q-commerce. The model offers two delivery-speed options: fast and ultra-fast, and requires customers to select their preferred service type. Ultra-fast delivery does not permit delays, whereas fast delivery allows delays with an associated penalty. To enhance system resilience and reduce the risk of service disruption, both in-house and platform riders are included, enabling a mix of fixed and flexible delivery capacity. Model performance is assessed through 15 simulated problem instances, demonstrating that the system generates accurate and reliable routing and assignment decisions. A seven-scenario sensitivity analysis further highlights the model's adaptability to changes in inter-node distances, customer delivery preferences, and rider employment costs. To incorporate service quality considerations, the model is then extended into a bi-objective formulation that includes customer satisfaction as a secondary objective, and an additional set of 15 simulated instances is solved using the augmented epsilon-constraint method. The resulting insights offer practical guidance for decision-makers in selecting rider types, assigning routes, and providing customers and store operators with more precise arrival-time estimates.

1. Introduction

Last-mile delivery has emerged as a significant global challenge encompassing all activities involved in transporting products to customers in urban areas (Ha et al., 2023). This challenge is driven by rapid urbanization and the continued expansion of Electronic Commerce (e-commerce), which are contributing to rising population density in cities and higher per capita online purchase volumes (Boysen et al., 2021). As a result, the volume of online orders has grown substantially, placing increasing pressure on urban logistics systems. Meeting these demands is difficult, as the greater number of delivery vehicles intensifies environmental concerns, urban congestion, and cost-related issues arising from traffic delays, limited parking availability, and unsuccessful deliveries (Lasota et al., 2024). These pressures also contribute to delivery delays and create heavy workloads for an aging workforce (Bachofner et al., 2022; Boysen et al., 2021). Consequently, last-mile delivery has become a complex and costly bottleneck in the broader supply chain, underscoring the need for more efficient and innovative problem-solving approaches.

On the other hand, the conventional last-mile paradigm is being

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disrupted by the rapid growth of Quick Commerce (Q-commerce). This super-fast delivery model delivers goods, groceries, and other products quickly. The transition from e-commerce to Q-commerce significantly intensifies the pressure on urban logistics (Datta & Bose, 2024). The customary promise to clients that the parcel will be delivered quickly creates new constraints: shorter time windows, from days to minutes; smaller order sizes; higher order frequency; and a shift from centralized warehouses to a network of high-density urban micro-fulfillment centers. The tenets of consolidation and route optimization are challenged by this operational model, which seeks to reduce the environmental footprint and costs associated with traditional e-commerce. As a result, Q-commerce creates extreme complexity and exacerbates existing issues, including heavy traffic, vehicle emissions, and operational inefficiency, while prioritizing instant customer satisfaction (Gund & Daniel, 2024).

The new paradigm mentioned focuses on conventional last-mile optimization strategies, whereas many current e-commerce logistics models are not sufficiently compelling. The approaches designed for consolidated deliveries with longer lead times cannot cope with the high speed and fragmented order patterns of Q-commerce. When no efficient, real-time vehicle routing model is available to handle this system effectively, the total mileage of delivery vehicles will increase significantly. It results in higher operational expenses and adverse environmental impacts. The literature review indicates that research on environmental emissions from traditional e-commerce is increasing (Zhang et al., 2026; Liu et al., 2024). However, there is a significant gap in the body of knowledge on modeling and mitigating the adverse environmental impacts of such ultra-fast networks. Hence, there is a strong need to conduct innovative research and to design mathematical models tailored to the unique operational needs of Q-commerce. In this way, costs are saved while goods are delivered on time, thereby ensuring customer satisfaction and reduced carbon emissions.

To address this gap, this study presents a decision support system (DSS) based on a novel mathematical modeling framework that effectively manages the complexities of Q-commerce logistics. A mixed-integer linear programming (MILP) model is developed for the vehicle routing problem (VRP) with time windows to optimize a network comprising online fulfillment centers and customers. The mentioned model directly handles the multi-modal nature of Q-commerce by enabling order allocation to committed in-house riders or platform riders. This allows both fast and ultra-fast delivery promises to be fulfilled. The objective function of the present model aims to minimize the network's total cost, including costs associated with using both in-house and platform riders.

Additionally, the cost function includes a penalty for any late delivery in the fast-delivery mode. It is worth noting that, because the objective function is derived from minimizing riders' distance traveled, it reduces carbon emissions. Thus, this objective function is environmentally friendly and also considers economic benefits. The proposed model is further extended using a customer satisfaction objective function. For this purpose, an objective function that minimizes the maximum arrival times is considered. The augmented epsilon-constraint method is employed next to solve the bi-objective model and generate Pareto-optimal solutions. Overall, this study addresses the following research questions:

- How can a multi-depot vehicle routing model be formulated to capture the operational complexities of Q-commerce logistics?
- How can fast and ultra-fast delivery requirements be incorporated into the Q-commerce framework?
- What strategies can enhance network resilience to ensure reliable order fulfillment?
- How can a bi-objective model balance customer satisfaction and network cost, and what solution approach is appropriate?

Accordingly, the main contributions of this study are as follows:

- Formulating a multi-depot MILP vehicle routing model to support decision-making in Q-commerce logistics.
- Integrating ultra-fast delivery with hard time windows and fast delivery with both hard and soft time windows.
- Enhancing network resilience by combining in-house and platform riders.
- Developing a bi-objective MILP model that balances network cost and customer satisfaction, solved using the augmented epsilon-constraint method to generate Pareto-optimal solutions.

The remainder of the article is organized as follows. Section 2 presents the literature review, and Section 3 introduces the proposed decision support system. Section 4 reports the results and discussion, while Sections 5 and 6 address the sensitivity analysis and the bi-objective model extension, respectively. Section 7 discusses the managerial implications, and Section 8 provides the conclusions.

2. Literature review

The literature review comprises two subsections. The first subsection examines the differences between Q-commerce and e-commerce. The second subsection reviews articles that have used VRP-based models for last-mile delivery in e-commerce or Q-commerce contexts.

2.1. Q-commerce versus e-commerce

Several factors, including delivery timeliness, cost, and product price, have been systematically examined in research on online purchasing decisions. In addition to speed, accuracy is critical to consumers, which means how reliable the promised delivery windows are (Murfield et al., 2017). The significance of this issue increases in Q-commerce, where the central premise is ultra-fast delivery of goods to meet urgent needs. The usefulness of these time-sensitive services is strongly felt, as they can meet customers' immediate needs or quickly replace a missing item in critical situations. Since these needs are so urgent, their usefulness is explicitly tied to their satisfaction within a short period. As a result, Q-commerce is not only responsible for selling goods but also for marketing time-critical services, where promptness is essential to their value proposition (Harter et al., 2025).

According to Davalos and Levingston (2022) and Woo (2022), orders placed with Q-commerce companies are often delivered within 30 min. However, the agreed-upon law stipulates that the item must be delivered within 1 h (Bogdanova, 2021). This service standard is the foundation for understanding market and consumer needs, making a significant contribution to establishing financial dynamism. For example, the value of the global Q-commerce sector in the United States was estimated at around \$20 billion to \$25 billion in 2020.[1] The impact of this growth has been evident, with global revenues reaching \$195 billion in 2025, up from the previous year. It is anticipated that revenues in the Q-commerce market will exceed \$283 billion worldwide by 2030.[2] These increasing statistics highlight a significant shift, as such services have led customers to request quick delivery.

On the other hand, few studies have examined delivery times in Q-commerce, as previous e-commerce research findings are not generalizable to Q-commerce (Harter et al., 2025). There are several significant differences between these two phenomena (as shown in Table 1), which can affect consumer responses. For example, the fulfillment of immediate needs is the primary target in Q-commerce delivery times (Taylor, 2018). Therefore, a significantly faster delivery process should be implemented compared to traditional E-Commerce, with the intended item delivered in minutes rather than days. Hence, customers value this fast delivery more than in conventional e-commerce. Another difference

[1] https://www.coresight.com.
[2] https://www.statista.com.

Table 1
Q-commerce versus e-commerce.

Dimension	E-commerce	Q-commerce
Immediate needs	No	Yes
Speed of delivery	Within days	Less than an hour
Arrival time	Typically coarse	Typically exact
Core product range	Consumer goods, clothing, household appliances, etc.	Grocery and supermarket products, meals, etc.
Product portfolio	Wide	Limited
Example	Amazon, Alibaba, Allbirds, Apple, Walmart, etc.	DoorDash, Uber Eats, Blinkit, Zepto, Getir, etc.

is that Q-commerce offers precise delivery times, thereby raising customer expectations for timeliness (Bai et al., 2019). In this regard, consumers in Q-commerce are likely to give more positive responses than those in traditional e-commerce, similar to those in initial deliveries. On the contrary, any delay in Q-commerce deliveries may have serious consequences, and customer satisfaction may be affected by the urgency of their needs.

2.2. Application of e-commerce and Q-commerce in VRP models

This section reviews articles that apply VRP models for last-mile delivery in the context of e-commerce or Q-commerce. Liu (2020) studied the last-mile distribution problem in the e-commerce context. The author employed VRP with a pickup-and-delivery strategy and developed a mathematical model to maximize the supply chain's profit. She used the ant colony optimization algorithm to solve her problem and evaluated its performance on five datasets across various dimensions. A mixed-integer nonlinear programming model was proposed by Zhang et al. (2021) to structure a logistics system comprising customers, distributors, and suppliers. They used VRP, taking into account the time window and pickup and delivery strategy, for this purpose. The objective of their model was to minimize the total shipment and penalty costs within the time window. Kunnapapdeelert et al. (2022) proposed a VRP-based model for e-commerce to minimize transportation costs and carbon emissions. They employed a pickup-and-delivery strategy to reduce transportation costs and carbon emissions, and developed a meta-heuristic algorithm to address the problem. Prajapati et al. (2022) investigated the use of e-commerce in the agro-food distribution system and developed a VRP-based optimization model to address this. The objective of their model was to minimize the costs of economic, environmental, and social impacts. It is worth noting that they defined environmental and social factors as costs, including carbon taxes and accident-related damages. Escudero-Santana et al. (2022) formulated a VRP-based optimization model for e-commerce that accounts for customer preferences. Customer preferences refer to the ability to receive an order from a customer at different locations and within various time windows. They showed that accounting for these preferences would increase distribution flexibility and reduce costs. Similarly, Sadati et al. (2022) developed an electric VRP-based model in the e-commerce context, considering flexibility. Flexibility allows customers to select multiple delivery locations, each with a separate time window. The results showed that flexible delivery reduces costs and increases efficiency in the distribution system. A mathematical model for structuring a socio-economic VRP for logistics systems that use e-commerce platforms was presented by Pilati and Tronconi (2022). The goal of their model was to strike a balance between economic and social objectives. They used a *meta*-heuristic algorithm to solve their problem. Cokyasar et al. (2023) proposed an electric VRP that accounts for time-limited capacity constraints in e-commerce parcel distribution. The authors developed an MILP model for this purpose, with the objective of minimizing total distance traveled. They validated their proposed model using data from a case study in the United States that included electric and conventional vehicles. To implement e-commerce in a multi-depot capacitated VRP, Zuhanda et al. (2023) presented a mathematical model. The objective of their model was to minimize costs for handling, fuel consumption, operations, oil changes, and maintenance. The results revealed that their model performed better compared to the classical model. Liu et al. (2024) formulated a VRP-based model for last-mile fresh food distribution in the e-commerce context. The objective functions of their model included cost minimization (economic dimension), carbon emission minimization (environmental dimension), and customer satisfaction maximization (social dimension). Pilati and Tronconi (2024) proposed a capacitated VRP-based model to structure sustainable logistics in the e-commerce context. They developed a multi-objective *meta*-heuristic algorithm to solve their problem. To reduce the distribution costs of fresh agricultural products, Zahran (2024) developed a VRP-based optimization model for e-commerce. Efficient energy use, reduced travel time, and prevention of freshness deterioration were among the features of their model. Hu and Tao (2025) examined the last-mile delivery problem in rural areas, accounting for government subsidies and uncertain e-commerce demand. They developed a VRP-based model that included simultaneous pickup and delivery and time windows. They further used fuzzy theory to address demand uncertainty. Wang et al. (2025) proposed a VRP-based model that incorporates time windows and split deliveries in e-commerce. They formulated an MILP model whose objective was to minimize total costs. Belbağ (2025) developed a VRP-based model for structuring an e-commerce logistics network that considers emissions and returns. The study formulated an MILP model with the objective of minimizing fuel consumption costs, vehicle supply costs, and unmet demand penalties. The results showed that the model is effective for product distribution and returns collection in the e-commerce context and significantly reduces emissions. Zhang et al. (2026) presented a low-carbon VRP-based model considering time windows and simultaneous pickup and delivery in e-commerce. They used *meta*-heuristic algorithms to solve their problem. The results showed that their algorithm reduces costs, improves network coordination, and provides optimal routes for simultaneous pickup and delivery within specified time windows.

The literature review reveals that few papers have employed mathematical programming tools for the VRP in Q-commerce. Ma et al. (2025) proposed an MILP model for the routing problem in Q-commerce. Their model uses vehicles and drones to deliver orders instantly. The objectives of their model were to minimize order delivery time, maximize customer satisfaction with delivery time, and maximize customer satisfaction with product quality. It is worth noting that they used a multi-objective memetic algorithm to solve the problem at large sizes. To increase the speed of order delivery to customers, Yang et al. (2024) integrated the micro-fulfillment center location problem and the VRP in Q-commerce. The goal of their model was to minimize the costs associated with establishing centers, sourcing products, processing, transportation, and penalties for late delivery. They developed a heuristic algorithm to solve this problem. The results indicated that using the proposed model significantly reduced costs. Although numerous articles have employed VRP-based models in e-commerce, these models have received less attention in Q-commerce. This study, for the first time, develops a DSS based on a VRP model for Q-commerce problems that accounts for customer preferences for delivery type and the use of both in-house and platform riders.

3. Proposed DSS

Businesses operating at the last level of the supply chain, particularly in last-mile delivery, continually seek to implement operational models that enhance customer satisfaction and, consequently, increase profitability. Q-commerce is an emerging operating model that provides businesses with a competitive advantage by reducing delivery times, thereby increasing market share. Take-out restaurants, grocery chains, and dark stores are among those that typically utilize Q-commerce to serve their customers. This section aims to develop a DSS based on an MILP model to implement Q-commerce in a grocery store chain. The studied network consists of several stores that serve customers in a specific area. The stores use two types of riders: in-house and platform riders to serve customers.

Two delivery options are available to customers: fast and ultra-fast delivery. Both soft and hard time windows are characteristic of fast delivery. The soft time window allows for delays subject to penalties, whereas the hard time window prevents unacceptable delays. In contrast, ultra-fast delivery does not permit any delays, and orders must be delivered within the stipulated time. This delivery option is therefore based solely on hard time windows. Customer orders are confirmed at specific intervals (e.g., every five minutes). At each interval, the system is updated, and once the orders are confirmed, the model is executed using the relevant data. This data includes customer locations, the number of available in-house riders, the number of platform riders near the stores, and the geographic and temporal distances between riders and stores. The general structure of the studied network is given in Fig. 1. Furthermore, the proposed DSS is depicted in Fig. 2. To better understand the problem under study, the following assumptions are made:

- The network comprises several stores and numerous customers.
- In-house riders of each store must return to the home store after serving customers.
- Platform riders must pick up orders from the store before visiting customers.
- Platform riders follow the open VRP structure, meaning their origin and destination are different.
- Both fast and ultra-fast delivery are available to customers.
- In ultra-fast delivery, exceeding the time window is not allowed.
- In fast delivery, exceeding the time window is allowed to a certain extent.
- For fast delivery, both soft and hard time windows are considered, while for ultra-fast delivery, only the hard time window is taken into account.
- Customer 1 is considered the store.
- The demand of each customer must be met by exactly one rider.

Fig. 1 presents the overall structure of the network under study, comprising two levels: stores and customers. Each store serves customers located within its designated coverage radius, ensuring that all customer demand is met. As illustrated in this figure, the delivery system incorporates two categories of riders. The first category consists of in-house riders, who are store employees. These riders depart from a store, serve their assigned customers, and then return to the same store, forming a closed vehicle routing structure. The second category consists of platform riders, who operate as third-party logistics providers positioned around the stores. These riders travel from their initial location to a store, collect customer orders, and then deliver them along a route that ends at the final customer. Their routes follow an open-vehicle routing structure. Unlike in-house riders, platform riders do not return to their

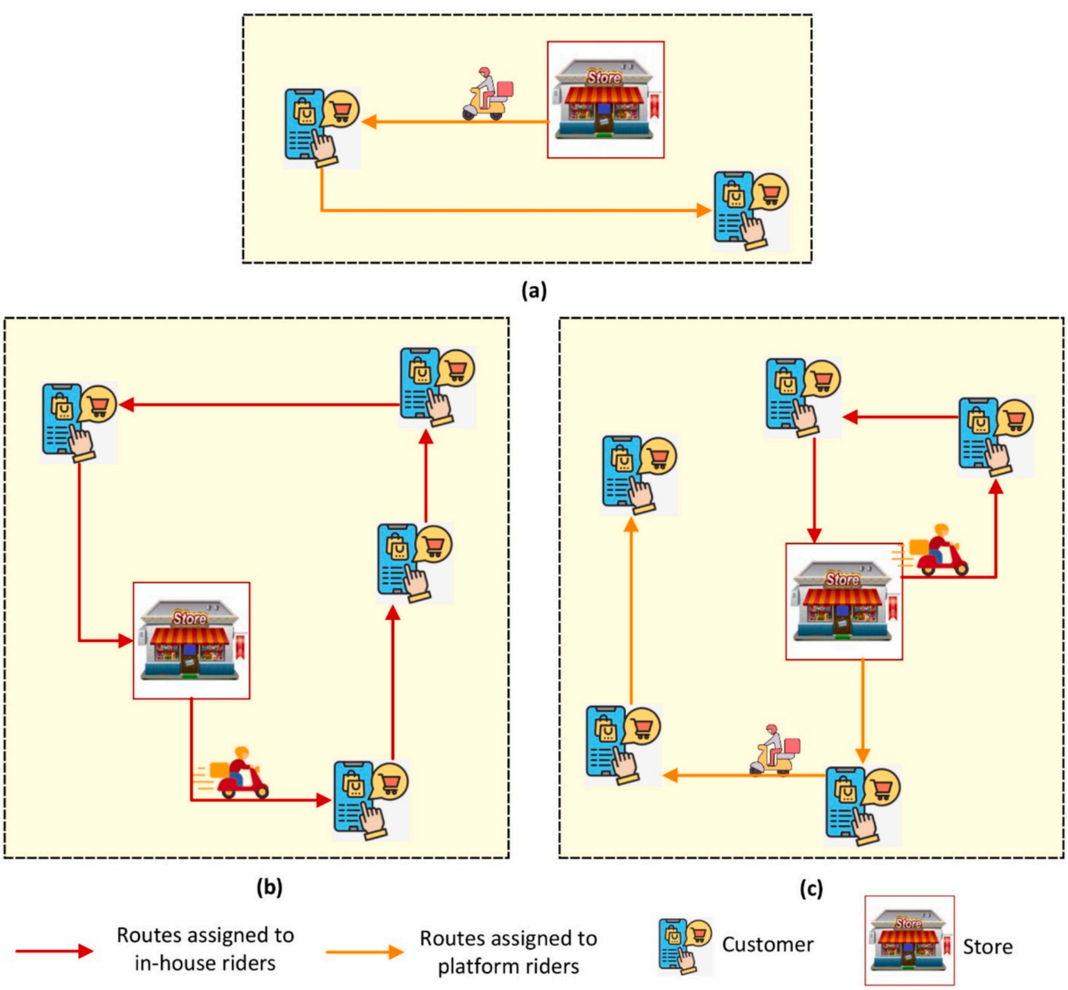


Fig. 1. The overall structure of the studied network.

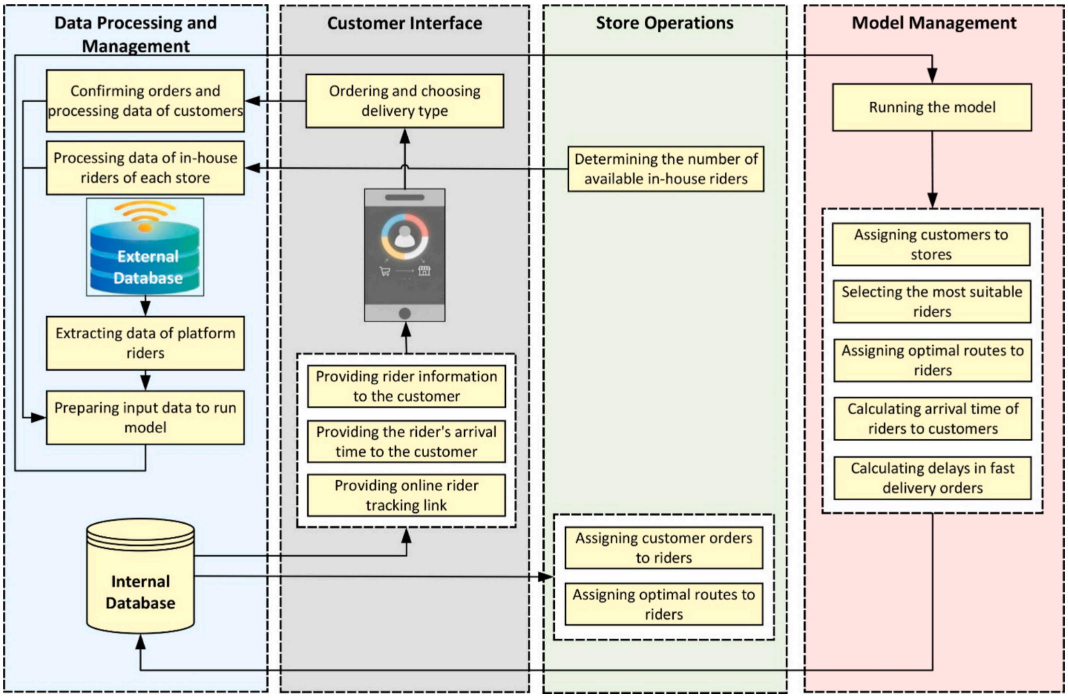


Fig. 2. The proposed DSS.

Table 2
Functions and values needed to simulate the data.

Parameter	Function/Value	Unit
γ^{ST}	0.5	USD
γ^{PLT}	0.45	USD
F	40	min
PF	60	min
SF	30	min
$\theta_{\bar{e}e}$	$\begin{cases} 0 & if\ \bar{e}=e\ \ or\ \ e=1 \\ Uniform(0.5,7) & Otherwise \end{cases}$	km
λ_{se}	$\begin{cases} 0 & if\ e=1 \\ Uniform(0.5,3.5) & Otherwise \end{cases}$	km
$T\theta_{\bar{e}e}$	$Uniform(2,3)\times\theta_{\bar{e}e}$	min
$T\lambda_{se}$	$Uniform(2,3)\times\lambda_{se}$	min
$T\delta_{as}$	$Uniform(2,4)$	min
ϖ	4	min
ω_e	$Round(uniform(0,0.7))$	–
κ_{bs}	$Round(uniform(0,1))\vert\sum_s\kappa_{bs}=1$	–
PE	0.2	USD
ϑ	999	–

origin, and their final destination is the last customer they visit. As shown in Fig. 1, the model decides among three modes for delivering orders to customers. Panel (a) of Fig. 1 describes the mode where the store uses platform riders to deliver orders. Panel (b) depicts the mode where the store employs in-house riders to satisfy customer demand. The third mode presented in Panel (c) involves the combined use of platform and in-house riders for order delivery.

Fig. 2 presents the general structure of the proposed DSS. After a customer places an order through the application or website and selects the preferred delivery type, the order is processed, and the relevant customer data is stored in the order database. The store then updates information on in-house rider availability, while data on platform riders is retrieved from an external database. The system integrates these inputs and runs the proposed model; the model output is then transferred to the internal database for additional processing. The resulting information is then communicated to both customers and stores. Customers receive details such as rider identification, estimated arrival time, and a tracking link. Stores receive information about order assignments and the model-generated optimal delivery routes.

The following is the proposed MILP model:

Mathematical Model

Indices

$e,\bar{e}$	Customer	$1\le e,\bar{e}\le E$
s	Store	$1\le s\le S$
a	Platform rider	$1\le a\le A$
b	In-house rider	$1\le b\le B$

Parameters

γ^{ST}	The cost of using the in-house rider per kilometer
γ^{PLT}	The cost of using the platform rider per kilometer
F	The maximum time allowed for order delivery without penalty for the fast delivery mode
PF	The maximum time allowed for order delivery is with a penalty for the fast delivery mode
SF	The maximum time allowed for order delivery for the ultra-fast delivery mode
$\theta_{\bar{e}e}$	The geographical distance of the customer $\bar{e}$ from the customer e
λ_{se}	The geographical distance of the store s from the customer e
$T\theta_{\bar{e}e}$	The time distance of the customer $\bar{e}$ from the customer e
$T\lambda_{se}$	The time distance of the store s from the customer e
$T\delta_{as}$	The time distance between the origin of platform rider a and store s
ϖ	Average stop time at each customer location
$\omega_e\begin{cases}1\\0\end{cases}$	If the customer e chooses ultra-fast delivery mode If the customer e chooses fast delivery mode
$\kappa_{bs}\begin{cases}1\\0\end{cases}$	If in-house rider b belongs to store s Otherwise
PE	Penalty cost per minute of delay
ϑ	A large number

Variables

$R_{ase}\begin{cases}1\\0\end{cases}$	If platform rider a goes from their origin to store e for delivering an order to customer e Otherwise
$\overline{R}_{a\bar{e}e}\begin{cases}1\\0\end{cases}$	If the route between customer $\bar{e}$ and customer e is assigned to platform rider a Otherwise

(*continued on next page*)

(continued)

$U_{b\bar{e}e} \begin{cases} 1 \\ 0 \end{cases}$	If the route between customer $\bar{e}$ and customer e is assigned to in-house rider b Otherwise
X_{ae}	The arrival time of platform rider a to customer e
Y_{be}	The arrival time of in-house rider b to customer e
Q_e	The amount of delay in delivering the order for the customer e

Objective functions

$$Min\,Z^{Cost} = \sum_{b,\bar{e}>1,e>1} \gamma^{ST} \times \theta_{\bar{e}e} \times U_{b\bar{e}e} + \sum_{b,s,e>1} \gamma^{ST} \times \kappa_{bs} \times \lambda_{se} \times (U_{b1e} + U_{be1}) + \sum_{a,s,e>1} \gamma^{PLT} \times \lambda_{se} \times R_{ase} + \sum_{a,\bar{e}>1,e>1} \gamma^{PLT} \times \theta_{\bar{e}e} \times \overline{R}_{a\bar{e}e} + \sum_{e} PE \times Q_e \tag{1}$$

s.t.

$$\sum_{a,\bar{e}} \overline{R}_{a\bar{e}e} + \sum_{b,\bar{e}} U_{b\bar{e}e} = 1 \quad \forall e > 1 \tag{2}$$

$$\sum_{\bar{e}} \overline{R}_{a\bar{e}e} = \sum_{\bar{e}} \overline{R}_{ae\bar{e}} \quad \forall a, e \tag{3}$$

$$\sum_{\bar{e}} U_{b\bar{e}e} = \sum_{\bar{e}} U_{be\bar{e}} \quad \forall b, e \tag{4}$$

$$\sum_{s} R_{ase} = \overline{R}_{a1e} \quad \forall a, e \tag{5}$$

$$X_{ae} + \vartheta \times (1 - R_{ase}) \geq T\delta_{as} + T\lambda_{se} \quad \forall a, s, e > 1 \tag{6}$$

$$X_{ae} + \vartheta \times (1 - \overline{R}_{a\bar{e}e}) \geq X_{a\bar{e}} + \varpi + T\theta_{\bar{e}e} \quad \forall a, \bar{e} > 1, e > 1 \tag{7}$$

$$Y_{be} + \vartheta \times (1 - U_{b1e}) \geq T\lambda_{se} \times \kappa_{bs} \quad \forall b, s, e > 1 \tag{8}$$

$$Y_{be} + \vartheta \times (1 - U_{b\bar{e}e}) \geq Y_{b\bar{e}} + \varpi + T\theta_{\bar{e}e} \quad \forall b, \bar{e} > 1, e \tag{9}$$

$$\sum_{a} X_{ae} + \sum_{b} Y_{be} - F \leq Q_e + \vartheta \times \omega_e \quad \forall e > 1 \tag{10}$$

$$\sum_{a} X_{ae} + \sum_{b} Y_{be} \leq PF + \vartheta \times \omega_e \quad \forall e > 1 \tag{11}$$

$$\sum_{a} X_{ae} + \sum_{b} Y_{be} \leq SF + \vartheta \times (1 - \omega_e) \quad \forall e > 1 \tag{12}$$

The objective function of the proposed model minimizes the costs of delivering orders to customers. The costs included in this objective function are: the cost of using in-house riders, the cost of using platform riders, and the penalty for delay in delivering orders to customers. This objective function, in addition to reducing delivery costs, also increases customer satisfaction. Constraint (2) ensures that each customer's demand is met by exactly one rider, either an in-house rider or a platform rider. Under the VRP condition, if a rider arrives at a customer's location, they must leave after serving that customer. This condition is included in constraints (3) and (4) for platform riders and in-house riders, respectively. The selected platform rider must travel from its origin to the designated store and, after picking up the orders, proceed to the customer's e. Constraint (5) guarantees this. Constraint (6) calculates the arrival time of platform riders to the first customer. Also, the arrival time of these riders to other customers is determined by constraint (7). It is noteworthy that the first customer on a route is the one visited immediately after leaving the store. Similarly, the arrival times of in-house riders to the first customer and to other customers are calculated using constraints (8) and (9), respectively. Constraint (10) is applied to determine the delay in delivering customer orders in the fast-delivery mode. Delivery of customer orders in both fast and ultra-fast modes should not exceed the specified maximum allowable delivery time. The conditions for fast and ultra-fast delivery modes are defined in constraints (11) and (12), respectively.

4. Results and discussion

In this section, the efficiency of the developed model is examined using simulated data of varying sample sizes. Table 2 presents the functions and values needed to simulate the data for each parameter.

For example, the numbers 0.5 and 0.45 in rows 1 and 2 of Table 2 indicate that the per-kilometer costs for in-house and platform riders are \$0.5 and \$0.45, respectively. A combination of round and uniform functions has been applied to simulate binary parameters, such as ω_e. For example, the parameter ω_e in the proposed model is defined so that a value of 1 indicates the customer has selected the ultra-fast delivery option. In contrast, a value of 0 indicates a preference for the fast delivery option. The function $Round(uniform(0, 0.7))$ has been developed to simulate this parameter. If, during the simulation, the value of this parameter is between 0 and 0.5, it is converted to "zero" by the round function, and the fast delivery option is given to the customer. However, if the random number is between 0.5 and 0.7, it is converted to "one" using the round function, and the ultra-fast option is given to the customer.

To validate the proposed model, we simulate 15 problems of varying sizes using the functions and values presented in Table 2. Table 3 denotes the dimensions of the simulated problems.

The proposed model was run on simulated data in GAMS using the CPLEX solver. The optimal objective function values for 15 simulated problems are given in Table 4.

The problem instances reported in Table 3 are designed so that each instance is larger than the previous one. For example, the number of customers and in-house riders in P2 is larger compared to P1. This trend holds for all 15 simulated problems. The runtimes presented in Table 4 show that increasing the problem size affects the model runtime. Fig. 3 depicts the model runtime for solving simulated problems of different

Table 3
The dimensions of the simulated problem.

Problem	e	s	a	b
P1	5	1	2	1
P2	7	1	2	2
P3	9	2	3	2
P4	11	2	4	2
P5	13	2	4	3
P6	15	3	5	4
P7	16	3	5	5
P8	17	3	6	5
P9	19	4	6	6
P10	21	4	7	6
P11	23	5	7	6
P12	25	5	8	7
P13	27	5	9	7
P14	29	6	9	8
P15	31	6	10	8

Table 4
The optimal value of the objective function of the simulated problem.

Problem	Objective function ($)	Runtime (seconds)
P1	2.709	0.407
P2	3.803	0.392
P3	4.789	0.684
P4	4.969	0.510
P5	5.015	1.088
P6	5.396	3.303
P7	5.705	3.624
P8	5.721	4.850
P9	6.648	5.199
P10	6.317	6.153
P11	6.772	6.643
P12	7.315	21.269
P13	7.940	38.872
P14	8.174	47.238
P15	8.438	56.901

sizes.

To ensure the accuracy of the results from the developed model, we analyze Problem 10 (P10) in detail as the base case. As shown in Table 3, P10 comprises 20 customers (including customer 1, which represents the store), four stores, seven platform riders, and six in-house riders. The parameter data for $\theta_{\bar{e}e}$, λ_{se}, $T\theta_{\bar{e}e}$, $T\lambda_{se}$, $T\delta_{as}$, ω_e, κ_{bs}, and P10 are simulated using the functions presented in Table 2 and are provided in the Appendix. By running the model in GAMS software through CPLEX solver for P10 data, the optimal values of the objective function and decision variables are calculated, which are given below:

- The optimal value of the objective function is $6.317.
- All four stores are selected for service.
- Platform riders are employed to provide service, and no in-house riders are used.
- There will be no delays in the delivery of orders for any customer.
- Platform riders 1, 6, and 7 are assigned to store 1, platform riders 2 and 4 to store 3, platform rider 3 to store 2, and platform rider 5 to store 4.
- The routes assigned to each platform rider are shown in Fig. 4. Additionally, their arrival times to customers are illustrated in this figure.

Fig. 4 illustrates the routes assigned to the riders for each store. Panels (a), (b), (c), and (d) of Fig. 4 show the routes assigned to platform riders allocated to stores 1 to 4, respectively. For example, Panel (a) shows that platform rider 1 begins at its origin, travels to store 1 to pick up the assigned orders, and then visits customers 17, 6, 16, 8, and 9 in sequence. This panel also displays the riders' arrival times at each customer location. For example, the value "10" on the route assigned to platform rider 1 indicates that the rider will reach customer 6 ten minutes after departing the origin. The remaining results in Fig. 4 can be interpreted similarly.

An important question arises regarding the reliability of the obtained results. Specifically, how can the accuracy of these outputs be validated? The following section addresses this question by evaluating the model's results using the input data.

- The model has decided to utilize platform riders to meet customer needs. This means that platform riders are prioritized over in-house riders. Given that the objective function of the proposed model is to minimize total costs, this is true only if the cost of using platform riders is lower than that of using in-house riders. The data presented in Table 2 shows that the cost of using platform riders is $0.45 per kilometer, while the cost for in-house riders is $0.50. Therefore, the model correctly prioritizes platform riders over in-house riders.
- In general, the objective function consists of three components: the cost of using in-house riders, the cost of using platform riders, and the penalty cost for delay in delivering orders to customers. The results indicate that in-house riders were not used, and there were no delays in order delivery. This means that the optimal value of the objective function is determined solely by the cost of using platform riders. In other words, if the model works correctly, the product of the total distance traveled by platform riders and the cost of using platform riders (i.e., 0.45) should be equal to the optimal value of the objective function (i.e., 6.317). Using the routes shown in Fig. 4 and the data provided in Tables A1 and A2, the total distance traveled by each platform rider can be calculated and is presented in Table 5.

From the results presented in Table 5, it can be concluded that the total distance traveled by all platform riders is 14.02 km. On the other hand, the cost of using platform riders per kilometer is $0.45. The product of these two numbers is $6.31, which yields the optimal value of the objective function.

- The next item to validate the results is the calculated values for the arrival time of riders to customers, as shown in Fig. 4. For instance, Fig. 4 shows that platform rider 1 arrives at customer 6, ten minutes

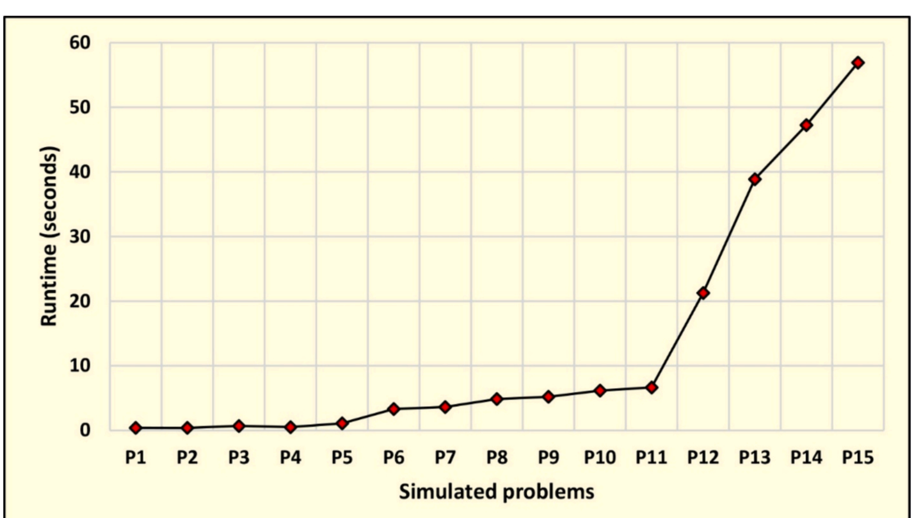


Fig. 3. The runtime for solving simulated problems of different sizes.

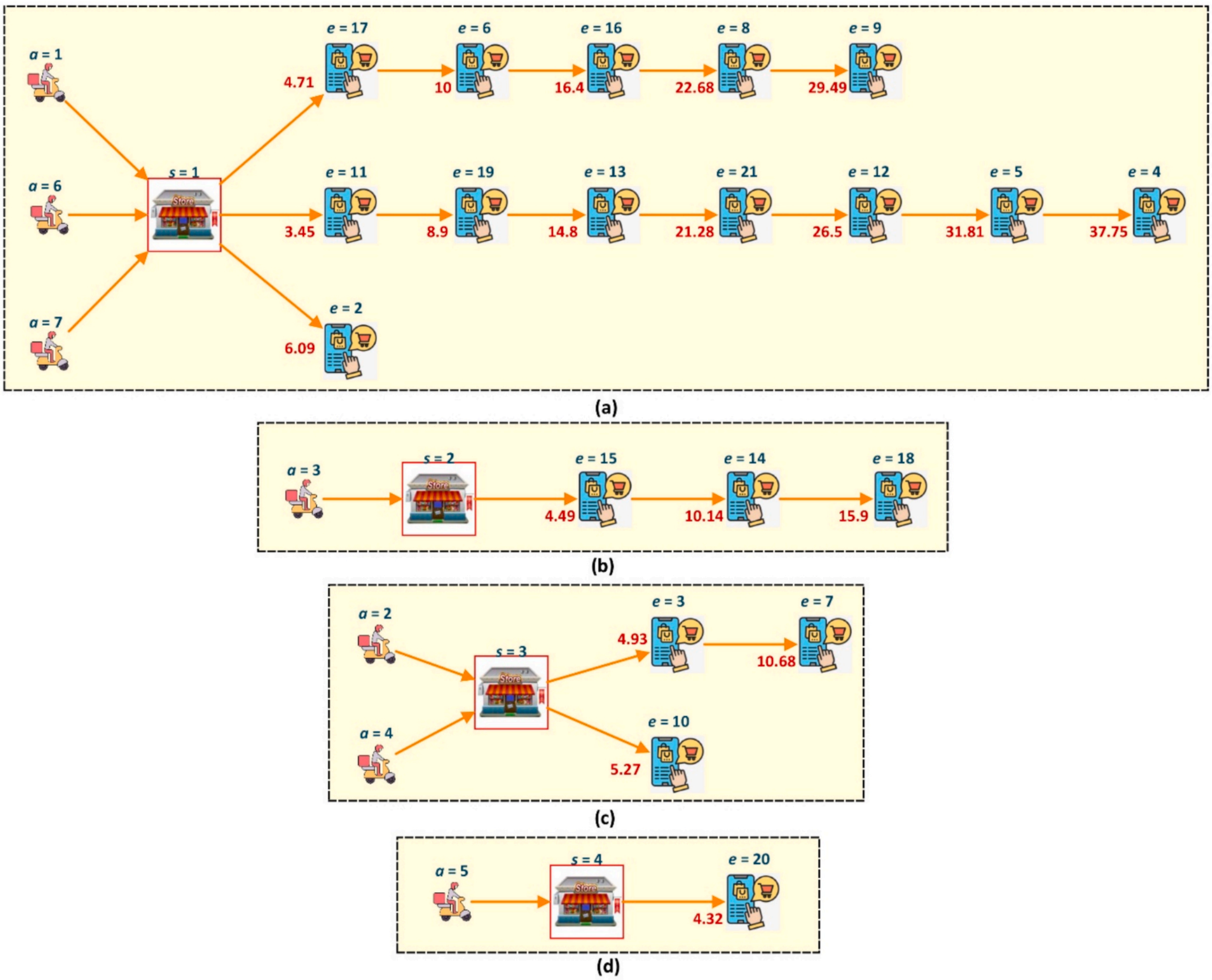


Fig. 4. The routes assigned to platform riders, along with their arrival times to customers.

after leaving its origin. To reach customer 6, this rider first goes to store 1. Then, it visits customer 17. After that, it moves to customer 6′s location. Table A5 shows that the time difference between platform rider 1 and store 1 is 3.26 min. On the other hand, Table A4 reveals that the time distance between store 1 and customer 17 is 1.45 min. Based on the data in Table 2, the average rider stop time at each customer location is 4 min. Furthermore, Table A3 indicates that the time difference between customers 17 and 6 is 1.29 min. Therefore, the sum of these times, 10 min, represents the arrival time of platform rider 1 at customer 6. This means the model correctly predicts the arrival time of platform riders for customers.

Generally, analyzing the results and matching them against the input data confirmed the validity of the proposed model. This means the model provides reliable, optimal results. To further ensure the accuracy of the proposed model's performance, the model's behavior is analyzed to assess changes in specific parameter values via a sensitivity analysis.

5. Sensitivity analysis

In this section, the performance accuracy of the developed model is evaluated using seven scenarios. The following presents the results of the sensitivity analysis for each scenario in problem 10 (P10).

Table 5
The total distance traveled by each platform rider.

Platform rider	Total distance traveled
$a = 1$	$\lambda_{1.17} + \theta_{17.6} + \theta_{6.16} + \theta_{16.8} + \theta_{8.9} = 0.63 + 0.54 + 0.83 + 0.79 + 1.16 = 3.95$
$a = 2$	$\lambda_{3.3} + \theta_{3.7} = 0.5 + 0.8 = 1.3$
$a = 3$	$\lambda_{2.15} + \theta_{15.14} + \theta_{14.18} = 0.66 + 0.61 + 0.68 = 1.95$
$a = 4$	$\lambda_{3.10} = 0.62$
$a = 5$	$\lambda_{4.20} = 0.57$
$a = 6$	$\lambda_{1.11} + \theta_{11.19} + \theta_{19.13} + \theta_{13.21} + \theta_{21.12} + \theta_{12.5} + \theta_{5.4} = 0.6 + 0.67 + 0.66 + 0.9 + 0.57 + 0.53 + 0.7 = 4.63$
$a = 7$	$\lambda_{1.2} = 1$

Table 6
Functions to simulate data in scenario 1.

Parameter	Function	Unit
$\theta_{\bar{e}e}$	$\begin{cases} 0 & if\ \bar{e} = e\ \ or\ \ e = 1 \\ Uniform(5,10) & Otherwise \end{cases}$	km
λ_{se}	$\begin{cases} 0 & if\ e = 1 \\ Uniform(3,6) & Otherwise \end{cases}$	km

5.1. Scenario 1

In this scenario, we assume that $\theta_{\overline{e}e}$ and λ_{se} functions change as shown in Table 6, while the data for the other parameters remain constant. It is expected that the optimal value of the objective function will increase when Scenario 1 is implemented. Obviously, if the model is formulated correctly, increasing the distance between nodes will increase the total distance riders travel, thereby increasing the objective function's optimal value.

As expected, implementing Scenario 1 increased the optimal value of the objective function from \$6.317 to \$45.939. Changing $\theta_{\overline{e}e}$ and λ_{se} also changes the simulated data for $T\theta_{\overline{e}e}$ and $T\lambda_{se}$. In other words, as the distance between nodes increases, the travel time between them increases. The increase in travel time between nodes leads to the use of in-house riders 3 and 4 in addition to all platform riders. Furthermore, orders for customers 4, 5, and 6 are delivered 2.03, 1.45, and 4.98 min late, respectively. A summary of the results of Scenario 1 is given in Table 7. The results from Scenario 1 were consistent with reasonable expectations, indicating that the proposed model behaved and performed as expected.

5.2. Scenario 2

In this scenario, we assume that all customers choose the ultra-fast delivery mode. In this case, we expect that the optimal value of the objective function will not improve (i.e., it will either remain constant or increase). The results from Scenario 2 show that the optimal objective function value of \$7.176 is consistent with logical expectations. In this scenario, as in P10, only platform riders delivered orders. A summary of the results obtained from this scenario is reported in Table 7.

5.3. Scenario 3

In this scenario, we assume that no platform riders are available and that orders can only be delivered by in-house riders. In this case, we expect the optimal value of the objective function to increase because the cost of using in-house riders is higher than that of platform riders. Table 7 shows that the output from implementing Scenario 3 aligns with expectations. In this scenario, the optimal value of the objective function is 9.474, and in-house riders 1, 3, 4, and 6 are used to deliver orders. In addition, no orders are delayed, and the delay cost in this scenario is zero. Note that the P10 results are identical to the scenario where in-house riders are not available, so this scenario has been omitted.

5.4. Scenario 4

In the base scenario P10, the per-kilometer costs for using the platform and in-house riders are \$0.45 and \$0.50, respectively. In this scenario, we assume the values of these two parameters are the same, at \$0.45. In this case, we expect platform riders to take priority over in-house riders because in-house riders travel farther than platform riders, as they must return to the stores after serving customers, whereas platform riders operate under an open VRP and do not.

Scenario 4 yields results identical to those of P10 because of identical selected platform riders, the stores and routes assigned to them, and the total distance they travel. This means that the model's performance aligns with reasonable expectations, as it has chosen platform riders in a scenario where the cost of using in-house and platform riders is the same. A summary of the results obtained from this scenario is represented in Table 7.

5.5. Scenario 5

The per-kilometer costs for using the platform and in-house riders are \$0.45 and \$0.50 in P10, respectively. In this scenario, we assume the cost per kilometer for in-house riders changes to \$0.40 and for platform riders to \$0.50. In this case, using in-house riders to provide service will take priority over platform riders, as they are less costly.

The results from Scenario 5 are consistent with expectations. In this scenario, the optimal value of the objective function is in line with expectations at \$6.945, and in-house riders 1, 3, 4, and 6 are used to deliver orders. However, unlike P10, fewer riders are used. The reason is that P10 uses platform riders (at a lower cost), and these riders follow the open VRP structure. In the open VRP structure, riders do not return to stores. At the same time, in-house riders must return to their stores. Therefore, the model uses fewer in-house riders to avoid the additional cost of returning to the store after the last customer. A summary of the results of this scenario is included in Table 7.

5.6. Scenario 6

This scenario combines Scenarios 1 and 2 and the data related to the

Table 7
Summary of the results obtained from the sensitivity analysis process.

Scenario	Changing parameters	Objective function	Platform riders	In-house riders	Total delay (min)
Base Scenario: Scenario 0 (P10)	No change	6.317	1, 2, 3, 4, 5, 6, and 7	–	–
Scenario 1	$\theta_{\overline{e}e} = \begin{cases} 0 & if\ \overline{e} = e\ or\ e = 1 \\ Uniform(5,10) & Otherwise \end{cases}$ $\lambda_{se} = \begin{cases} 0 & if\ e = 1 \\ Uniform(3,6) & Otherwise \end{cases}$	45.939	1, 2, 3, 4, 5, 6, and 7	3 and 4	8.468
Scenario 2	$\omega_e = 1$	7.176	1, 2, 3, 4, 5, 6, and 7	–	–
Scenario 3	$Numberofplatformriders = 0$	9.474	–	1, 3, 4, and 6	–
Scenario 4	$\gamma^{ST} = \gamma^{PLT} = 0.45$	6.317	1, 2, 3, 4, 5, 6, and 7	–	–
Scenario 5	$\gamma^{ST} = 0.4$ $\gamma^{PLT} = 0.5$	6.945	–	1, 3, 4, and 6	–
Scenario 6	$\theta_{\overline{e}e} = \begin{cases} 0 & if\ \overline{e} = e\ or\ e = 1 \\ Uniform(5,10) & Otherwise \end{cases}$ $\lambda_{se} = \begin{cases} 0 & if\ e = 1 \\ Uniform(3,6) & Otherwise \end{cases}$ $\omega_e = 1$	46.791	1, 2, 3, 4, 5, 6, and 7	1, 5, and 6	–
Scenario 7	$\theta_{\overline{e}e} = \begin{cases} 0 & if\ \overline{e} = e\ or\ e = 1 \\ Uniform(5,10) & Otherwise \end{cases}$ $\lambda_{se} = \begin{cases} 0 & if\ e = 1 \\ Uniform(3,6) & Otherwise \end{cases}$ $Numberofplatformriders = 0$	63.564	–	1, 3, 4, and 6	10.06

parameters $\theta_{\overline{e}e}$ and λ_{se} are simulated by the functions presented in Table 6, as all customers choose the ultra-fast delivery mode. The optimal objective function values for scenarios 1 and 2 are $45.939 and $7.176, respectively, and we expect the optimal value for this scenario to be at least $45.939.

Table 7 summarizes the results of Scenario 6, with an optimal objective function value of $46.791, indicating that the proposed model performed as expected. In this scenario, in addition to using all platform riders, in-house riders 1, 5, and 6 deliver orders. Obviously, there are no delays in delivering orders, as all customers have chosen the ultra-fast delivery mode, which does not permit delays.

5.7. Scenario 7

This scenario combines Scenarios 1 and 3, in which we assume that the data for the parameters are simulated by the functions presented in Table 6, and that no platform rider is available. The optimal objective function values for scenarios 1 and 3 are $45.939 and $9.474, respectively. Therefore, if the model performs as expected, the optimal value for this scenario should be at least $45.939. Table 7 summarizes the results of Scenario 7, with an optimal objective function value of $63.564, confirming that the proposed model performs as expected. In this scenario, in-house riders 1, 3, 4, and 6 are utilized to deliver orders. Furthermore, orders for customers 10, 17, and 21 are delivered 3.68, 3.53, and 2.85 min late, respectively.

Table 7 shows the objective function value for P10; scenarios 2 and 3 include the costs of using platform riders, while the objective function values for scenarios 3 and 5 include the costs of using in-house riders. On the other hand, Scenario 6 consists of the cost of using both the platform and in-house riders. However, unlike the other scenarios, Scenario 1 also incurs delay costs in addition to platform and in-house rider costs. In other words, Scenario 7 includes the cost of using in-house riders and the cost of delays. Fig. 5 illustrates the cost components that constitute the objective function value for each scenario.

In this section, a sensitivity analysis was conducted across seven scenarios to evaluate the robustness and behavioral consistency of the proposed model. A summary of the key findings is presented below:

Scenario 1: Increasing the geographical distance between nodes leads to a higher number of riders being deployed, which consequently increases total distribution costs.

Scenario 2: Assigning the ultra-fast delivery option to all orders reduces routing flexibility and introduces tighter operational constraints, resulting in higher distribution costs.

Scenario 3: Eliminating platform riders and relying exclusively on in-house riders increases total distribution costs, since the cost of using in-house riders exceeds that of platform riders.

Scenario 4: Due to the open VRP structure, platform riders do not return to the store after serving their final customer. When the cost parameters of both rider types are similar, the model prioritizes platform riders because their total traveled distance cost is lower.

Scenario 5: When the cost of in-house riders falls below that of platform riders, the model accordingly prioritizes in-house riders to minimize total distribution costs.

Scenario 6: Simultaneously increasing geographical distances and assigning ultra-fast delivery to all orders further restricts routing flexibility, increases the number of required riders, and significantly raises distribution costs.

Scenario 7: When geographical distances increase and rider availability is limited, the model is forced to rely more heavily on in-house riders, leading to higher overall costs.

Across all scenarios, the model's responses are economically intuitive and operationally consistent. The observed outcomes align with theoretical expectations, confirming the formulation's correctness and supporting the accuracy and reliability of the computational results.

6. Bi-objective model extension

Cost and customer satisfaction form two interdependent drivers of performance in last-mile delivery operations. To capture this relationship, the proposed model is extended with a second objective function reflecting customer satisfaction, and a Pareto-based analysis is conducted to examine the resulting trade-offs. Several approaches can be used to incorporate customer satisfaction into the proposed model. These include minimizing the mean delay and minimizing the mean delivery time. However, these measures focus on the system's average performance. Optimal average performance does not necessarily imply that all customers are satisfied. To address this issue, minimizing the order-to-delivery time is an effective measure of customer satisfaction. Accordingly, we formulate an objective function that minimizes the maximum arrival time. By reducing the worst-case delivery time, this objective not only mitigates delays but also promotes fairness in service delivery. Achieving shorter delivery times generally requires deploying additional riders, which increases overall operating costs. The bi-objective formulation, therefore, seeks an appropriate balance

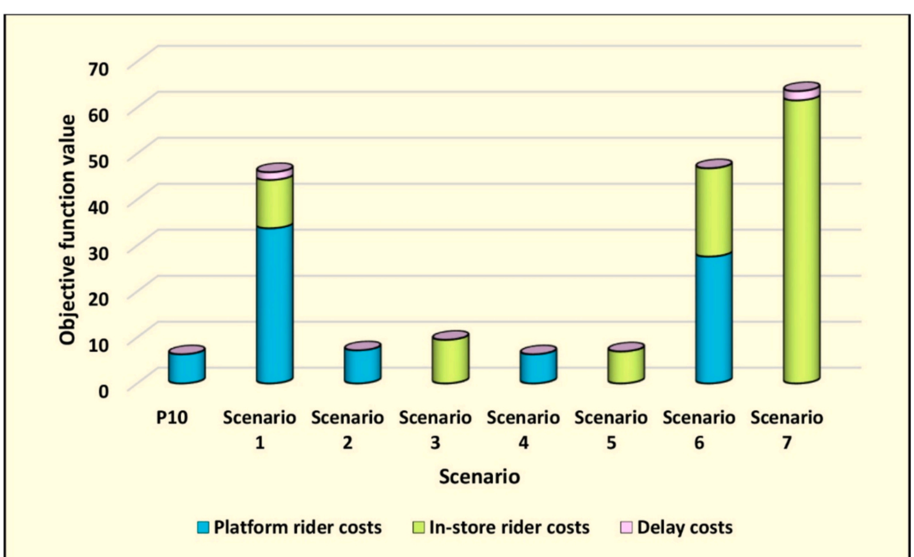


Fig. 5. Cost separation in the sensitivity analysis process.

between cost minimization and service improvement. The second objective function is defined as follows:

$$Min\, Z^{Satisfaction} = Max\{X_{ae}, Y_{be}\} \tag{13}$$

The second objective function minimizes the maximum arrival times of platform and in-house riders to customers, which increases customer satisfaction.

This objective function has a nonlinear structure. To linearize it, the positive variable β is defined and replaced by the expression $Max\{X_{ae}, Y_{be}\}$. Therefore, Eqs. (14) and (15) always hold:

$$\beta \geq X_{ae} \quad \forall a, e \tag{14}$$

$$\beta \geq Y_{be} \quad \forall b, e \tag{15}$$

In general, the bi-objective model can be expressed as follows:

$$Min\, Z^{Cost} = \sum_{b,\bar{e}>1,e>1} \gamma^{ST} \times \theta_{\bar{e}e} \times U_{b\bar{e}e} + \sum_{b,s,e>1} \gamma^{ST} \times \kappa_{bs} \times \lambda_{se} \times (U_{b1e} + U_{be1}) + \sum_{a,s,e>1} \gamma^{PLT} \times \lambda_{se} \times R_{ase} + \sum_{a,\bar{e}>1,e>1} \gamma^{PLT} \times \theta_{\bar{e}e} \times \overline{R}_{a\bar{e}e} + \sum_{e} PE \times Q_e \tag{16}$$

$$Min\, Z^{Satisfaction} = \beta \tag{17}$$

s.t.

Constraints (2) to (12), (14), and (15).

To achieve a single-objective model, we use the augmented epsilon-constraint method presented by Mavrotas (2009). By using this method, the bi-objective model becomes a single-objective one as follows:

$$Min \left(Z^{Cost} - \partial \times \frac{\wp}{Z^{Satisfaction-UP} - Z^{Satisfaction-LW}} \right) \tag{18}$$

s.t.

$$Z^{Satisfaction} + \wp = eps \tag{19}$$

$$Z^{Cost} = \sum_{b,\bar{e}>1,e>1} \gamma^{ST} \times \theta_{\bar{e}e} \times U_{b\bar{e}e} + \sum_{b,s,e>1} \gamma^{ST} \times \kappa_{bs} \times \lambda_{se} \times (U_{b1e} + U_{be1}) + \sum_{a,s,e>1} \gamma^{PLT} \times \lambda_{se} \times R_{ase} + \sum_{a,\bar{e}>1,e>1} \gamma^{PLT} \times \theta_{\bar{e}e} \times \overline{R}_{a\bar{e}e} + \sum_{e} PE \times Q_e \tag{20}$$

$$Z^{Satisfaction} = \beta \tag{21}$$

Constraints (2) to (12), (14), and (15).

where $Z^{Satisfaction-LW}$ and $Z^{Satisfaction-UP}$ represent the lower and upper bounds of the second objective function. Additionally, $\wp$ represents the slack variable associated with the second constrained objective function. Furthermore, ∂ is a very small parameter that, according to the literature, should be set between [10^{-6},10^{-3}]. Hence, in this article, the value of this parameter is considered to be 10^{-6}. It should be noted that if G represents the number of initial grid points determined by the decision-makers, then eps_g corresponding to grid point g is calculated as follows:

$$eps_g = Z^{Satisfaction-LW} + \frac{Z^{Satisfaction-UP} - Z^{Satisfaction-LW}}{G-1} \times g \quad \forall g = 0, 1, \ldots, G-1 \tag{22}$$

We apply the lexicographic technique presented by Govindan et al. (2023) to calculate the lower and upper bounds of the second objective function. The model is first solved for the primary objective function, and the corresponding optimal value is saved. Let $Z^{Cost-LW}$ represent the optimal value of the first objective function. Then, the model is run for the second objective function, and its optimal value is considered to be $Z^{Satisfaction-LW}$. Once again, by adding the constraint $Z^{Cost} \leq Z^{Cost-LW}$ to the existing constraints, the model is run for the second objective function to calculate the value of $Z^{Satisfaction-UP}$. Accordingly, the lower bound of the first objective function and the lower and upper bounds of the second objective function are calculated for 15 simulated problems, as shown in Table 8.

Table 8
The lower and upper bounds of the second objective function.

Simulated problems	$Z^{Cost-LW}$	$Z^{Satisfaction-LW}$	$Z^{Satisfaction-UP}$
P1	2.709	10.4	21.87
P2	3.803	9.99	22.29
P3	4.789	10.17	35.81
P4	4.969	10.46	23.07
P5	5.015	11.45	23.9
P6	5.396	10.44	35.83
P7	5.705	10.84	29.82
P8	5.721	9.54	33.37
P9	6.648	11.28	29.87
P10	6.317	11.72	37.75
P11	6.772	10.88	25.79
P12	7.315	11.02	32.25
P13	7.940	10.79	33.54
P14	8.174	11.72	31.47
P15	8.438	11.35	36.26

Ten grid points are used to solve the bi-objective model via the augmented epsilon-constraint method. By applying Eq. (22), the value of *eps* is computed for each grid point in each simulated problem, as reported in Table 9. The corresponding optimal values of the objective functions and the slack variable for each grid point are also presented in Table 9. The results indicate that, in several simulations, multiple grid points yield identical objective values. For instance, in Problem P10, the optimal values of objective functions G3 and G4 coincide, and similarly, the values of G8 and G9 are equal. This implies that the Pareto frontier for P10 contains 8 distinct grid points, as illustrated in Fig. 6. Fig. 7 presents the Pareto frontiers obtained across all 15 simulated problems in two- and three-dimensional spaces.

The Pareto frontier derived for each simulated problem provides

Table 9
Results obtained from the augmented epsilon-constraint method for simulated problems.

Simulated problems	Objective functions	Grid points									
		G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
P1	*eps*	10.4	11.68	12.95	14.23	15.5	16.77	18.05	19.32	20.6	21.87
	$\wp$	0	1.28	2.55	0.14	1.41	2.68	3.96	5.23	6.51	0
	Z^{Cost}	5.945	5.945	5.945	3.574	3.574	3.574	3.574	3.574	3.574	2.709
	$Z^{Satisfaction}$	10.40	10.40	10.40	14.09	14.09	14.09	14.09	14.09	14.09	21.87
P2	*eps*	9.99	11.36	12.72	14.09	15.46	16.82	18.19	19.56	20.92	22.29
	$\wp$	0	0.12	1.48	0.17	0.65	1.24	2.61	0.83	2.19	0
	Z^{Cost}	7.775	6.810	6.810	6.662	5.476	5.346	5.346	4.255	4.255	3.803
	$Z^{Satisfaction}$	9.99	11.24	11.24	13.92	14.81	15.58	15.58	18.73	18.73	22.29
P3	*eps*	10.17	13.02	15.87	18.72	21.57	24.41	27.26	30.11	32.96	35.81
	$\wp$	0	0.09	1.06	0.16	3.01	0.24	2.11	1.46	4.31	0
	Z^{Cost}	9.793	7.527	5.961	5.304	5.304	5.027	4.893	4.865	4.865	4.789
	$Z^{Satisfaction}$	10.17	12.93	14.81	18.56	18.56	24.17	25.15	28.65	28.65	35.81
P4	*eps*	10.46	11.86	13.26	14.66	16.06	17.47	18.87	20.27	21.67	23.07
	$\wp$	0	0.24	1.24	0.31	0.94	2.35	0.15	0.15	1.01	0
	Z^{Cost}	8.363	6.897	6.140	5.844	5.609	5.609	5.576	5.421	5.280	4.969
	$Z^{Satisfaction}$	10.46	11.62	12.02	14.35	15.12	15.12	18.72	20.12	20.66	23.07
P5	*eps*	11.45	12.83	14.22	15.6	16.98	18.37	19.75	21.13	22.52	23.9
	$\wp$	0	0.48	1.21	2.59	0.65	1.12	1.32	2.7	4.09	0
	Z^{Cost}	8.330	6.296	5.993	5.993	5.681	5.265	5.221	5.221	5.221	5.015
	$Z^{Satisfaction}$	11.45	12.35	13.01	13.01	16.33	17.25	18.43	18.43	18.43	23.90
P6	*eps*	10.44	13.26	16.08	18.9	21.72	24.55	27.37	30.19	33.01	35.83
	$\wp$	0	0.44	0.39	0.17	0.3	1.56	4.38	1.61	4.43	0
	Z^{Cost}	10.153	7.380	7.109	5.986	5.678	5.556	5.556	5.496	5.496	5.396
	$Z^{Satisfaction}$	10.44	12.82	15.69	18.73	21.42	22.99	22.99	28.58	28.58	35.83
P7	*eps*	10.84	12.95	15.06	17.17	19.28	21.38	23.49	25.6	27.71	29.82
	$\wp$	0	0.43	1.59	0.07	2.18	4.28	0.37	1.79	3.9	0
	Z^{Cost}	11.680	8.162	7.854	6.282	6.282	6.282	6.129	5.972	5.972	5.705
	$Z^{Satisfaction}$	10.84	12.52	13.47	17.10	17.10	17.10	23.12	23.81	23.81	29.82
P8	*eps*	9.54	12.19	14.84	17.48	20.13	22.78	25.43	28.07	30.72	33.37
	$\wp$	0	0.11	0.42	0.55	3.2	5.85	1.22	3.86	6.51	0
	Z^{Cost}	9.077	6.964	6.373	5.765	5.765	5.765	5.727	5.727	5.727	5.721
	$Z^{Satisfaction}$	9.54	12.08	14.42	16.93	16.93	16.93	24.21	24.21	24.21	33.37
P9	*eps*	11.28	13.35	15.41	17.48	19.54	21.61	23.67	25.74	27.8	29.87
	$\wp$	0	0.24	0.22	0.02	1.51	3.58	0.54	1.87	3.93	0
	Z^{Cost}	11.226	8.702	7.665	6.994	6.968	6.968	6.884	6.824	6.824	6.648
	$Z^{Satisfaction}$	11.28	13.11	15.19	17.46	18.03	18.03	23.13	23.87	23.87	29.87
P10	*eps*	11.72	14.61	17.5	20.4	23.29	26.18	29.07	31.97	34.86	37.75
	$\wp$	0	0.89	0.61	3.51	1.16	0.07	0.627	0.36	3.25	0
	Z^{Cost}	12.621	10.071	6.701	6.701	6.579	6.566	6.384	6.350	6.350	6.317
	$Z^{Satisfaction}$	11.72	13.72	16.89	16.89	22.13	26.11	28.443	31.61	31.61	37.75
P11	*eps*	10.88	12.54	14.19	15.85	17.51	19.16	20.82	22.48	24.13	25.79
	$\wp$	0	1.38	0.43	0.3	0.14	1.79	0.03	0.34	1.55	0
	Z^{Cost}	11.516	9.997	9.842	7.618	7.187	7.187	7.130	6.860	6.833	6.772
	$Z^{Satisfaction}$	10.88	11.16	13.76	15.55	17.37	17.37	20.79	22.14	22.58	25.79
P12	*eps*	11.02	13.38	15.74	18.1	20.46	22.81	25.17	27.53	29.89	32.25
	$\wp$	0	0.01	0.01	2.37	0.3	0.3	0.31	2.67	0.52	0
	Z^{Cost}	12.736	10.263	8.364	8.364	8.125	7.890	7.612	7.612	7.437	7.315
	$Z^{Satisfaction}$	11.02	13.37	15.73	15.73	20.16	22.51	24.86	24.86	29.37	32.25
P13	*eps*	10.79	13.32	15.85	18.37	20.9	23.43	25.96	28.48	31.01	33.54
	$\wp$	0	0	0.01	0.08	0.22	2.75	0.33	0.35	2.88	0
	Z^{Cost}	13.261	10.408	8.766	8.534	8.382	8.382	8.127	8.069	8.069	7.940
	$Z^{Satisfaction}$	10.79	13.32	15.84	18.29	20.68	20.68	25.63	28.13	28.13	33.54

(*continued on next page*)

Table 9 (*continued*)

Simulated problems	Objective functions	Grid points G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
P14	*eps*	11.72	13.91	16.11	18.3	20.5	22.69	24.89	27.08	29.28	31.47
	$\wp$	0	0	0.02	0.06	0.07	2.26	0.18	1.15	3.35	0
	Z^{Cost}	13.592	10.813	9.310	8.864	8.633	8.633	8.405	8.318	8.318	8.174
	$Z^{Satisfaction}$	11.72	13.91	16.09	18.24	20.43	20.43	24.71	25.93	25.93	31.47
P15	*eps*	11.35	14.12	16.89	19.65	22.42	25.19	27.96	30.72	33.49	36.26
	$\wp$	0	0.3	0.11	0.1	2.87	0.18	0.07	2.83	0.21	0
	Z^{Cost}	14.089	11.023	9.874	9.501	9.501	8.943	8.712	8.712	8.500	8.438
	$Z^{Satisfaction}$	11.35	13.82	16.78	19.55	19.55	25.01	27.89	27.89	33.28	36.26

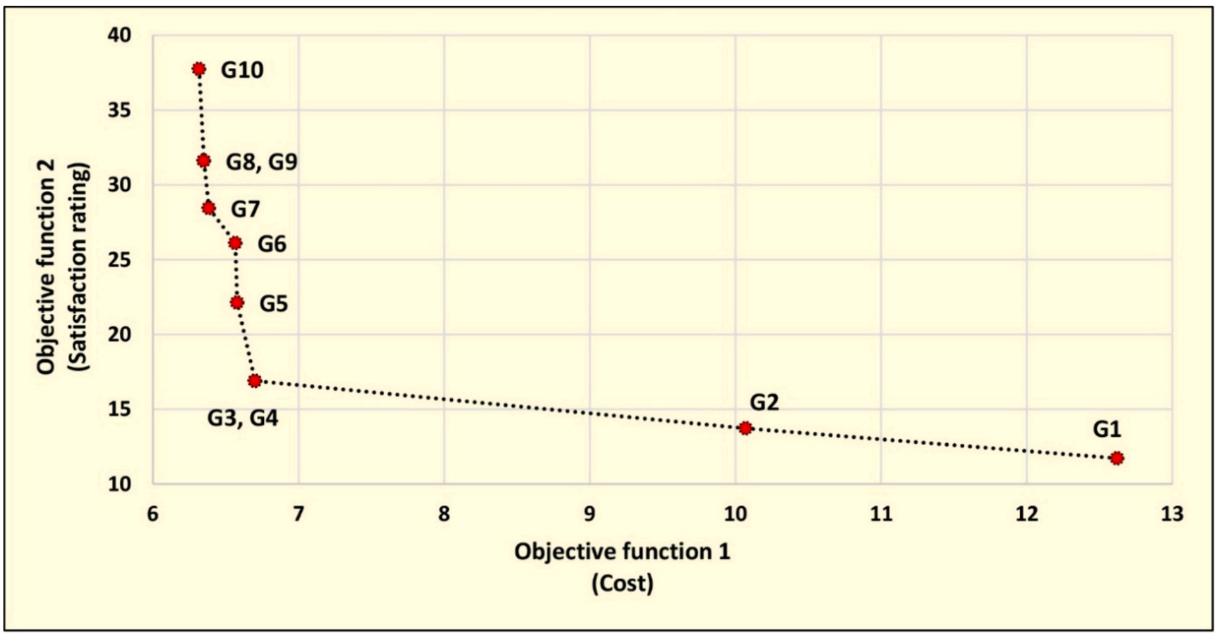


Fig. 6. Pareto frontier obtained for P10.

decision-makers with a clear view of the trade-offs between cost and customer satisfaction. Decision-makers who place greater emphasis on customer satisfaction can select solutions near G1 or adjacent grid points, while those who prioritize cost efficiency may favor G10 or nearby points. These frontiers thus offer a structured basis for choosing operating strategies that align with managerial priorities and service expectations.

7. Managerial implications

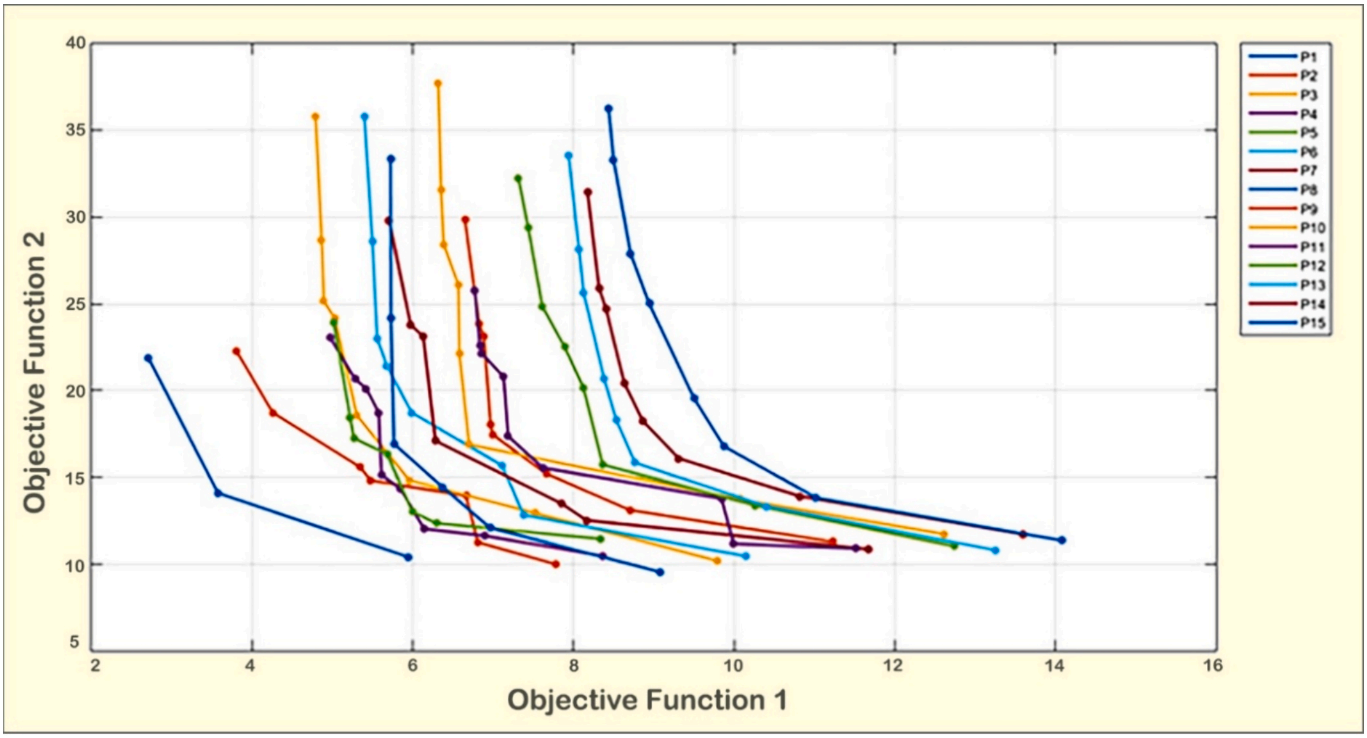
This study provides practical guidance for operations managers on designing a resilient and cost-effective last-mile delivery system. The results show that operational performance depends on an integrated workforce strategy that combines an in-house rider team with flexible platform riders. Relying only on in-house riders increases the risk of system breakdowns during peak demand, while complete dependence on third-party platforms reduces managerial control and increases volatility. A balanced mix allows firms to guarantee ultra-fast service through in-house riders and effectively absorb demand surges through platform riders.

A Q-commerce DSS enables operations managers to control delivery costs and fleet size in real time by balancing rider costs and delay penalties. Since platform riders follow open routes and do not require return trips, they are often more cost-effective during peak-demand periods. The model helps determine the optimal number of in-house riders and supports strategic trade-offs between idle capacity costs, service reliability, and dependence on external platforms.

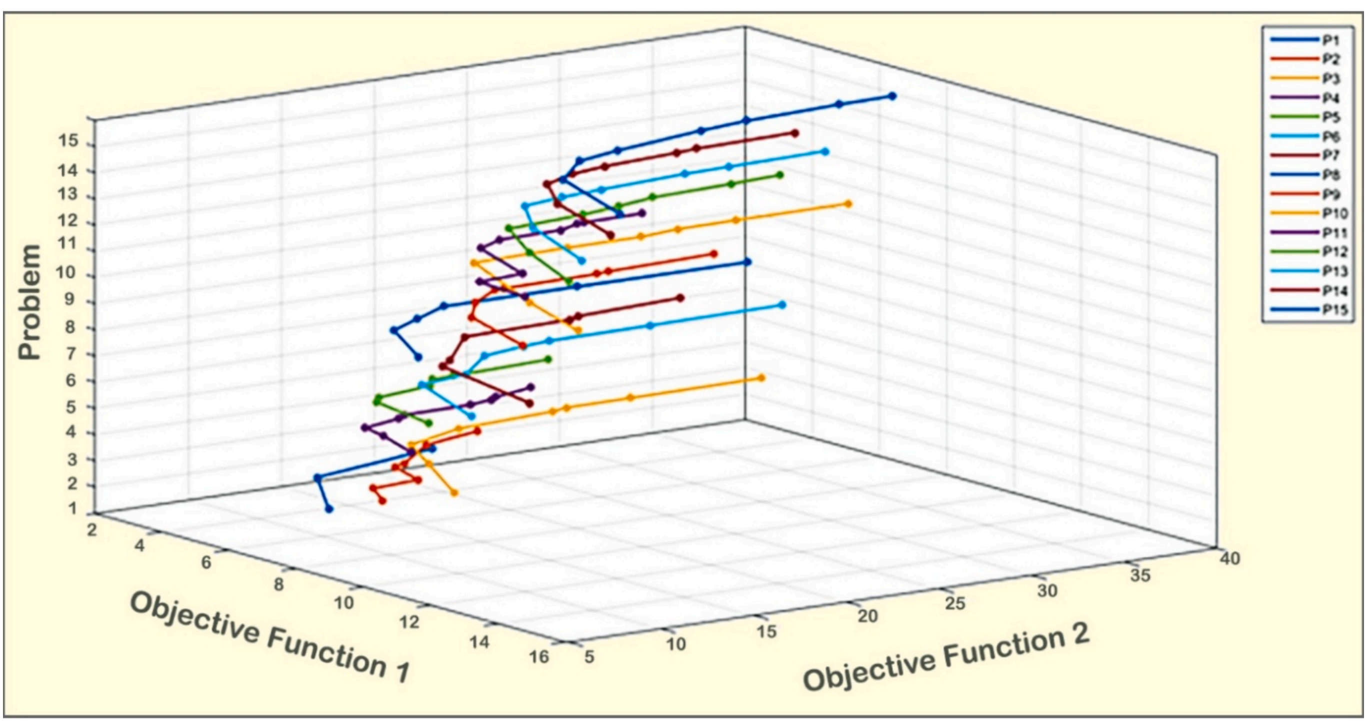
The model also supports service tier design. Offering only ultra-fast delivery leads to inefficient and expensive routing. Introducing a second "fast" service tier with soft time windows increases routing flexibility, improves order consolidation, and reduces costs. Accurate delivery time predictions also improve customer expectation management and perceived reliability, turning logistics performance into a competitive advantage.

The bi-objective version of the model provides operations managers with a quantitative tool for strategic trade-offs between cost and delivery speed. The Pareto frontier allows firms to select faster but more expensive solutions for market growth, or more cost-efficient solutions for profitability, thereby making service-level decisions transparent and data-driven.

Finally, successful implementation requires a data-driven operational culture. Real-time data on traffic, rider locations, and orders are critical. Managers should invest in integrated technologies such as Global Positioning System (GPS) and traffic Application Programming Interfaces (APIs) and shift from experience-based dispatching to algorithm-supported decision-making. The model supports both daily routing decisions and long-term network planning, helping firms continuously redesign store locations and delivery capacity.



(a) Pareto frontier obtained for all simulated problems in two-dimensional space



(b) Pareto frontier obtained for all simulated problems in three-dimensional space

Fig. 7. Pareto frontier obtained for all simulated problems.

In summary, this study offers a practical roadmap for operations managers to integrate fixed and flexible capacity, design multiple service tiers, optimize rider allocation in real time, and use Pareto-based analysis for strategic planning. Together, these actions enable firms to build a last-mile network that is both resilient and cost-effective.

8. Conclusion

This study developed a decision support system grounded in a multi-depot vehicle routing model to manage last-mile delivery activities in the Q-commerce environment. The framework differentiates between two delivery options: ultra-fast delivery, which permits no delay, and fast delivery, which allows delay at a penalty cost. To enhance operational resilience and mitigate service disruptions, the model integrates both in-house riders with fixed capacity and platform riders with flexible capacity. The system was evaluated through 15 simulated problem instances, and the results demonstrate that the proposed approach generates accurate, reliable, and practical routing and assignment decisions. These insights offer decision-makers valuable guidance on selecting rider types, constructing efficient routes, and providing customers and store operators with precise estimates of rider arrival times.

The model was further extended by introducing a secondary objective function that represents customer satisfaction, formulated as the minimization of the order-to-delivery interval. The two objectives were balanced through the augmented epsilon-constraint method, and the resulting Pareto frontiers revealed clear trade-offs between operational cost and service performance. This extension enables decision-makers to align solutions with their strategic priorities, whether focused on cost efficiency or on elevated customer service.

Despite these contributions, several avenues remain open for future research. First, the study assumes deterministic travel and service times, whereas real-world Q-commerce operations are subject to variability arising from traffic conditions, rider behavior, and customer availability. Incorporating uncertainty through stochastic programming or robust optimization would enhance the model's realism. Second, the mathematical programming approach presented here can be combined with machine-learning methods to handle large-scale, high-frequency Q-commerce environments better and support predictive decision-making. Finally, the model is static and does not account for real-time events, such as order cancellations, delivery location changes, or dynamic rider availability. Addressing these challenges through dynamic or online optimization models would further strengthen the applicability of the proposed framework in rapidly evolving operational settings.

CRediT authorship contribution statement

Madjid Tavana: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Esmaeel Saberi:** Writing – original draft, Validation, Investigation, Data curation. **Amin Poost Dooz:** Writing – original draft, Validation, Investigation. **Hassan Mina:** Writing – original draft, Validation, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1
The geographical distance of customer $\bar{e}$ from customer e (kilometer).

$\theta_{\bar{e}e}$	$e=2$	$e=3$	$e=4$	$e=5$	$e=6$	$e=7$	$e=8$	$e=9$	$e=10$	$e=11$	$e=12$	$e=13$	$e=14$	$e=15$	$e=16$	$e=17$	$e=18$	$e=19$	$e=20$	$e=21$
$\bar{e}=2$	0	2.78	1.35	1.48	4.33	5.9	2	4.83	5.54	2.47	1.22	3.77	1.54	6.17	2.22	2.36	4.36	5.2	4.58	3.51
$\bar{e}=3$	2.78	0	3.19	1.27	2.54	0.8	2.7	1.68	4.7	4.14	5.5	2.44	4.8	5.41	4.58	2.35	1.06	1.17	4.67	4.04
$\bar{e}=4$	1.35	3.19	0	0.7	5.65	0.97	1.64	3.92	5.38	1.66	0.72	4.3	4.54	3.03	2.83	2.08	2.1	1.35	6.57	2.97
$\bar{e}=5$	1.48	1.27	0.7	0	5.59	2.45	1.32	5.37	0.95	1.81	0.53	2.25	3.75	1.48	1.63	2.65	2.56	2.59	6.77	6.96
$\bar{e}=6$	4.33	2.54	5.65	5.59	0	2.9	2.92	5.52	3.08	6.44	1.28	5.28	0.86	4.25	0.83	0.54	3.11	3.88	4.59	1.97
$\bar{e}=7$	5.9	0.8	0.97	2.45	2.9	0	3.07	2.29	1.49	6.59	3.25	1.38	3.01	2.94	2.25	6.66	1.73	2.43	0.98	3.11
$\bar{e}=8$	2	2.7	1.64	1.32	2.92	3.07	0	1.16	3	2.61	1.75	1.23	4.38	3.82	0.79	5.59	6.65	4.38	4.45	2.86
$\bar{e}=9$	4.83	1.68	3.92	5.37	5.52	2.29	1.16	0	4.36	4.92	3.79	1.54	4.77	3.91	1.31	6.91	1.98	4.89	5.55	6.56
$\bar{e}=10$	5.54	4.7	5.38	0.95	3.08	1.49	3	4.36	0	1.81	2.43	1.78	2.1	4.7	5.28	1.06	1.48	3.32	1.72	5
$\bar{e}=11$	2.47	4.14	1.66	1.81	6.44	6.59	2.61	4.92	1.81	0	5.46	1.51	3.03	5.02	6	4.48	6.84	0.67	1.72	1.07
$\bar{e}=12$	1.22	5.5	0.72	0.53	1.28	3.25	1.75	3.79	2.43	5.46	0	4.01	1.32	5.27	1.24	3.67	5.67	3.7	3.97	0.57
$\bar{e}=13$	3.77	2.44	4.3	2.25	5.28	1.38	1.23	1.54	1.78	1.51	4.01	0	4.04	3.43	6.84	1.7	1.56	0.66	1.66	0.9
$\bar{e}=14$	1.54	4.8	4.54	3.75	0.86	3.01	4.38	4.77	2.1	3.03	1.32	4.04	0	0.61	5.93	4.41	0.68	1.77	6.68	2.68
$\bar{e}=15$	6.17	5.41	3.03	1.48	4.25	2.94	3.82	3.91	4.7	5.02	5.27	3.43	0.61	0	4.36	2.18	4.66	1.51	3.49	3.06
$\bar{e}=16$	2.22	4.58	2.83	1.63	0.83	2.25	0.79	1.31	5.28	6	1.24	6.84	5.93	4.36	0	5.74	4.02	3.04	4.13	6.56
$\bar{e}=17$	2.36	2.35	2.08	2.65	0.54	6.66	5.59	6.91	1.06	4.48	3.67	1.7	4.41	2.18	5.74	0	2.77	0.55	6.67	4.22
$\bar{e}=18$	4.36	1.06	2.1	2.56	3.11	1.73	6.65	1.98	1.48	6.84	5.67	1.56	0.68	4.66	4.02	2.77	0	2.67	6.89	5.48
$\bar{e}=19$	5.2	1.17	1.35	2.59	3.88	2.43	4.38	4.89	3.32	0.67	3.7	0.66	1.77	1.51	3.04	0.55	2.67	0	1.22	6.97
$\bar{e}=20$	4.58	4.67	6.57	6.77	4.59	0.98	4.45	5.55	1.72	1.72	3.97	1.66	6.68	3.49	4.13	6.67	6.89	1.22	0	4.27
$\bar{e}=21$	3.51	4.04	2.97	6.96	1.97	3.11	2.86	6.56	5	1.07	0.57	0.9	2.68	3.06	6.56	4.22	5.48	6.97	4.27	0

Table A2
The geographical distance of store s from customer e (kilometer).

λ_{se}	$e=2$	$e=3$	$e=4$	$e=5$	$e=6$	$e=7$	$e=8$	$e=9$	$e=10$	$e=11$	$e=12$	$e=13$	$e=14$	$e=15$	$e=16$	17	18	19	20	21
$s=1$	1	2.43	1.53	3.24	3.2	0.55	1.61	2.49	2.28	0.6	3.03	3.3	2.02	1.4	1.99	0.63	2.82	2.1	2.74	2.66
$s=2$	2.39	0.84	3.41	2.62	3.46	3.06	2.36	2.6	2.6	2.87	2.33	0.66	1.96	0.66	2.6	1.08	1.18	2.94	3.48	2.75
$s=3$	2.66	0.5	1.29	2.97	2.96	3.08	1.14	1.87	0.62	1.47	1.82	1.45	0.9	2.93	1.75	0.93	1.9	1.35	3.19	0.69
$s=4$	1.74	1.52	1.9	2.43	2.43	1.51	0.8	3.22	1.15	3.26	1.86	0.77	1.62	1.74	1.71	0.84	2.75	2.91	0.57	1.94

Table A3
The time distance of customer $\bar{e}$ from customer e (minute).

$T\theta_{\bar{e}e}$	$e=2$	$e=3$	$e=4$	$e=5$	$e=6$	$e=7$	$e=8$	$e=9$	$e=10$	$e=11$	$e=12$	$e=13$	$e=14$	$e=15$	$e=16$	$e=17$	$e=18$	$e=19$	$e=20$	$e=21$
$\bar{e}=2$	0	6.98	3.49	4.01	11.62	11.92	5.68	13.08	11.95	6.46	3.24	8.26	3.64	16.19	6.07	5.69	9.41	10.46	9.21	10.38
$\bar{e}=3$	8.26	0	6.82	2.59	6.49	1.75	8.09	4.73	10.83	8.65	13.38	5.72	10.16	14	11.2	5.66	3.09	2.58	10.38	10.28
$\bar{e}=4$	3.15	6.85	0	1.59	11.65	2.25	3.35	11.05	11.99	4	1.66	10.52	12.33	7.86	6.03	4.49	4.87	3.47	14.9	6.05
$\bar{e}=5$	3.95	2.95	1.95	0	15	6.55	3.72	13.5	2.17	4.63	1.29	4.67	10.52	3.46	3.4	6.81	5.18	7.11	19.66	17.82
$\bar{e}=6$	11.76	6.39	16.31	15.5	0	6.58	7.84	13.52	9.13	19.03	3.7	12.29	2.11	11.02	2.4	1.17	8.19	10.75	11.79	3.99
$\bar{e}=7$	13.45	1.95	2.27	6.34	7.48	0	7.93	6.83	3.46	18.2	9.62	4.06	6.79	6.82	4.97	14.49	4.72	5.53	2.72	8.14
$\bar{e}=8$	5.48	5.42	4.71	2.65	7.1	7.25	0	2.8	7.64	6.11	4.72	3.61	10.81	8.47	1.99	13.22	19.51	9.05	11.14	6.83
$\bar{e}=9$	12.21	4.36	9.19	12.09	14.06	5.84	2.39	0	12.97	11.71	8.18	3.8	11.43	8.61	3.44	13.85	4.96	9.79	13.99	18.61
$\bar{e}=10$	15.3	10.76	12.07	2.31	7.29	3.81	6.21	12.69	0	5.1	6.79	4.74	5.03	11.35	15.12	3.14	3.8	7.69	4.21	11.86
$\bar{e}=11$	5.16	11.67	4.16	4.96	18.18	15.9	7.62	11.78	4.42	0	14.61	3.87	6.59	13.07	15.51	12.23	15.37	1.45	4.97	2.6
$\bar{e}=12$	3.54	12.85	2.16	1.31	3.23	7.11	3.85	10.03	6.81	14.12	0	10	3.14	14.9	3.49	7.46	16.59	7.41	10.39	1.14
$\bar{e}=13$	10	6.37	9.74	4.66	10.8	2.97	3.02	3.33	4.58	4.31	8.17	0	9.43	8.53	15.45	4.9	4.45	1.74	4.95	2.48
$\bar{e}=14$	4.27	13.59	11.73	9.65	2.2	7.84	13.03	12.18	6.17	7.31	3.72	8.07	0	1.47	11.96	9.18	1.76	4.53	17.49	7.73
$\bar{e}=15$	14.98	11.73	8.75	3.97	12.16	6.14	11.46	10.22	9.41	13.1	11.46	7.93	1.66	0	10.65	5.81	11.59	3.5	10.17	6.68
$\bar{e}=16$	5.46	11.26	6.01	3.43	1.86	5.25	2.28	3.72	14.9	14.88	3.6	20.04	12.5	10.25	0	13.42	8.89	8.9	9.74	18.87
$\bar{e}=17$	5.79	5.32	4.78	5.6	1.29	19.41	12.59	14.54	2.27	10.7	7.52	3.43	9.5	4.53	16.22	0	6.69	1.65	14.96	9.96
$\bar{e}=18$	9.78	2.23	5.06	6.35	6.67	4.34	19.18	4.08	3.7	18.92	16.9	4.25	1.94	10.73	11.06	7.87	0	7.08	16.4	12.93
$\bar{e}=19$	11.72	2.86	3.97	6.06	7.95	6.83	11.96	14.28	7.75	1.49	7.57	1.9	3.71	4.28	7.49	1.11	5.75	0	2.77	18.36
$\bar{e}=20$	13.58	11.74	17.01	17.37	9.31	2.92	11.54	11.43	4.36	3.66	9.6	4.77	18.15	8.07	12.35	13.7	18.06	3.41	0	12.64
$\bar{e}=21$	9.25	10.58	7.49	14.9	5.58	8.99	7.7	15.17	11.79	2.94	1.22	2.44	7.95	7.46	14.86	10.31	13.14	16.49	11.2	0

Table A4
The time distance of store s from customer e (minute).

$T\lambda_{se}$	$e=2$	$e=3$	$e=4$	$e=5$	$e=6$	$e=7$	$e=8$	$e=9$	$e=10$	$e=11$	$e=12$	$e=13$	$e=14$	$e=15$	$e=16$	17	18	19	20	21
$s=1$	2.9	5.92	3.17	9.51	9.1	1.62	4.14	5.07	5.49	1.24	7.66	6.96	5.86	3.14	5.26	1.45	7.94	4.59	6.85	7.82
$s=2$	5.23	2.43	7.39	6.37	9.59	9.13	6.96	5.86	7.51	8.28	6.91	1.82	5.18	1.81	6.55	2.91	3.17	8.43	9.72	6.1
$s=3$	7.76	1.31	2.63	8.65	7.59	7.16	2.72	4.3	1.36	4.15	3.92	4.27	1.84	8.02	3.69	2.3	4.48	2.99	9.32	1.7
$s=4$	3.66	3.78	5.19	5.91	5.25	3.18	2.25	7.72	2.44	9.36	3.98	1.68	4.13	4.31	4.98	2.27	5.96	6.77	1.47	5.01

Table A5
The time distance between the origin of platform rider a and store s (minute).

$T\delta_{as}$	$s=1$	$s=2$	$s=3$	$s=4$
$a=1$	3.26	2.05	2.26	2.13
$a=2$	2.62	3.16	3.62	3.36
$a=3$	3.47	2.68	2.45	3.8
$a=4$	3.66	2.63	3.9	2.51
$a=5$	3.25	3.94	3.92	2.85
$a=6$	2.21	2.15	3.29	2.62
$a=7$	3.19	3.21	3.27	3.92

Table A6
The delivery type selected by the customers.

	$e=2$	$e=3$	$e=4$	$e=5$	$e=6$	$e=7$	$e=8$	$e=9$	$e=10$	$e=11$	$e=12$	$e=13$	$e=14$	$e=15$	$e=16$	17	18	19	20	21
ω_e	1	0	0	0	0	0	1	0	0	1	0	1	1	0	0	0	0	0	0	0

Table A7
The available in-house riders for each store.

κ_{bs}	$s=1$	$s=2$	$s=3$	$s=4$
$b=1$	1	0	0	0
$b=2$	0	1	0	0
$b=3$	0	1	0	0
$b=4$	0	0	1	0
$b=5$	1	0	0	0
$b=6$	0	0	0	1

Data availability

Data will be made available on request.

References

Bachofner, M., Lemardelé, C., Estrada, M., Pagès, L., 2022. City logistics: challenges and opportunities for technology providers. J. Urban Mobility 2, 100020.
Bai, J., So, K.C., Tang, C.S., Chen, X., Wang, H., 2019. Coordinating supply and demand on an on-demand service platform with impatient customers. Manuf. Serv. Oper. Manag. 21 (3), 556–570.
Belbağ, S., 2025. a model for vehicle routing problem under returns and emission consideration in B2C E-commerce logistics. Verimlilik Dergisi, (Productivity for Logistics) 63–76.
Bogdanova, M., 2021. "Quick Commerce in Western Europe: Trends, Operational Models and Prospects," (accessed August 13, 2023), available at:.
Boysen, N., Fedtke, S., Schwerdfeger, S., 2021. Last-mile delivery concepts: a survey from an operational research perspective. OR Spectr. 43 (1), 1–58.
Cokyasar, T., Subramanyam, A., Larson, J., Stinson, M., Sahin, O., 2023. Time-constrained capacitated vehicle routing problem in urban e-commerce delivery. Transp. Res. Rec. 2677 (2), 190–203.
Datta, J., Bose, S., 2024. A Study on the Growth Prospects of Q-Commerce and Its Role Play in eCommerce Business in Present-Day India. In: Sustainability in Marketing Practice (pp. 155-168). Apple Academic Press.
Davalos, J., Levingston, I., 2022. "The 15-Minute Ultrafast Delivery Craze Slams into Reality," Bloomberg Businessweek. April 8, available at: https://www.bloomberg.com/news/articles/ 2022-04-08/15-minute-grocery-delivery-services-hit-reality.
Escudero-Santana, A., Muñuzuri, J., Lorenzo-Espejo, A., Muñoz-Díaz, M.L., 2022. Improving e-commerce distribution through last-mile logistics with multiple possibilities of deliveries based on time and location. J. Theor. Appl. Electron. Commer. Res. 17 (2), 507–521.
Govindan, K., Salehian, F., Kian, H., Hosseini, S.T., Mina, H., 2023. A location-inventory-routing problem to design a circular closed-loop supply chain network with carbon tax policy for achieving circular economy: an augmented epsilon-constraint approach. Int. J. Prod. Econ. 257, 108771.
Gund, H.P., Daniel, J., 2024. Q-commerce or E-commerce? A systematic state of the art on comparative last-mile logistics greenhouse gas emissions literature review. Int. J. Indust. Eng. Operat. Manage. 6 (3), 185–207.
Ha, N.T., Akbari, M., Au, B., 2023. Last mile delivery in logistics and supply chain management: a bibliometric analysis and future directions. BIJ 30 (4), 1137–1170.
Harter, A., Stich, L., Spann, M., 2025. The effect of delivery time on repurchase behavior in quick commerce. J. Service Res., 28(2), 211-227 https://www.euromonitor.com/article/quick-commerce-in-western-europe-trends-operational-models-and-prospects.
Hu, H., Tao, F., 2025. Vehicle routing problem for simultaneous pickup and delivery in rural areas: considering uncertain demand and government subsidy. Ann. Oper. Res. https://doi.org/10.1007/s10479-025-06877-1.
Kunnapapdeelert, S., Johnson, J.V., Phalitnonkiat, P., 2022. Green last-mile route planning for efficient e-commerce distribution. Eng. Manage. Prod. Services 14 (1), 1–12.
Lasota, M., Zabielska, A., Jacyna, M., Gołębiowski, P., Żochowska, R., Wasiak, M., 2024. Method for delivery planning in urban areas with environmental aspects. Sustainability 16 (4), 1571.
Liu, W., 2020. Route optimization for last-mile distribution of rural E-commerce logistics based on ant colony optimization. IEEE Access 8, 12179–12187.
Liu, X., Gou, X., Xu, Z., 2024. Multi-objective last-mile vehicle routing problem for fresh food e-commerce: a sustainable perspective. Int. J. Inform. Technolo. Decision Making 23 (06), 2335–2363.
Ma, H., Tsang, Y.P., Lee, C.K.M., 2025. Optimizing multi-objective instant logistics with trucks and drones for the quick commerce order fulfilment. J. Ind. Prod. Eng. 42 (5), 516–532.
Mavrotas, G., 2009. Effective implementation of the ε-constraint method in multi-objective mathematical programming problems. Appl. Math Comput. 213 (2), 455–465.
Murfield, M., Boone, C.A., Rutner, P., Thomas, R., 2017. Investigating logistics service quality in omni-channel retailing. Int. J. Phys. Distrib. Logistics Manage. 47 (4), 263–296.
Pilati, F., Tronconi, R., 2022. Social-economic sustainable Vehicle Routing Problem for local e-commerce platforms. IFAC-PapersOnLine 55 (10), 470–475.
Pilati, F., Tronconi, R., 2024. Tri-objective vehicle routing problem to optimize the distribution process of sustainable local e-commerce platforms. Sustainability 16 (5), 1810.
Prajapati, D., Chan, F.T., Daultani, Y., Pratap, S., 2022. Sustainable vehicle routing of agro-food grains in the e-commerce industry. Int. J. Prod. Res. 60 (24), 7319–7344.
Sadati, M.E.H., Akbari, V., Çatay, B., 2022. Electric vehicle routing problem with flexible deliveries. Int. J. Prod. Res. 60 (13), 4268–4294.
Taylor, T.A., 2018. On-demand service platforms. Manuf. Serv. Oper. Manag. 20 (4), 704–720.
Wang, L., Cui, L., Han, X., Xu, D., 2025. A multi-commodity two-echelon vehicle routing problem with split-delivery and time windows for decisions of delivery-terminal systems. Ind. Manag. Data Syst. 125 (12), 3049–3078.
Woo, Erin, 2022. "Gopuff Does Deliveries in 30 Minutes or Less. It's Also Buying Time for Itself," The New York Times. April 14, available at: https://www.nytimes.com/2022/04/14/technology/ gopuff-delivery.html.
Yang, X., Ostermeier, M., Hübner, A., 2024. Winning the race to customers with micro-fulfillment centers: an approach for network planning in quick commerce. CEJOR 32 (2), 295–334.
Zahran, S., 2024. Optimizing supply chain management of fresh E-commerce agri-consumer products using energy-efficient vehicle routing. IEEE Trans. Consum. Electron. 70 (1), 1685–1693.
Zhang, M., Pratap, S., Zhao, Z., Prajapati, D., Huang, G.Q., 2021. Forward and reverse logistics vehicle routing problems with time horizons in B2C e-commerce logistics. Int. J. Prod. Res. 59 (20), 6291–6310.
Zhang, M., Yang, W., Wang, P.P., Zhao, Z., Wang, S., Huang, G.Q., 2026. Towards low-carbon e-commerce return logistics: optimization for simultaneous pickup and delivery. Ind. Manag. Data Syst. 126 (1), 147–174.
Zuhanda, M.K., Suwilo, S., Sitompul, O.S., Caraka, R.E., 2023. Optimization of vehicle routing problem in the context of E-commerce logistics distribution. Eng. Lett. 31 (1).