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Emergency logistics network optimization with time window assignment

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\begin{abstract}
During natural disasters or accidents, an emergency logistics network aims to ensure the distribution of relief supplies to victims in time and efficiently. When the coronavirus disease 2019 (COVID-19) emerged, the government closed the outbreak areas to control the risk of transmission. The closed areas were divided into high-risk and middle-/low-risk areas, and travel restrictions were enforced in the different risk areas. The distribution of daily essential supplies to residents in the closed areas became a major challenge for the government. This study introduces a new variant of the vehicle routing problem with travel restrictions in closed areas called the two-echelon emergency vehicle routing problem with time window assignment (2E-EVRPTWA). 2E-EVRPTWA involves transporting goods from distribution centers (DCs) to satellites in high-risk areas in the first echelon and delivering goods from DCs or satellites to customers in the second echelon. Vehicle sharing and time window assignment (TWA) strategies are applied to optimize the transportation resource configuration and improve the operational efficiency of the emergency logistics network. A tri-objective mathematical model for 2E-EVRPTWA is also constructed to minimize the total operating cost, total delivery time, and number of vehicles. A multi-objective adaptive large neighborhood search with split algorithm (MOALNS-SA) is proposed to obtain the Pareto optimal solution for 2E-EVRPTWA. The split algorithm (SA) calculates the objective values associated with each solution and assigns multiple trips to shared vehicles. A non-dominated sorting strategy is used to retain the optimal labels obtained with the SA algorithm and evaluate the quality of the multi-objective solution. The TWA strategy embedded in MOALNS-SA assigns appropriate candidate time windows to customers. The proposed MOALNS-SA produces results that are comparable with the CPLEX solver and those of the self-learning non-dominated sorting genetic algorithm-II, multi-objective ant colony algorithm, and multi-objective particle swarm optimization algorithm for 2E-EVRPTWA. A real-world COVID-19 case study from Chongqing City, China, is performed to test the performance of the proposed model and algorithm. This study helps the government and logistics enterprises design an efficient, collaborative, emergency logistics network, and promote the healthy and sustainable development of cities.
\end{abstract}

1. Introduction

The coronavirus disease 2019 (COVID-19) outbreak has affected human lives and global economic activities considerably (Cheramin et al., 2021; Mitrega and Choi, 2021). According to WORLDMETER (2021), by December 2021, the COVID-19 pandemic had infected about 260 million people in different countries. Each country applies different measures to control the spread of COVID-19, including border control and strict travel restrictions. Residents are encouraged to be vaccinated, group activities are restricted or prohibited and the affected areas are closed to reduce the risk of COVID-19 transmission (BSGUO, 2021). In several affected areas in China, residents are required to quarantine in homes and daily essential supplies are delivered to the corresponding nodes (e.g., community gate) by logistics enterprises. In addition, travel restrictions are implemented by setting up cross-regional quarantine inspection sites at the junctions of affected areas. Vehicles delivering...
supplies across different affected areas must undergo cross-regional quarantine inspections, which increase the travel time of vehicles and the difficulty of timely delivery (Yang et al., 2021). Designing efficient emergency logistics networks in areas affected by COVID-19 and any future disaster is therefore imperative.

The areas affected by COVID-19 are divided into two types, namely, high risk, and middle/low risk, on the basis of confirmed cases. Vehicles that need to pass areas with travel restrictions are subject to cross-regional quarantine inspections. Cross-regional quarantine inspection varies in different risk areas. For vehicles in middle-/low-risk areas, cross-regional quarantine inspection includes testing the body temperature and traffic code of drivers, which can be performed by smart devices and thus consumes little time. For vehicles in high-risk areas, cross-regional quarantine inspection adds disinfection and quarantine of vehicles based on the inspection results in middle-/low-risk areas, and the inspection time cannot be neglected (Wang et al., 2021b). Measures should be adopted to reduce the time impact of cross-regional quarantine inspections. Hence, in this study, a collaborative logistics network is established among distribution centers (DCs) to coordinate customer resources, and satellites, which serve as transfer nodes, are set up in high-risk areas, and then a two-echelon logistics network is formulated.

To ensure the timeliness of delivery service and reduce the travel time of vehicles, a time window assignment (TWA) strategy, which assigns appropriate time windows to customers with irrational time windows, is adopted in middle-/low-risk areas. The key points in the emergency delivery of supplies include the timeliness of the delivery service and the utilization of the available fleet of vehicles (Moreno et al., 2016; Choi, 2021; Gultekin et al., 2022). In an emergency logistics network, available transportation resources are limited (François et al., 2016; Rivera et al., 2016). Thus, a major challenge in building efficient collaborative emergency logistics is to improve the utilization of vehicles. To address this challenge, a vehicle sharing (VS) strategy is applied to maximize the utilization of transportation resources. Compared with the traditional VS strategy, which shares vehicles in different periods and logistics facilities (Wang et al., 2021a), in the VS strategy in this study, vehicles are shared in a single facility or area to decrease the risk of COVID-19 transmission. Each vehicle performs multiple trips from each DC or satellite to improve the utilization of vehicles. Hence, designing efficient delivery routes and assigning them to vehicles reasonably is key to achieving operational efficiency in a collaborative emergency logistics network.

In this study, a two-echelon emergency vehicle routing problem with time window assignment (2E-EVRPTW) is investigated to construct an efficient collaborative emergency logistics network. Collaboration among DCs is established to coordinate customer resources in emergency modes. A tri-objective mixed-integer programming model that considers the risk level of each area and travel restrictions is formulated to minimize the total operating cost, total delivery time and number of vehicles for MDVRPTW and extended the k-means algorithm of MOALNS-SA (Sadati et al., 2020; Xue et al., 2012). Different strategies, such as TWA and VS have been developed to improve the operational efficiency of logistics networks (Cattaruzza et al., 2014; Spliet and Gabor, 2015; Subramanyam et al., 2018; Zhen et al., 2020; Wang et al., 2021c; Marques et al., 2022). In addition, disasters have occurred frequently in recent years, so studies have focused on improving the response speed and reducing the losses in emergency logistics networks (Gentili, Michandhan, Agnetis, & Ghezelli, 2022; W. Wang, Wu, Wang, Zhen, & Qu, 2021d; Y. Wang et al., 2021c; Wolfinger, Gausterer, Doerner, & Popper, 2021). Several studies related to 2E-EVRPTW in MDVRPTW, 2E-VRPTW, TWA, VS and EVRP are reviewed.

2. Literature review

Several studies dedicated to vehicle routing optimization through different modes and strategies in logistics networks are reviewed in this section. MDVRPTW and 2E-VRPTW have been studied by many researchers and received much attention in the past decades (Tu et al., 2014; Calvet et al., 2016; Wang et al., 2018; Sadati et al., 2020; Xue et al., 2012). Different strategies, such as TWA and VS have been developed to improve the operational efficiency of logistics networks (Cattaruzza et al., 2014; Spliet and Gabor, 2015; Subramanyam et al., 2018; Zhen et al., 2020; Wang et al., 2021c; Marques et al., 2022). In this study, a two-echelon emergency vehicle routing problem with time window assignment (2E-EVRPTW) is investigated to construct an efficient collaborative emergency logistics network. Compared with the traditional VS strategy, which shares vehicles in different periods and logistics facilities (Wang et al., 2021a), in the VS strategy in this study, vehicles are shared in a single facility or area to decrease the risk of COVID-19 transmission. Each vehicle performs multiple trips from each DC or satellite to improve the utilization of vehicles. Hence, designing efficient delivery routes and assigning them to vehicles reasonably is key to achieving operational efficiency in a collaborative emergency logistics network.

In this study, a two-echelon emergency vehicle routing problem with time window assignment (2E-EVRPTW) is investigated to construct an efficient collaborative emergency logistics network. Collaboration among DCs is established to coordinate customer resources in emergency modes. A tri-objective mixed-integer programming model that considers the risk level of each area and travel restrictions is formulated to minimize the total operating cost, total delivery time and number of vehicles in the emergency logistics network. Multi-objective adaptive large neighborhood search with the split algorithm (MOALNS-SA) is developed to optimize delivery routes in different risk areas for 2E-EVRPTW. The split algorithm (SA) divides the delivery trips and assigns them to vehicles as a VS strategy. A non-dominated sorting strategy is used to evaluate the quality of each split solution and retain the optimal one. Moreover, the TWA strategy embedded in MOALNS-SA assigns candidate time windows to customers in middle-/low-risk areas to find the Pareto optimal solution. The application of 2E-EVRPTW in the real world is demonstrated through a case study in Chongqing City, China, during the outbreak of COVID-19. The results indicate that TWA and VS strategies are useful for the design of the two-echelon collaborative emergency logistics network.

Compared with previous researches, the main contributions to 2E-EVRPTW in this study are as follows. (1) A two-echelon distribution system that considers travel restrictions in different areas is introduced to improve the response speed of the emergency logistics network. (2) TWA and VS strategies are developed to maximize the utilization of vehicles with limited transportation resources and to optimize vehicle schedules for enhancing the efficiency of the emergency logistics network. (3) A three-objective mixed-integer programming model is formulated to account for the operational modes of the two-echelon distribution system, TWA and VS strategies in different risk areas and minimizing the total operating cost, delivery time, and number of vehicles. (4) MOALNS-SA is proposed to solve the optimization model, split and assign trips to vehicles, assign appropriate time windows to customers, and find a near-optimal solution for 2E-EVRPTW.

The remainder of this study is organized as follows. Section 2 reviews the literature related to the multi-depot vehicle routing problem with time window (MDVRPTW), two-echelon vehicle routing problem with time window (2E-VRPTW), TWA and VS strategies, and emergency vehicle routing problem (EVRP). Section 3 presents 2E-EVRPTW in detail with an example. Section 4 introduces definition and mathematical model of 2E-EVRPTW. Section 5 proposes the MOALNS-SA algorithm. Section 6 provides the algorithm comparison and numerical experiments on a real-world COVID-19 case study in Chongqing City, China. The conclusions and future research directions are discussed in Section 7.
solution of high quality. Meanwhile, Zhen et al. (2022) established a mixed-integer programming model to minimize the operating cost and developed a column generation-based algorithm to tackle MDVRPTW.

### 2.2. Two-echelon vehicle routing problem with time windows

2E-VRPTW has two levels that use different fleets of vehicles. The first echelon is the delivery from depots to satellites by first-echelon trucks, and the second echelon is the delivery from the satellites to customers by second-echelon vehicles (Li et al., 2016; Bevilaqua et al., 2019; Slijik et al., 2022). Groner et al. (2016) investigated 2E-VRPTW by considering multiple trips on the second echelon and developed an ALNS algorithm that includes customer destruction and a repair heuristic to solve the problem. A simulation-based Tabu search algorithm was proposed by Liu et al. (2017) to solve 2E-VRPTW. This algorithm uses the Monte Carlo sampling method to assess each movement in neighborhood search. Breunig et al. (2019) developed a large neighborhood search (LNS) algorithm and an exact mathematical algorithm to solve 2E-VRPTW. The feasible first-level solutions are enumerated based on the bounding functions and second-level route enumeration in these algorithms. Bevilaqua et al. (2019) studied 2E-VRPTW on the basis of a real wholesale company in Brazil and aimed to minimize the travel cost and load capacity.

### 2.3. Vehicle sharing and time window assignment strategies

Unlike the vehicles in traditional VRP, which are only served on a trip, each vehicle performs several trips in the vS strategy (François, Arda, Crama, & Laporte, 2016; He & Li, 2019; Wang, Peng, Zhou, Mahmoudi, & Zhen, 2020b; Marques et al., 2022). A hybrid genetic algorithm (GA) with a split algorithm that assigns trips to vehicles to realize the vS strategy was proposed by Cattaruzza et al. (2014), Coelho et al. (2016) developed a trajectory search heuristic algorithm consisting of iterated local search, variable neighborhood descent, and greedy randomized adaptive search to assign trips to vehicles to realize the vS strategy and minimize the total cost. He and Li (2019) developed a memetic algorithm that includes GA and a local search procedure to assign trips to shared vehicles, and the results showed that the proposed operators can split appropriate trips and yield high-quality solutions. Zhen et al. (2020) presented the labeling procedure in hybrid PSO and GA algorithms to assign trips to vehicles and obtain delivery routes. A segment-based evaluation scheme was developed by Pan et al. (2021) to accelerate computing time and assign trips to shared vehicles. Marques et al. (2022) proposed a branch-cut-and-price algorithm to assign multiple trips to shared vehicles. For vehicles, the vS strategy is implemented under the premise of meeting the customer service time window and load capacity.
Fig. 1. An emergency logistics network in three different scenarios.
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Table 2
Data sources for customers.

| Customer | Demands | Customer | Demands | Customer | Demands |
|----------|---------|----------|---------|----------|---------|
| C1       | 2       | C6       | 1       | C12      | 2       |
| C2       | 1       | C7       | 2       | C13      | 3       |
| C3       | 4       | C8       | 5       | C14      | 4       |
| C4       | 4       | C9       | 2       | C15      | 1       |
| C5       | 1       | C10      | 4       | C16      | 2       |

Presented by Hoogeboom et al. (2021) to minimize travel time and the risk of time window violations in TWA-VRP.

2.4. Emergency vehicle routing problem

Most previous studies related to EVRP focused on the emergency facility location and routing problem for post-disaster emergency relief supplies (Chang et al., 2014; Zhang et al., 2018; Wei et al., 2020; Gentili et al., 2022). Tuzkaya et al. (2014) investigated the location and routing problem in a multi-echelon emergency logistics network, and a multi-criteria analysis was conducted to determine the locations of centers first and the delivery routes of emergency relief supplies second. Caunhye et al. (2016) proposed a two-stage non-linear model that considers the uncertainty of facilities and demands for EVRP, and the location and routing problem was addressed through this model. Zhang et al. (2018) studied the multi-depot emergency location and routing problem based on uncertain information. They established a multi-objective mathematical model to minimize travel time, emergency relief costs, and CO₂ emissions and designed an intelligent algorithm to solve the model.

From the perspective of humanitarian relief, several studies on EVRP focused on the optimization of delivery routes for daily life and medical supplies to ensure the normal operation of cities (Ahmadi et al., 2015; Kirac and Milburn, 2018; Rout et al., 2020; Govindan et al., 2021). Shin et al. (2019) proposed a mixed-integer linear model to minimize the last completed travel time and designed an ACO algorithm for the delivery routing problem of emergency relief goods. Rodríguez-Espindola et al. (2020) presented a bi-objective model to minimize the number of customers without assistance and the total cost and designed a branch-and-cut method to solve this problem. Wang et al. (2021b) investigated the routing problem for daily life delivery routes in consideration of the obstruction and interruption of road traffic connectivity in an emergency logistics network. In addition, a state–space–time bi-objective mathematical model was constructed, and a two-stage hybrid heuristic was proposed to obtain the Pareto optimal solution. Zhao et al. (2021) presented a bi-objective emergency routing optimization model considering the COVID-19 transmission risk to optimize the delivery routes for daily life supplies, and designed an ANS to solve this problem. Table 1 lists the main characteristics and solution methods of previous studies that addressed MDVRPTW, 2E-VRPTW, vS- TWA, and EVRP.

The most relevant previous studies are summarized in Table 1. Despite the aforementioned efforts to address 2E-VRPTW, the following issues remain. (1) Research on the suitability of the two-echelon distribution system for multi-depot collaborative emergency logistics networks is lacking. (2) The TWA and vS strategies adopted in each satellite to maximize the utilization of transportation resources and minimize the transportation cost. In addition, a set of candidate time windows are assigned to customers with irrational time windows in middle-/low-risk areas to reduce time window violations and improve the operational efficiency of the emergency logistics network. Therefore, building an emergency logistics network is imperative to improving the emergency response speed and operational efficiency.

Fig. 1(c) shows the optimized collaborative emergency logistics network with TWA and vS strategies. The geographical location of Satellite 1 (S1) is similar to that of Customer 18 (C18), and S1 is viewed as a transfer station in the high-risk area. In the high-risk area, customer demands are transported in a centralized manner to S1 by semitrailer trucks, and the vehicles depart from S1 to serve customers. Compared with vehicles crossing travel restrictions, centralized transportation by semitrailer trucks can reduce the total travel restriction time. To reduce the risk of COVID-19 transmission, vehicles are shared in each DC or each satellite to maximize the utilization of transportation resources and reduce the transportation cost. In addition, a set of candidate time windows are assigned to customers with irrational time windows in middle-/low-risk areas to reduce time window violations and improve the operational efficiency of the emergency logistics network. Therefore, building an emergency logistics network is imperative to improving the emergency response speed and operational efficiency and reducing operating costs.

The advantages of the two-echelon emergency logistics network with TWA and vS strategies can be proven through related optimization results. The centralized transportation time for semitrailer trucks from DCs to satellites is set as one unit time. The preparation time of vehicles for the next route is set as two unit time. Furthermore, we make the following assumptions. The transportation cost from DCs to satellites and the transportation cost from DCs or satellites to customers can be set as

| Customer | Demands | Customer | Demands | Customer | Demands |
|----------|---------|----------|---------|----------|---------|
| C1       | 2       | C6       | 1       | C12      | 2       |
| C2       | 1       | C7       | 2       | C13      | 3       |
| C3       | 4       | C8       | 5       | C14      | 4       |
| C4       | 4       | C9       | 2       | C15      | 1       |
| C5       | 1       | C10      | 4       | C16      | 2       |

...
areas can be shared within these areas and vehicles in middle
strategy is applied in each DC and each satellite
Assumption 4
in the emergency logistics network. Through the TWA strategy, the sum
4. Optimization model
of waiting and delayed time shows an obvious reduction that ensures the
Assumption 3
semitrailer trucks
livery time of logistics networks (Li, Zhou, Kundu,
4.1. Optimization objective
optimization model with TWA and vS strategies is constructed
to obtain the minimum total operating cost, delivery time, and number
Assumption 5. To improve the response speed of emergency logistics
networks, a TWA strategy is adopted for customers in middle-/low-risk areas.

A two-echelon emergency logistics network is established through
the tri-objective mathematical model (Li et al., 2020; Wang et al.,
2021b). The definitions and explanations of several parameters and variables are shown in Table 4.

A tri-objective optimization model that considers TWA and vS strategies is constructed to design an emergency logistics network. The mathematical model is formulated to minimize the total operating cost in Eq. (1), the total delivery time in Eq. (2), and the number of vehicles in Eq. (3).

Min \( Z_1 = TC_1 + TC_2 \) (1)

Min \( Z_2 = \sum_{p \in D,W} \sum_{q \in C} \sum_{k \in OD} \sum_{t \in W} (t_{pp} + IT) \times y_{pp} + \sum_{s \in W} \sum_{k \in OD} \sum_{t \in W} t_{pp} \times x_{atk}^{\text{me}} + \sum_{t \in W} \sum_{k \in OD} \sum_{a \in Ag} W_{at} + \sum_{p \in D,W} \sum_{q \in C} \sum_{k \in OD} \sum_{t \in W} W_{pt} \) (2)

Min \( Z_3 = \sum_{a \in Ag} \sum_{i \in V} \sum_{j \in C} \sum_{s \in W} \sum_{q \in C} x_{atk}^{\text{me}} + 1 \) (3)

In Eq. (1), \( Z_1 \) includes two components: \( TC_1 \) and \( TC_2 \). \( TC_2 \) in Eq. (4) represents the costs including transportation, maintenance, and penalty costs, for overdue service of semitrailer trucks in the first echelon. \( TC_2 \) in Eq. (5) represents the costs, including distribution, maintenance, and penalty costs for overdue service of vehicles and the TWA cost in the second echelon. In Eq. (2), \( Z_2 \) expresses the total delivery time in the two echelons, \( \sum_{p \in D,W} \sum_{q \in C} \sum_{k \in OD} \sum_{t \in W} (t_{pp} + IT) \times y_{pp} \) and \( \sum_{p \in D,W} \sum_{q \in C} \sum_{k \in OD} \sum_{t \in W} W_{pt} \) represent the traveling and waiting times in the first echelon, \( \sum_{a \in Ag} \sum_{i \in V} \sum_{j \in C} \sum_{s \in W} \sum_{q \in C} x_{atk}^{\text{me}} + 1 \) and \( \sum_{a \in Ag} \sum_{i \in V} \sum_{j \in C} \sum_{s \in W} \sum_{q \in C} x_{atk}^{\text{me}} \) represent the traveling and waiting times in the second echelon. In Eq. (3), \( Z_3 \) indicates the number of vehicles in the second echelon, \( \sum_{a \in Ag} \sum_{i \in V} \sum_{j \in C} \sum_{s \in W} \sum_{q \in C} x_{atk}^{\text{me}} + 1 \) represent the number of used vehicles in high-risk and middle-/low-risk areas.

\[ TC_1 = \sum_{p \in D,W} \sum_{q \in C} \sum_{k \in OD} \sum_{t \in W} t_{pp} \times y_{pp} \times \sum_{p \in D,W} \sum_{q \in C} \sum_{k \in OD} y_{pp} \times MC, \]

\[ + \sum_{p \in D,W} \sum_{q \in C} \sum_{k \in OD} \max \{ t_{pp} - \alpha, 0 \} \times y_{pp} \times \alpha \]

**Table 3**
Result comparison of the logistics network with and without emergency modes.

| Scenario       | Case          | Delivery time | Waiting time | Delayed time | Assigned time | Transportation cost ($) | Assignment cost ($) | NV | NS | Total rental cost ($) | Total cost ($) |
|----------------|---------------|---------------|--------------|--------------|---------------|------------------------|-------------------|----|---|----------------------|---------------|
| Non-emergency  | Initial network | 52            | 42           | 14           | –             | 1360                  | –                 | 6  | – | 1200 ($\text{0}^*$)  | 2560          |
| Emergency      | Initial network | 64            | 39           | 20           | –             | 1525                  | –                 | 6  | – | 1200 ($\text{0}^*$)  | 2725          |
| Optimized      | Network       | 59            | –            | –            | 9             | 650                   | 90                | 3  | 1 | 900 ($3^*$)          | 1640          |

*: The number of shared vehicles; NV: Number of vehicles; NS: Number of semitrailer trucks.
Table 4
Symbol definitions and explanations.

| Set | Definition |
|-----|------------|
| $A$ | Set of areas in the logistics network, $A=(a|a=1,2,3,...,\rho)$ and $\rho$ is the total number of areas |
| $A_H$ | Set of high-risk areas in the logistics network, $A_H \subseteq A$ |
| $A_M$ | Set of middle/low-risk areas in the logistics network, $A_M \subseteq A$ |
| $D$ | Set of DCs, $D=\{dp|p=1,2,3,...,\sigma\}$ and $\sigma$ is the total number of DCs |
| $W$ | Set of satellites, $W=\{q|q=1,2,3,...,\eta\}$ and $\eta$ is the total number of satellites |
| $C$ | Set of delivery customers, $C=\{i|j=1,2,3,...\}$ and $j$ is the total number of customers |
| $V$ | Set of vehicles for delivery, $V=\{v|v=1,2,3,...,\delta\}$ and $\delta$ is the total number of vehicles |
| $S$ | Set of semitrailer trucks for transferring goods from DCs to satellites, $S=\{s|s=1,2,3,...,\phi\}$ and $\phi$ is the total number of semitrailer trucks |

| $O_v$ | Set of delivery routes of vehicle $v$, $O_v=\{k|k=1,2,3,...,v\}, v \in V$ |

**Input parameter**

| Parameter | Definition |
|-----------|------------|
| $d_i$ | Delivery demand quantity of customer $i$, $i \in C$ |
| $d_q$ | Delivery demand quantity of satellite $q$, $q \in W$ |
| $s_i$ | Distance from customer $i$ to customer $j$, $i, j \in C$ |
| $s_{pq}$ | Distance from DC or satellite $p$ to DC or satellite $q$, $p, q \in D \cup W$ |
| $MC_V$ | Maintenance cost for each vehicle $v$ in one planning period, $v \in V$ |
| $MC_S$ | Maintenance cost for each semitrailer truck in one planning period, $s \in S$ |
| $U_s$ | Usage cost of semitrailer truck $s$, $s \in S$ (unit: dollar/km) |
| $U_v$ | Usage cost of vehicle $v$, $v \in V$ (unit: dollar/km) |
| $Q_v$ | Maximum capacity of semitrailer truck $s$, $s \in S$ |
| $Q_v$ | Maximum capacity of vehicle $v$, $v \in V$ |
| $Q_p$ | Maximum capacity of DC $p$, $p \in D$ |
| $Q_q$ | Maximum capacity of satellite $q$, $q \in W$ |
| $[\text{ea}, \text{ln}] \cup [\text{ta}, \text{ln}]$ | Candidate time window assigned to customer $i$, $i \in C$ |
| $[\text{wa}, \text{ln}]$ | Service time window of DC $p$, $p \in D$ |
| $\alpha$ | Penalty cost for early or late arrival per unit time |
| $\beta$ | Cost coefficient when customer’s time window changes to the assigned time window per unit time |
| $q_{iv}$ | Travel time of vehicle $v$ between entities $i$ and $j$, $i, j \in D \cup W \cup C$, $v \in V$ |
| $t_{iv}$ | Travel time of semitrailer truck $s$ between entities $p$ and $q$, $p, q \in D \cup W$, $s \in S$ |
| $BN$ | Large number |
| $\text{MaxT}$ | Maximal delivery time of a vehicle |
| $PT$ | Preparation time of a vehicle for the next route |
| $IT$ | Each cross-regional quarantine inspection time in high-risk areas |
| $+$ | Working days in one planning period |

**Decision variable**

| $d_{ap}$ | Departure time of the $k$th route of vehicle $v$ from DC or satellite $q$ in area $a$, $v \in V$, $q \in D \cup W$, $a \in A$ |
| $d_{sp}$ | Departure time of semitrailer truck $s$ from DC $p$, $s \in S$, $p \in D$ |
| $a_{iv}$ | Arrival time of the $k$th route of vehicle $v$ at DC or satellite $q$ in area $a$, $v \in V$, $q \in W \cup D \cup C$, $v \in V$, $a \in A$ |
| $a_{iv}$ | Arrival time of the $k$th route of vehicle $v$ at customer $i$ in area $a$, $v \in V$, $i \in D \cup W \cup C$, $v \in V$, $a \in A$ |
| $a_{sp}$ | Arrival time of semitrailer truck $s$ at satellite $q$, $s \in S$, $q \in W$ |
| $W_{ai}$ | Waiting time of the $k$th route of vehicle $v$ at customer $i$ in area $a$, $v \in V$, $i \in C$, $v \in V$, $a \in A$ |
| $W_{ai}$ | Waiting time of the semitrailer truck at satellite $q$, $q \in W$, $s \in S$, $a \in A$ |
| $CLa$ | Load of vehicle $v$ in the $k$th route when it departs from DC or satellite $q$ in area $a$, $v \in V$, $q \in D \cup W$, $a \in A$ |
| $CLa$ | Load of semitrailer truck $s$ when it departs from DC or satellite $q$ in area $a$, $v \in V$, $q \in D \cup W$, $s \in S$, $a \in A$ |
| $a{nk}_{iv}$ | If the $k$th route of vehicle $v$ travels from node $i$ in area $a$ to node $j$ in area $j$, then $a{nk}_{iv}=1$; otherwise, $a{nk}_{iv}=0$, $i \in D \cup W \cup C$, $v \in V$, $a \in A$, $a \in A$ |
| $a{nk}_{iv}$ | If vehicle $v$ operates the $k$th route from DC or satellite $q$ in area $a$ to serve customer $i$ in area $a$, then $a{nk}_{iv}=1$; otherwise, $a{nk}_{iv}=0$, $v \in V$, $i \in C$, $q \in D \cup W$, $a \in A$ |
| $a{nk}_{iv}$ | If semitrailer truck $s$ transports between DC or satellite $p$ and DC or satellite $q$, then $a{nk}_{iv}=1$; otherwise, $a{nk}_{iv}=0$, $p, q \in D, p \in D, q \in D \cup W$, $s \in S$, $a \in A$ |

**Objective function**

$$TC_2 = \sum_{i \in C, j \in D \cup W \cup C, k \in V, a \in A} \sum_{a \in A} \sum_{j \in D \cup W \cup C} S_{ij} \times U_s \times x_{ijk}^{\text{nl}} = \sum_{i \in C, j \in D \cup W \cup C, k \in V, a \in A} \sum_{a \in A} \sum_{j \in D \cup W \cup C} S_{ij} \times U_s \times x_{ijk}^{\text{nl}} =$$

$$+ \sum_{i \in C} \min \left\{ \sum_{j \in D \cup W \cup C} \sum_{k \in V} x_{ijk}^{\text{nl}}, 1 \right\} + \sum_{k \in V} \min \left\{ \sum_{j \in D \cup W \cup C} x_{ijk}^{\text{nl}}, 1 \right\} \times MC_V + \sum_{i \in C} \min \left\{ \sum_{j \in D \cup W \cup C} x_{ijk}^{\text{nl}}, 1 \right\} \times MC_V + \sum_{i \in C} \min \left\{ \sum_{j \in D \cup W \cup C} x_{ijk}^{\text{nl}}, 1 \right\} \times MC_V \times \alpha$$

$$+ \sum_{a \in A} \sum_{i \in C} \sum_{j \in D \cup W \cup C} \sum_{k \in V} \sum_{x \in C} \max \left\{ a_{nk}^{\text{nl}}, 1 \right\} \times x_{ijk}^{\text{nl}} \times \alpha + \sum_{a \in A} \sum_{i \in C} CT_{ai} \min \left\{ |e_i - a|_{\text{ln}}, |l_i - l_{i-1}| \right\} \times \beta$$

(5)
Zbest
Zinit
Update adaptive weight of each operator by:
Assign customers in high-risk areas to the corresponding satellites and customers in middle-/low-risk areas to the nearest DCs.
Update the customers in middle-/low-risk areas of DCs.
Check if customers in middle-/low-risk areas need to be adjusted among DCs.
For each satellite or each DC:
If \(Z_{\text{best}}(\tilde{Z}, \tilde{A})\) dominates \(Z_{\text{current}}(\tilde{Z}, \tilde{A})\) and update the score of the selected removal and insertion operators.
If \(Z_{\text{current}}(\tilde{Z}, \tilde{A})\) meets the acceptance criterions and update the score of the selected removal and insertion operators.
If \(Z_{\text{best}}(\tilde{Z}, \tilde{A})\) non-dominates \(Z_{\text{current}}(\tilde{Z}, \tilde{A})\) and dominates \(Z_{\text{current}}(\tilde{Z}, \tilde{A})\) and update the score of the selected removal and insertion operators.
Update and calculate \(T_n\) by Eqs. (35)-(37) and select a solution from \((\tilde{Z}', \tilde{A})\) to be \(Z_{\text{current}}(\tilde{Z}, \tilde{A})\) randomly.
Update adaptive weight of each operator by Eqs. (36)-(37) and reset the score to 0.
Perform IWA operation on \(Z_{\text{current}}(\tilde{Z}, \tilde{A})\) and update time windows of customers.

Constraints on satellites:
\[
\begin{align*}
\sum_{p \in D} \sum_{w \in S} y_{\text{ps}} &\leq 1, \forall q \in W \\
\sum_{p \in D} y_{\text{ps}} &\leq 1, \forall q \in W, s \in S \\
\sum_{q \in W} y_{\text{ps}} - \sum_{q \in W} y_{\text{qg}} &\geq 0, \forall p, g \in W \cup D, s \in S \\
\sum_{p \in D} y_{\text{ps}} &\leq 1, q \in W, s \in S \\
C_{\text{ps}} &\leq Q, \forall p \in D, s \in S \\
d_{\text{ps}} + IT + t_{\text{ps}} - BN(1 - y_{\text{ps}}) \leq at_{\text{ps}}, \forall p \in D, q \in W, s \in S \\
d_{\text{ps}} + IT + t_{\text{ps}} - BN(1 - y_{\text{ps}}) \geq at_{\text{ps}}, \forall p \in D, q \in W, s \in S \\
at_{\text{ps}} + IT + t_{\text{ps}} - BN(1 - y_{\text{ps}}) \leq at_{\text{ps}}, \forall q \in W, m \in W \cup D, s \in S \\
at_{\text{ps}} + IT + t_{\text{ps}} - BN(1 - y_{\text{ps}}) \geq at_{\text{ps}}, \forall q \in W, m \in W \cup D, s \in S \\
at_{\text{ps}} + IT + t_{\text{ps}} \geq \min_{p \in D} L_p, \forall q \in W, p \in D, s \in S
\end{align*}
\]

Constraint (6) ensures that each satellite is served once by one semitrailer truck. Constraints (7) and (9) indicate that the semitrailer truck should depart from the DC and return to the DC. Constraint (8) indicates the flow balance, which means the number of arrivals at the
satellite equals the number of departures from the satellite for each used 
semitrailer truck. Constraint (10) calculates the transportation quantity 
of each semitrailer truck, and Constraint (11) refers to the maxima 
capacity of semitrailer trucks. Constraints (12) and (13) guarantee the 
continuous departure time of semitrailer trucks at DCs. Constraints (14) 
and (15) ensure the continuous arrival time of semitrailer trucks at 
satellites. Constraint (16) indicates that semitrailer trucks should respect 
the time windows of DCs.

**Constraints on customers:**

$$ \sum_{i \in C} \sum_{v \in V} x_{vi}^{ab} \leq 1, \forall v \in W \cup D \cup C, a, b \in A $$ \hspace{1cm} (17)

$$ \sum_{i \in C \cup D \cup W, v \in V} x_{vi}^{ab} = 1, \forall i, v \in C \cup D \cup W, a, b \in A $$ \hspace{1cm} (18)

$$ \sum_{i \in C \cup D, v \in V, k \in O_v} x_{vi}^{ab} = 0, \forall i, m \in C \cup W \cup D, v \in V, k \in O_v, a, b, f \in A $$ \hspace{1cm} (19)

$$ \sum_{i \in C \cup D, v \in V} \sum_{k \in O_v} x_{vi}^{ab} = 1, \forall v, k \in O_v, a, b \in A $$ \hspace{1cm} (20)

$$ CT^T_{qvi} = \sum_{a \in A} d_{qvi}^{ab}, \forall v, k \in O_v, q \in W \cup D, a, b \in A $$ \hspace{1cm} (21)

$$ CT^L_{qvi} \leq Q_v, \forall v \in W \cup D, v \in V, k \in O_v, a \in A $$ \hspace{1cm} (22)

$$ \sum_{i \in S} \sum_{v \in V} \sum_{k \in O_v} CT^L_{qvi} \leq Q_v, \forall v \in D $$ \hspace{1cm} (23)

$$ \sum_{i \in S} \sum_{v \in V} \sum_{k \in O_v} CT^T_{qvi} \leq Q_v, \forall v \in W, a \in A $$ \hspace{1cm} (24)

$$ \sum_{i \in C \cup D \cup W} \sum_{a \in A} \sum_{v \in V} \sum_{k \in O_v} x_{vi}^{ab} + \sum_{i \in C \cup D \cup W} \sum_{a \in A} \sum_{v \in V} \sum_{k \in O_v} x_{vi}^{ab} \cdot t_{iv} + PT \times 1 \leq \max T, \forall i \in W, a, b \in A $$ \hspace{1cm} (25)

$$ [(1 - CT^T_{vi})e_i + CT^T_{vi}e_i] \sum_{i \in C \cup D \cup W} \sum_{a \in A} \sum_{v \in V} \sum_{k \in O_v} x_{vi}^{ab} \leq [1 - (1 - CT^L_{vi})e_i + CT^L_{vi}e_i] \sum_{i \in C \cup D \cup W, v \in V, k \in O_v} x_{vi}^{ab}, $$ \hspace{1cm} (26)

$$ \forall i \in C, v \in V, k \in O_v, a, b \in A $$

$$ E_v^{ab} \leq d_{qvi}^{ab}, \forall i \in C, q \in W \cup D, v \in V, k \in O_v, a, b \in A $$ \hspace{1cm} (27)

$$ E_v^{ab} \leq d_{qvi}^{ab}, \forall i \in C, q \in W \cup D, v \in V, k \in O_v, a, b \in A $$ \hspace{1cm} (28)

$$ dt^T_{qvi} + t_{qv} + \text{BN}(1 - x_{qvi}^{ab}) \leq at^T_{qv}, \forall q \in W \cup D, i \in C, v \in V, k \in O_v, a, b \in A $$ \hspace{1cm} (29)

$$ dt^L_{qvi} + t_{qv} + \text{BN}(1 - x_{qvi}^{ab}) \leq at^L_{qv}, \forall q \in W \cup D, i \in C, v \in V, k \in O_v, a, b \in A $$ \hspace{1cm} (30)

$$ a_{vi}^{ab} + w_{qvi}^{ab} + t_{qv} - \text{BN}(1 - x_{qvi}^{ab}) \leq at_{qv}^{ab}, $$ \hspace{1cm} (31)

$$ \forall i \in C, j \in C \cup W \cup D, a, b \in A $$

$$ a_{vi}^{ab} + w_{qvi}^{ab} + t_{qv} + \text{BN}(1 - x_{qvi}^{ab}) \geq at_{qv}^{ab}, $$ \hspace{1cm} (32)

$$ \forall i \in C, j \in C \cup W \cup D, a, b \in A $$

$$ a_{vi}^{ab} + PT - \text{BN}(1 - t_{qvi}^{ab-1}) \geq at_{qv}^{ab-1}, \forall q \in W \cup D, v \in V, k \in O_v, a, b \in A $$ \hspace{1cm} (33)

Constraint (17) ensures that each customer is served once by one 
vehicle. Constraint (18) indicates that vehicles depart from the DC 
(satellite) initially in each trip. Constraint (19) indicates the flow balance 
of each customer. Constraint (20) refers to vehicles’ return to the 
DC (satellite). Constraint (21) calculates the transportation quantity 
of vehicles in each trip. Constraint (22) refers to the maximal capacity 
of vehicles in each trip. Constraint (23) guarantees that the demands 
of customers and satellites served by a DC should not exceed their capacity. 
Constraint (24) guarantees that the demands of customers served by a 
satellite should not exceed its capacity. Constraint (25) indicates that 
the total travel time of vehicles should respect the maximal delivery time. 
Constraint (26) indicates that vehicles should respect the time window 
of customers. Constraints (27) and (28) ensure that vehicles respect the 
time windows of DCs (satellites). Constraints (31) and (32) ensure the continuous arrival time of vehicles at cus-
tomers, and Constraint (33) ensures the continuous departure time of 
shared delivery routes of each vehicle.

**Binary decision:**

$$ x_{qvi}^{ab} = \{0, 1\}, \forall p, q \in W \cup D \cup C, v \in V, k \in O_v, a, b \in A $$

$$ y_{qvr} = \{0, 1\}, \forall p, q \in D \cup W, s \in S $$

$$ r_{qvi}^{ab} = \{0, 1\}, \forall i, v \in C \cup W \cup D, v \in V, k \in O_v, a, b \in A $$

$$ \kappa_{qvi} = \{0, 1\}, \forall i, v \in D, q \in W \cup D, s \in S $$

$$ CT^T_i = \{0, 1\}, \forall a \in A, i \in C $$

5. **Multi-objective adaptive large neighborhood search with split algorithm**

As an extension of the LNS algorithm, ALNS was first proposed by 
Ropke and Pisinger (2006) to solve VRP, and has been widely applied to 
address many VRP variants in recent years (Aziz et al., 2014; Ghilas et al., 
2016a; Kirac and Milburn, 2018; Sun et al., 2020). Unlike in the LNS 
algorithm where removal and insertion operations are performed by a 
single operator, the ALNS algorithm performs removal and insertion 
operations through a series of operators. The performance of removal 
and insertion operators is recorded at each iteration, and the well-
performed operators have a high probability of being selected in the 
next iteration (Jie et al., 2019; Yu et al., 2021). The adaptive adjustment 
procedure of the ALNS can maintain a balance between intensification 
and diversification in each search process (Gu et al., 2019; Chen et al., 
2021; Mara et al., 2022). In this study, the ALNS framework is further 
modified to find the Pareto optimal solutions for the multi-objective 
function. The procedure of MOALNS-SA is shown in Fig. 2. run and 
nummax indicate the number of optimization runs and the maximal 
number of iterations, γ expresses the number of iterations needed to 
update the adaptive weight of operators and perform the TWA 
operation, Z_{opt}(Z_1, Z_2, Z_3) indicates the initial solution, and Z_{seed}(Z_1, 
Z_2, Z_3) denotes the current solution and Z_{seed}(Z_1, Z_2, Z_3) expresses the 
Pareto optimal solution.

The main procedure of the proposed algorithm is shown in Fig. 2. In 
this algorithm, SA is developed based on Zhen et al. (2020) to realize 
vehicle sharing among different routes. The customer sequence of each 
nearhood is split and transferred into initial solutions with multiple 
objective function values through SA. In each split procedure, new 
solutions are generated first, and then a non-dominated sorting strategy is 
applied to remain the non-dominated solutions and remove the dominated 
solutions, thereby speeding up the solution efficiency. Furthermore, 
the removal and insertion operators are selected by a roulette 
strategy to reconstruct the non-dominated solutions and repair them to 
generate new solutions. Different operators of removal and insertion 
operations in each iteration can effectively avoid being trapped in local 
optimal solutions. The traditional adaptive procedure evaluates new
Three possible trips for serving a new customer.
solutions by measuring a single objective value with current and best solutions, which is not suitable for multi-objective optimization problems (Rifai et al., 2021). The improved adaptive procedure is proposed to evaluate new solutions with current and best solutions based on the multi-objective function values. Moreover, an efficient feasibility evaluation can decrease the computational burden and remain an elite solution for the multi-objective optimization problem. The pseudo-code of MOALNS-SA is given in Algorithm 1.

**Input:** Risk levels in each area, geographical coordinates and time windows of customers, satellites and logistics facilities, candidate time windows \(ctw\), removal operators \(Q\), insertion operators \(I\), initial temperature \(T\), cooling rate \(c\), number of iterations to update the score of operators \(\gamma\)

**Output:** Pareto optimal solution \(Z_{\text{best}}(Z_1, Z_2, Z_3)\)

1. For each satellite or DC (Customers in high-risk areas are assigned to the corresponding satellites (DCs) and customers in middle-low-risk areas are assigned to the nearest DCs)

2. Generate an initial solution \(Z_{\text{init}}(Z_1, Z_2, Z_3)\), assign trips to each vehicle and calculate the objective functions \((Z_1, Z_2, Z_3)\) through SA (Selection 5.1)

3. Initialize selective probability \(sp\) of removal and insertion operators

4. \(Z_{\text{current}}(Z_1, Z_2, Z_3) = Z_{\text{best}}(Z_1, Z_2, Z_3)\) 

5. For a number of iterations do

6. Select a removal operator \(q_1 \in Q\) through roulette-wheel strategy with selective probability \(sp_{q_1}\) and apply removal operation on \(Z_{\text{current}}(Z_1, Z_2, Z_3)\) (Section 5.3)

7. Select an insertion operator \(p_1 \in I\) through roulette-wheel strategy with selective probability \(sp_{p_1}\) and apply insertion operation on \(Z_{\text{current}}(Z_1, Z_2, Z_3)\) to obtain \(Z_{\text{new}}(Z_1, Z_2, Z_3)\) (Section 5.4)

8. Calculate objective function \((Z_1, Z_2, Z_3)\) of \(Z_{\text{new}}\) through the SA (Section 5.1)

9. If \((Z_{\text{new}}(Z_1, Z_2, Z_3))\) dominates \(Z_{\text{best}}(Z_1, Z_2, Z_3)\) (Section 5.2) then

10. Set \(Z_{\text{best}}(Z_1, Z_2, Z_3) = Z_{\text{new}}(Z_1, Z_2, Z_3)\) and add score \(\mu_i\) (Section 5.6) to the selected operators \(q_1\) and \(p_1\)

11. else if \((Z_{\text{new}}(Z_1, Z_2, Z_3))\) non-dominates \(Z_{\text{best}}(Z_1, Z_2, Z_3)\) and dominates \(Z_{\text{current}}(Z_1, Z_2, Z_3)\) (Section 5.2) then

12. Insert \(Z_{\text{new}}(Z_1, Z_2, Z_3)\) to \(A\) and add score \(\mu_i\) (Section 5.6) to the selected operators \(q_1\) and \(p_1\)

13. else

14. if \((Z_{\text{new}}(Z_1, Z_2, Z_3))\) meets the acceptance criterions (Section 5.5) then

15. Set \(Z' = Z_{\text{new}}(Z_1, Z_2, Z_3)\) and add score \(\mu_i\) (Section 5.6) to the selected operators \(q_1\) and \(p_1\)

16. End

17. End

18. Update and Calculate \(T_m\) by Eqs. (35)-(37) (Section 5.5)

19. Randomly select a solution from \((Z', A)\) to be \(Z_{\text{current}}(Z_1, Z_2, Z_3)\)

20. If iterations reach the \(j\)th \(\gamma\) iterations

21. Update the adaptive weight of each operator by Eqs. (38)-(39)

22. Set all scores to zero

23. If the area is the middle-low-risk area then

24. Apply TWA strategy to assign \(ctw\) to customers with irrational time windows based on \(Z_{\text{best}}(Z_1, Z_2, Z_3)\) and update \(Z_{\text{best}}(Z_1, Z_2, Z_3)\) (Section 5.7)

25. End

26. End

27. End

28. End

29. End

In Algorithm 1, each neighborhood has a sequence of \(n\) nodes and \(n\) is the total number of customers in this area (Cattaruzza et al., 2014). The sequence can be regarded as a TSP solution and split by SA to assign trips to vehicles. Three methods can be utilized to generate the initial solution, and each method is selected randomly in each run.

1. Greedy insertion method (Ghilas et al., 2016b): This operator is performed based on distance. First, the customer closest to the DC or satellite is selected as the first node. Second, the customer closest to the previous node is selected as the next node. Third, the former step is repeated until all nodes are selected and a sequence \(S\) is generated.

2. Median time window method: This operator ranks nodes based on the time windows of customers. Nodes are sorted in ascending order.
by the values of median time windows, and a sorted sequence \( S \) is generated.

3. Random method: This operator ranks nodes randomly and a random sequence \( S \) is generated to help diversify the initial solution.

5.1. Split algorithm

In recent years, SA has been used to split sequences and assign trips to vehicles (Cattaruzza et al., 2014; Zhen et al., 2020). In this problem, SA is associated with MOALNS to turn neighborhoods into solutions. For each neighborhood, labels are generated from the first node to the \( n \)th node in turn in accordance with the sequence \( S \) through SA, and the labels for \( n \) nodes include the trip assignments. Each label has \((\delta + 5)\) elements, and \(\delta\) represents the number of vehicles. The first \(\delta\)th elements express the time to get ready to start the next trip for the \(\delta\)th vehicle, and they are sorted in descending order. The \((\delta + 1)\)th element indicates the total operating cost \(Z_1\), The \((\delta + 2)\)th element indicates the total delivery time \(Z_2\). The \((\delta + 3)\)th element indicates the number of used vehicle \(Z_3\). The \((\delta + 4)\)th element is the loading of this trip, and the \((\delta + 5)\)th element is the predecessor node (i.e., DCs, satellites, customers) of the label. The pseudo-code of SA is shown in Algorithm 2.

**Input:** Current sequence \( S \), time windows of customers \( tw \), demands of customers \( d \), maximal load of vehicle \( cap \), number of vehicles \( \delta \), speed of vehicle \( v \), distance of nodes \( dist \)

**Output:** Label with trips and objectives

```plaintext
1. Labellist = (0,…,0,0,0,0,0), Labellistcurrent ← Labellist
2. current = 0
3. While current < |S| do
4.   succ = current + 1
5.   load = \( d_{suc} \)
6.   labelcurrent = Ø
7.   For all \( L \) ∈ Labellistcurrent
8.     For \( k = 1 \rightarrow 2*Z_3 \)
9.       If \( f = 1 \) (Value help to split trips)
10.          time = \( 2*dist_{0,\text{current}}/v \)
11.          \( L' = L, L'_{Δ} = L_{Δ} + \text{time}, L_{Δ+4} = \text{load} \)
12.          \( L_{Δ+1} = Z_1, L_{Δ+2} = Z_2, L_{Δ+3} = Z_3 \)
13.          \( L_{Δ+4} = \text{current}, \text{labelcurrent} ← \text{labelcurrent} \cup L' \)
14.      else
15.          time = \( \text{dist}_{\text{current},1,\text{current}} + \text{dist}_{0,\text{current}}/v - \text{dist}_{0,\text{current},1} \)
16.          \( L' = L, L'_{Δ} = L_{Δ} + \text{time}, L_{Δ+4} = L_{Δ+4} + \text{load} \)
17.          \( L_{Δ+1} = Z_1, L_{Δ+2} = Z_2, L_{Δ+3} = Z_3 \)
18.          \( L_{Δ+4} = \text{current}, \text{labelcurrent} ← \text{labelcurrent} \cup L' \)
19.     End
20.   End
21. End
22. For \( k = 2*Z_3 + 1 \)
23.     time = \( 2*dist_{0,\text{current}}/v \)
24.     \( L' = L, L'_{Δ} = L_{Δ} + \text{time}, L_{Δ+4} = \text{load} \)
25.     \( L_{Δ+1} = Z_1, L_{Δ+2} = Z_2, L_{Δ+3} = Z_3 \)
26.     \( L_{Δ+4} = \text{current}, \text{labelcurrent} ← \text{labelcurrent} \cup L' \)
27. End
28. Perform non-dominated sorting and remain elite label labelcurrent-elite
29. Labelcurrentcurrent ← labelcurrent-elite
30. End
31. Output the Pareto optimal label
```

SA is associated with MOALNS to turn neighborhoods into solutions. For each neighborhood, labels are generated from the first node to the \( n \)th node in turn in accordance with the sequence \( S \) through SA, and the labels for \( n \) nodes include the trip assignments. Each label has \((\delta + 5)\) elements, and \(\delta\) represents the number of vehicles. The first \(\delta\)th elements express the time to get ready to start the next trip for the \(\delta\)th vehicle, and they are sorted in descending order. The \((\delta + 1)\)th element indicates the total operating cost \(Z_1\), The \((\delta + 2)\)th element indicates the total delivery time \(Z_2\). The \((\delta + 3)\)th element indicates the number of used vehicle \(Z_3\). The \((\delta + 4)\)th element is the loading of this trip, and the \((\delta + 5)\)th element is the predecessor node (i.e., DCs, satellites, customers) of the label. The pseudo-code of SA is shown in Algorithm 2.

In Algorithm 2, when extending a label, \((2*Z_3 + 1)\) new labels are produced which include all possible trips for vehicles. For each used vehicle, namely, the time value of the vehicle is not zero, two situations...
are considered to perform the next trip. One is to travel from the DC or satellite to perform the next trip, and the other is to travel from the previous node to continue the previous trip. In addition, an unused vehicle can be assigned to perform the next trip. An example is shown in Fig. 3.

Fig. 3 shows three possible situations for adding a new customer to trips and the travel time of vehicles. In Fig. 3(a), Customer 3 (C3) joins the trip, which includes Customer 1 (C1) and Customer 2 (C2) and is served by the used Vehicle 1 (V1). When V1 has finished the delivery service of C1 and C2 at time two, it travels from C2 directly and waits one unit time to serve C3 at time four. As indicated in Fig. 3(b), C3 starts a new trip and is served by V1. V1 finishes the last trip and returns to the DC (satellite) at time three. Then, V1 spends one unit time to prepare for the next trip and starts a new trip from the DC (satellite) at time five to serve C3. As shown in Fig. 3(c), C3 is served at time four by the new V2.

5.2. Non-dominated sorting strategy

The non-dominated sorting strategy was proposed by Deb et al. (2002) to retain the Pareto optimal solution in multi-objective optimization problems. In MOALNS-SA, non-dominated sorting strategy is utilized to select elite labels in SA (shown in Section 5.1) and measure the quality of the solution in the adaptive score adjustment procedure (shown in Section 5.6) (Rifai, Nguyen, & Dawal, 2016; Wang et al., 2020b). The pseudo-code of the non-dominated sorting strategy used in SA is shown in Algorithm 3.

\[ \text{Input: Labels(solutions) with all objectives } (Z_1, Z_2, \ldots Z_m) \]
\[ \text{Output: Pareto optimal labels(solutions)} \]
\[ 1 \text{ Rank } = 0 \]
\[ 2 \text{ While all labels(solutions) are assigned rank do } \]
\[ 3 \text{ \hspace{1cm} Rank } = \text{Rank } + 1 \]
\[ 4 \text{ For each label(solution) } i \text{ do } \]
\[ 5 \text{ \hspace{1cm} } k = 1 (\text{Value help to assigned rank}) \]
\[ 6 \text{ For each label(solution) } j \text{ (except label } i \text{) do } \]
\[ 7 \text{ \hspace{2cm} For } n = 1 : m \]
\[ 8 \text{ \hspace{3cm} If any objectives } (Z_1, Z_2, \ldots Z_m) \text{ of label } i \text{ is inferior objectives } (Z_1, Z_2, \ldots Z_m) \text{ of label } j \text{ then } \]
\[ 9 \text{ \hspace{4cm} } k = 0 \]
\[ 10 \text{ \hspace{4cm} Break } \]
\[ 11 \text{ \hspace{4cm} End } \]
\[ 12 \text{ End } \]
\[ 13 \text{ If } k = 1 \text{ then } \]
\[ 14 \text{ \hspace{1cm} Rank of label(solution) } i \leftarrow \text{Rank } \]
\[ 15 \text{ \hspace{1cm} End } \]
\[ 16 \text{ End } \]
\[ 17 \text{ End } \]
\[ 18 \text{ End } \]

directly. Therefore, \((2^mZ_0 + 1)\) labels with different trip assignments and objective values are generated. In addition, the non-dominated sorting strategy is adopted to evaluate the quality of labels for each node based on the objectives. Labels with high quality are retained to yield labels for the next node, and labels with low quality are eliminated. When obtaining the labels of the last nodes, the best labels that include trips and objectives are selected to perform the removal and insertion operations.

5.3. Removal operators

Six removal operators are presented in this algorithm. The first four and the fifth were originally proposed by Ropke and Pisinger (2006) and Wang, Lei, Zhang, and Lee (2020a), respectively. Each removal operator removes a series of customers from the current solution and adds them to a removal list. The pseudo-code of the generic removal operation is shown in Algorithm 4.
In Algorithm 4, the selected removal operator removes customers from the current solution \( Z_{current} = (Z_1, Z_2, Z_3) \) and returns to the partially-destroyed solution \( Z_p \). The removed customers are added in removal list \( L \) when the number of removed customers reaches \( N_{removed} \).

1. Random removal

This operator selects customers to remove from the current solution \( Z_{current} = (Z_1, Z_2, Z_3) \) randomly. Although the random removal operation has a low probability of leading the optimal solution, it can retain the diversity of the search space.

2. Route removal

This operator selects routes to remove from the current solution \( Z_{current} = (Z_1, Z_2, Z_3) \) randomly, namely, customers from these routes are removed. In addition, the number of removed routes is randomly generated between 1 to half of the total routes in this study.

3. Worst cost removal

This operator removes customers that generate the maximal marginal cost of the current solution. Worst cost removal in this study is operated in the following steps. First, the cost of the current solution \( Z_{current} = (Z_1, Z_2, Z_3) \) and the cost of the current solution \( Z_{current\{i\}} = (Z_1, Z_2, Z_3) \) without customer \( i \) are computed. Second, the marginal cost of customer \( i \) is the gap between \( Z_{current} = (Z_1, Z_2, Z_3) \) and \( Z_{current\{i\}} = (Z_1, Z_2, Z_3) \); Third, customers with the highest marginal cost are selected for removal from the current solution.

4. Shawn removal

This operator selects a customer \( i \) randomly, calculates its relatedness with other customers, and removes the most relevant customer in the current solution (Ghilas et al., 2016a). The relatedness of two customers is calculated with Eq. (34):

\[
R_{ij} = \psi_1 \times \frac{S_{ij}}{\max_{j \in C} S_{ij}} + \psi_2 \times \frac{|d_i - d_j|}{\max_{j \in C} |d_j| - \min_{j \in C} |d_j|} + \psi_3 \times \frac{|a_i - a_j|}{\max_{j \in C} |a_j| - \min_{j \in C} |a_j|} + \psi_4 \times l_{ij}
\]

(34)

In Eq. (34), \( \psi_1-\psi_4 \) are normalized weights. In the first component, \( S_{ij} \) represents the distance between customers \( i \) and \( j \), \( \max_{j \in C} S_{ij} \) denotes the

### Table 5

| No. | Solution by CPLEX | Solution by proposed approach | GAP_CL(%) | UB ($) | LB ($) | Time (s) | Cost ($) | Time (s) |
|-----|-------------------|-------------------------------|----------|--------|--------|----------|----------|----------|
| 1   | 882.1             | 882.1                         | 0        | 782.1  | 882.1  | 31.9     | 0        | 0        |
| 2   | 908.5             | 908.5                         | 0        | 865.2  | 911.8  | 34.3     | 0.36     | 0.20     |
| 3   | 927.6             | 927.6                         | 0        | 883.9  | 929.5  | 27.6     | 0        | 0        |
| 4   | 863.7             | 863.7                         | 0        | 749.6  | 863.7  | 30.1     | 0        | 0        |
| 5   | 934.2             | 934.2                         | 0        | 916.4  | 934.2  | 39.8     | 0        | 0        |
| 6   | 925.1             | 925.1                         | 0        | 897.3  | 925.1  | 37.7     | 0        | 0        |
| 7   | 920.2             | 920.2                         | 0        | 961.2  | 923.3  | 41.5     | 0.34     | 0.20     |
| 8   | 866.8             | 866.8                         | 0        | 817.8  | 866.8  | 33.2     | 0        | 0        |
| 9   | 973.3             | 973.3                         | 0        | 998.5  | 973.3  | 40.8     | 0        | 0        |
| 10  | 986.7             | 986.7                         | 0        | 1016.7 | 989.9  | 43.4     | 0.32     | 0.13     |
| Average | 918.8             | 918.8                         | 0        | 936.2  | 920.0  | 36.0     | 0.13     | 0.13     |

This operator removes customers that generate the maximal marginal cost of the current solution. Worst cost removal in this study is operated in the following steps. First, the cost of the current solution \( Z_{current} = (Z_1, Z_2, Z_3) \) and the cost of the current solution \( Z_{current\{i\}} = (Z_1, Z_2, Z_3) \) without customer \( i \) are computed. Second, the marginal cost of customer \( i \) is the gap between \( Z_{current} = (Z_1, Z_2, Z_3) \) and \( Z_{current\{i\}} = (Z_1, Z_2, Z_3) \); Third, customers with the highest marginal cost are selected for removal from the current solution.
maximum distance of customers. In the second component, \( d_i \) is the demand of customer \( i \). In the third component, \( a_t \) is the time when the vehicle arrives at customer \( i \). In the fourth component, \( l_{ij} = 1 \) if customers \( i \) and \( j \) are served by the same vehicle on the same route, and 1 otherwise.

5. Waiting time removal

This operator removes customers with the highest waiting time in the current solution \( Z_{\text{current}}(Z_1, Z_2, Z_3) \) to avoid wasting the delivery time of vehicles.

6. Worst load route removal

This operator removes routes with low load from the current solution \( Z_{\text{current}}(Z_1, Z_2, Z_3) \). If the load of a vehicle for a route does not reach 1/3 of the maximum load of the vehicle, then customers on the route will be removed from the current solution \( Z_{\text{current}}(Z_1, Z_2, Z_3) \).

5.4. Insertion operators

The insertion operators are implemented after the removal operation. The customers in removal list \( L \) are inserted in partiality removal solution \( Z_p \) to obtain a new solution. In this algorithm, the first two operators are inspired by Ropke and Pisinger (2006) and the third operator is inspired by Ghilas et al. (2016b). The pseudo-code of the generic insertion operation is shown in Algorithm 5.

\[
\text{Input: Partiality removal solution } Z_p, \text{ removal list } L
\]
\[
\text{Output: New solution } Z_{\text{new}}(Z_1, Z_2, Z_3)
\]
\[
1 \quad \text{The new solution } Z_{\text{new}} \leftarrow Z_p
\]
\[
2 \quad \text{While isempty } |L|
\]
\[
3 \quad \text{For (each customer } i \text{ in removal list } L \text{ do}
\]
\[
4 \quad \text{Insert customer } i \text{ in the new solution } Z_{\text{new}}
\]
\[
5 \quad \text{Remove customer } i \text{ from } L
\]
\[
6 \quad \text{End}
\]
\[
7 \quad \text{End}
\]

Table 6
Settings of instances.

| Instance | No. | NHA | NMLA | ND | NC | VC |
|----------|-----|-----|------|----|----|----|
| pr01     | 1   | 1   | 1    | 4  | 48 | 200|
| pr02     | 2   | 2   | 2    | 4  | 48 | 200|
| pr03     | 3   | 2   | 3    | 4  | 48 | 200|
| pr04     | 4   | 1   | 1    | 4  | 96 | 195|
| pr05     | 5   | 2   | 2    | 4  | 96 | 195|
| pr06     | 6   | 2   | 3    | 4  | 96 | 195|
| pr07     | 7   | 1   | 1    | 4  | 144| 190|
| pr08     | 8   | 2   | 2    | 4  | 144| 190|
| pr09     | 9   | 2   | 3    | 4  | 144| 190|
| pr10     | 10  | 1   | 1    | 4  | 192| 185|
| pr11     | 11  | 2   | 2    | 4  | 192| 185|
| pr12     | 12  | 2   | 3    | 4  | 192| 185|
| pr13     | 13  | 1   | 1    | 4  | 240| 180|
| pr14     | 14  | 2   | 2    | 4  | 240| 180|
| pr15     | 15  | 2   | 3    | 4  | 240| 180|
| pr16     | 16  | 1   | 1    | 4  | 48 | 200|
| pr17     | 17  | 2   | 2    | 4  | 48 | 200|
| pr18     | 18  | 2   | 3    | 4  | 48 | 200|
| pr19     | 19  | 1   | 1    | 4  | 96 | 195|
| pr20     | 20  | 2   | 2    | 4  | 96 | 195|
| pr21     | 21  | 2   | 3    | 4  | 96 | 195|
| pr22     | 22  | 1   | 1    | 4  | 144| 190|
| pr23     | 23  | 2   | 2    | 4  | 144| 190|
| pr24     | 24  | 2   | 3    | 4  | 144| 190|
| pr25     | 25  | 1   | 1    | 4  | 192| 185|
| pr26     | 26  | 2   | 2    | 4  | 192| 185|
| pr27     | 27  | 2   | 3    | 4  | 192| 185|
| pr28     | 28  | 1   | 1    | 4  | 240| 180|
| pr29     | 29  | 2   | 2    | 4  | 240| 180|
| pr30     | 30  | 2   | 3    | 4  | 240| 180|

Table 7
Parameters used in SNSGA-II and MOACO.

| Algorithms | Definitions                          | Values |
|------------|--------------------------------------|--------|
| SNSGA-II   | The population size                  | 100    |
|            | The maximum iterations               | 300    |
|            | The initial crossover probability    | 0.9    |
|            | The initial mutation probability     | 0.1    |
|            | The forgetting probability           | 0.7    |
| MOACO      | The pheromone evaporation rate       | 0.01   |
|            | The amount of pheromone              | 3      |
|            | The maximum iterations               | 300    |
| MOPSO      | Inertia weight                       | 0.9    |
|            | Personal confidence                  | 2      |
|            | Social learning confidence           | 3      |
|            | The maximum iterations               | 300    |
1. Greedy insertion

This operator inserts removal customers with minimum incremental cost in the partiality removal solution \( Z_p \) (Jie et al., 2019). The incremental cost is the difference between the cost of the current solution and the cost of the solution when customer \( i \) is inserted. The procedure of greedy insertion (GI) is shown in Algorithm 6.

In Algorithm 6, the incremental costs of customers in all potential positions are calculated. The smallest one is selected in each iteration and the corresponding customer is inserted into the corresponding position to generate a new solution. This step is repeated until all customers in removal list \( L \) are inserted into the new solution.

2. K-regret insertion

This operator is an improved version of GI (Fontaine, 2021). It inserts

Table 8

| Inst. | MOALNS-SA | SNSGA-II | MOACO | MOPSO |
|-------|-----------|----------|-------|-------|
| \( Z_1 \) | \( Z_2 \) (min) | \( Z_3 \) | \( CT \) (s) | \( Z_1 \) | \( Z_2 \) (min) | \( Z_3 \) | \( CT \) (s) | \( Z_1 \) | \( Z_2 \) (min) | \( Z_3 \) | \( CT \) |
|-------|-----------|----------|-------|-------|
| 1     | 1257      | 582      | 2     | 533   |
| 2     | 1302      | 562      | 3     | 542   |
| 3     | 1581      | 573      | 4     | 575   |
| 4     | 1977      | 902      | 4     | 992   |
| 5     | 1932      | 882      | 4     | 1005  |
| 6     | 2244      | 884      | 5     | 1018  |
| 7     | 2615      | 1254     | 5     | 1422  |
| 8     | 2701      | 1198     | 6     | 1465  |
| 9     | 2997      | 1154     | 7     | 1491  |
| 10    | 3458      | 1587     | 7     | 1874  |
| 11    | 3648      | 1548     | 8     | 1899  |
| 12    | 3669      | 1490     | 8     | 1917  |
| 13    | 5367      | 2278     | 12    | 2154  |
| 14    | 5499      | 2299     | 12    | 2184  |
| 15    | 5572      | 2107     | 13    | 2249  |
| 16    | 6150      | 2680     | 13    | 2533  |
| 17    | 6102      | 2663     | 14    | 2575  |
| 18    | 6311      | 2663     | 14    | 2575  |
| 19    | 1657      | 780      | 3     | 733   |
| 20    | 1592      | 762      | 3     | 742   |
| 21    | 1741      | 736      | 4     | 775   |
| 22    | 2657      | 1095     | 5     | 1433  |
| 23    | 2762      | 992      | 6     | 1427  |
| 24    | 2731      | 980      | 6     | 1475  |
| 25    | 4332      | 2106     | 9     | 1897  |
| 26    | 4418      | 1997     | 9     | 1895  |
| 27    | 4375      | 1963     | 9     | 1990  |
| 28    | 6109      | 2874     | 12    | 2208  |
| 29    | 6177      | 2892     | 12    | 2196  |
| 30    | 6289      | 2807     | 13    | 2214  |
| Average | | | | |

\[ t \text{-test} = -14.25, -7.20, -16.53, -9.13, -12.22, -8.02 \]  
\[ p \text{-value} = 1.3 \times 10^{-14}, 6.2 \times 10^{-08}, 2.7 \times 10^{-16}, 5 \times 10^{-10}, 5.9 \times 10^{-13}, 7.7 \times 10^{-09} \]
customers with maximum regret values into partiality removal solution \( Z_p \). The regret value is the gap between the costs of the best and second-best insertion positions. Let \( f_{i,\text{min}} \) be the insertion cost of the \( n \)th potential insertion position for customer \( i \). The minimum insertion cost \( f_{i,\text{min}} \) and the second minimum insertion cost \( f_{i,\text{second-min}} \) are determined. The regret value of customer \( i \) is \( \Delta f_i = f_{i,\text{second-min}} - f_{i,\text{min}} \). In each iteration, the customer with maximum regret values is selected and inserted in partiality removal solution \( L \). This step is repeated until all customers in removal list \( L \) are inserted in partiality removal solution \( Z_p \) and \( Z_{\text{new}}(Z_1, Z_2, Z_3) \) is obtained.

3. Second-best insertion

This operator is a variant of GI. Unlike in GI, the customer with the second minimum incremental cost is selected for insertion into the partiality removal solution \( Z_p \) through second-best insertion (SI). In addition, SI helps diversify the search. An example is shown in Fig. 4.

As indicated in Fig. 4, Route 1 (R1) has 11 customers, and Customer 11(C11) is to be inserted into R1. The corresponding incremental cost of the 12 positions in R1 is calculated, and C11 is inserted into the position with the second minimum incremental cost.

5.5. Acceptance criterion

The simulated annealing criterion is used to decide whether to accept or reject a new solution (Li et al., 2020, 2021b; Ropke & Pisinger, 2006). Three acceptance criteria can be applied to different cases. If the new solution \( Z_{\text{new}}(Z_1, Z_2, \ldots, Z_m) \) dominates the current solution and the best solution, the new solution will be accepted and updated as the best solution. If the new solution and current solution do not dominate each other, the new solution will be accepted as a candidate solution for the next generations. If the current solution dominates over the new solution, the new solution will be accepted based on acceptance probability \( \varphi \) as calculated in Eqs. (35)-(37).

\[
T_{n,\text{start}} = \frac{0.05}{\ln(5)} Z_{n,0} \tag{35}
\]

\[
T_n = T_{n,\text{start}} \times c^{\text{iteration}} \tag{36}
\]

\[
\varphi = \sum_{m=1}^{m} \left( \frac{Z_{n,\text{new}} - Z_{n,\text{current}}}{m} \right) \tag{37}
\]

In Eq. (35), \( Z_{n,0} \) and \( T_{n,\text{start}} \) are the initial value and initial temperature of \( n \)th objectives, respectively. In Eq. (36), the temperature of \( n \)th objectives varies with the initial temperature \( T_{n,\text{start}} \), cooling rate \( c \), and number of iterations. In Eq. (37), \( m \) is the number of objectives, \( Z_{n,\text{new}} \) and \( Z_{n,\text{current}} \) represent the new and current values of \( n \)th objectives. Unlike in the single-objective optimization problem, which calculates the acceptance probability through one objective, the acceptance probability of a multi-objective optimization problem is the average
acceptance probability of each objective.

5.6. Adaptive score adjustment procedure

The roulette-wheel strategy is used to select removal and insertion operators on the basis of the selective probability in each iteration of MOALNS-SA (Rifai et al., 2016; Sun et al., 2020). Initially, each operator is assigned the same probability, namely, each operator has the same opportunity to be selected. With the increase in iterations, the selective probability sp of each operator is updated according to the quality of the new obtained solution. Solutions with different qualities acquire different scores to change the selective probability. Solutions are divided into three categories, and the scores for the corresponding categories are as follows:

**Category 1**: If the m objectives of the new solution (\(Z_{1,new}, Z_{2,new}, \ldots, Z_{m,new}\)) are superior to the m objectives of the current best solution (\(Z_{1,best}, Z_{2,best}, \ldots, Z_{m,best}\)), that is, the new solution dominates over the current best solution, the score will be increased by \(\mu_1\).

**Category 2**: If the m objectives of the new solution (\(Z_{1,new}, Z_{2,new}, \ldots, Z_{m,new}\)) do not dominate over the m objectives of the current best solution (\(Z_{1,best}, Z_{2,best}, \ldots, Z_{m,best}\)) but dominate over those of the current solution (\(Z_{1,current}, Z_{2,current}, \ldots, Z_{m,current}\)), the score will be increased by \(\mu_2\).

**Category 3**: If the m objectives of the new solution (\(Z_{1,new}, Z_{2,new}, \ldots, Z_{m,new}\)) are inferior to those of the current solution (\(Z_{1,current}, Z_{2,current}, \ldots, Z_{m,current}\)), and the new solution is accepted through the acceptance criterion, the score will be increased by \(\mu_3\).

Given \(T\) iterations, the scores of operators (i.e., removal and insertion operators) are utilized to update the selective probability sp of each operator in the roulette-wheel strategy. The sp of each operator is calculated with Eqs. (38)-(39).

\[
\begin{align*}
sp_{i,j}^{t+1} &= \sum_{i,j} sp_{i,j}^{t+1} \\
&= \frac{\sum_{j} O_{j} + \omega \cdot \text{Score}_{i,j}^{t}}{\sum_{j} O_{j}}
\end{align*}
\]

In Eq. (38), the adaptive weight \(\omega\) of each operator is calculated. \(O_{j}\) is the number of times that operator \(i\) is selected, and \(\text{Score}_{i,j}\) is the total score of operator \(i\) during the \(j\)th \(T\) iterations. \(\omega\) controls the inertia in the weight-update quotation; when \(\omega\) is close to 1, the new adaptive weight depends greatly on the recent scores; otherwise, it depends on the former adaptive weights (Azi et al., 2014). In this study, the value of \(\omega\) is \(\min((0.002)^{T}0.001,0.999)\). Then, the selective probability of each operator is computed by Eq. (39).

5.7. Time window assignment strategy

The TWA strategy assigns candidate time windows to customers to optimize logistics networks (Wang et al., 2021b). When customers have irrational service time windows and candidate time windows are suited to the customers, the TWA strategy is applied to assign candidate time windows to the customers. The pseudo-code of the TWA strategy is shown in Algorithm 7.
As indicated in Algorithm 7, customers served beyond time windows will adjust time windows to optimize the travel time in the logistics network. For each customer served beyond the current time window, if the arrival time is within the initial time window of the customer, then the time window of the customer will recover to the initial time window. If the arrival time at the customer is within the candidate time window, then the candidate time windows will be assigned to customers.

Table 10
Distribution and numbering of DCs and satellites.

| Facility | Area   | Area number |
|----------|--------|-------------|
| DC1      | Yubei  | A7          |
| DC2      | Dadukou| A2          |
| DC3      | Beibei | A9          |
| DC4      | Banan  | A8          |
| S1       | Yuzhong| A1          |
| S2       | Jiangbei| A3         |
| S3       | Jiulongpo| A4        |

Fig. 8. Spatial distribution of customers and DCs.

Table 11
Number of customers in different areas.

| Area     | The number of customers |
|----------|-------------------------|
| Yuzhong  | 20                      |
| Dadukou  | 23                      |
| Jiangbei | 22                      |
| Jiulongpo| 22                      |
| Nanan    | 25                      |
| Beibei   | 24                      |
| Yubei    | 27                      |
| Banan    | 28                      |
| Shapingba| 24                      |
| Total    | 215                     |
Table 12
Relevant parameter values used in the model and algorithm.

| Notation | Definition                                      | Value          |
|----------|------------------------------------------------|----------------|
| $Q_v$    | Maximum capacity of a semitrailer truck         | 600            |
| $Q_s$    | Maximum capacity of a vehicle                   | 300            |
| $Q_1$    | Maximum capacity of DC1                         | 1800           |
| $Q_2$    | Maximum capacity of DC2                         | 1000           |
| $Q_3$    | Maximum capacity of DC3                         | 1200           |
| $Q_4$    | Maximum capacity of DC4                         | 1500           |
| $Q_{S1}$ | Maximum capacity of S1                          | 500            |
| $Q_{S2}$ | Maximum capacity of S2                          | 800            |
| $Q_{S3}$ | Maximum capacity of S3                          | 600            |
| $U_{ctw}$| Usage cost of a semitrailer truck (dollar/km)  | 0.75           |
| $U_v$    | Usage cost of a vehicle (dollar/km)             | 0.5            |
| $MC_v$   | Maintenance cost for semitrailer truck s in one planning period | 300 |
| $MC_v$   | Maintenance cost for vehicle v in one planning period | 200 |
| $\alpha$ | Penalty cost for early or late arrival (dollar/hour) | 30  |
| $\beta$  | Assignment cost (dollar/hour)                   | 15             |
| $\psi_1$ | Speed of the semitrailer truck and vehicle(km/hour) | 30  |
| $MaxT$   | Maximal delivery time of the vehicle (hour)     | 12             |
| $PT$     | Prepare time of the vehicle for next route(hour) | 0.2           |
| $IT$     | Each cross-regional quarantine inspection time (hour) | 0.2 |
| $\gamma$ | The working days in one planning period          | 5              |
| $runmax$ | Maximum number of optimization runs             | 300            |
| $N_{rem}$| The number of customers need to removed          | 10             |
| $\psi_1$ | First Shaw parameters                           | 0.5            |
| $\psi_2$ | Second Shaw parameters                          | 0.2            |
| $\psi_3$ | Third Shaw parameters                           | 0.1            |
| $\psi_4$ | Fourth Shaw parameters                          | 0.2            |
| $\rho_1$ | New best solution score                         | 5              |
| $\rho_2$ | Dominant current solution score                 | 3              |
| $\rho_3$ | Deterioration solution score                    | 1              |
| $c$      | Cooling rate                                    | 0.99975        |
| $c_{tw1}$| First candidate time window                      | (120,200)      |
| $c_{tw2}$| Second candidate time window                     | (240,320)      |
| $c_{tw3}$| Third candidate time window                      | (480,560)      |

Table 13
Detailed results of three cases.

| Scenario                              | DT (min) | NV | NS | OC1 ($) | OC2 ($) | TC ($) |
|---------------------------------------|----------|----|----|---------|---------|--------|
| Non-emergency initial logistics network | 16,870   | 20 | –  | 9755    | 9755    |        |
| Initial emergency logistics network    | 18,430   | 20 | –  | 10,508  | 10,508  |        |
| Optimized emergency logistics network  | 10,345   | 10 | 3  | 1039    | 5426    | 6465   |

6. Empirical analyses

6.1. Small-scale instances

In order to illustrate solution quality and the performance of the proposed MOALNS-SA algorithm, this study randomly selects 20 small-scale instances from datasets R101 and RC101 on the basis of Solomon’s benchmark (Solomon, 1987). There are 30 customers in each of the first 10 instances, and the second 10 instances each include 60 customers. All customers in these 20 instances are assumed to be served by two depots, and the locations of two depots are randomly generated in where the delivery customers are located. The proposed problem can be seen as a variant of the MDVRPTW in this study. The CPLEX solver and the proposed MOALNS-SA algorithm are used to solve the single-objective optimization model of minimum logistics operating cost. In addition, the execution time of the CPLEX solver is set to not exceed 3000 and 6000 s for the first and second 10 instances, respectively. The proposed algorithm is terminated when the best solution cannot be found after 20 consecutive iterations. Furthermore, the proposed algorithm is performed 20 separate runs for each instance, and the optimal cost and corresponding computing time values can be obtained from these 20 runs. These small-scale instances are implemented using ILOG CPLEX Optimization Studio 12.10 and the proposed algorithm. Furthermore, the upper bound (UB), lower bound (LB), computing time (Time), GAP_UL (i.e., the gap percentage between UB and LB with respect to UB), and GAP_CL (i.e., the gap percentage of the minimum objective function value from LB) are compared from the CPLEX and MOALNS-SA algorithm for all instances in Table 5.

As shown in Table 5, the proposed MOALNS-SA algorithm can provide feasible optimal solutions in a reasonable computing time, while the CPLEX solver can obtain slightly better solutions than the proposed algorithm in a longer computing time. For example, CPLEX can obtain the optimal solution in about 782 s and 4875 s for instances 1 and 11, respectively, while the proposed algorithm only takes about 32 s and 66 s. In addition, the GAP_UL value calculated by CPLEX is also further obtained through the time setting in advance. For example, the GAP_UL value is 53 % in 300 s, 33 % in 500 s, and 12 % in 700 s for instance 1, while the GAP_UL value is 61 % in 2000 s, 43 % in 3000 s, and 14 % in 4000 s for instance 11. Meanwhile, for each of the first 10 instances, CPLEX can attain the optimal solutions within 1000 s, whereas the proposed MOALNS-SA algorithm can obtain the feasible solutions within a gap of 0.36 % and computing time of 44 s. Furthermore, for the second 10 instances, the proposed MOALNS-SA algorithm can quickly attain the optimal or feasible optimal solutions, whereas CPLEX can obtain the optimal solutions in more than 4700 s for instances 11, 12, 13,
MOALNS-SA algorithm outperforms the CPLEX solver by obtaining good non-dominated genetic algorithm-II (SNSGA-II), multi-objective ant robustness in addressing the MDVRPTW. Therefore, the proposed solutions with gaps of about 2% for instances 18 and 19. These results -

Table 14
Optimized delivery routes in nine areas.

| Area | Vehicle Routes |
|------|----------------|
| A1   | V1 S1 → A1-10 → A1-2 → A1-12 → A1-7 → A1-9 → A1-5 → A1-8 → A1-17 → A1-6 → A1-1 → S1 |
| A2   | V2 S2 → A2-37 → A2-5 → A2-13 → A2-9 → A2-35 → A2-11 → A2-17 → A2-21 → A2-39 → S2 |
| A3   | V3 S3 → A3-4 → A3-10 → A3-7 → A3-4 → A3-12 → A3-9 → A3-10 → A3-20 → A3-22 → A3-3 → A3-1 → S3 |
| A4   | V4 S4 → A4-1 → A4-10 → A4-7 → A4-19 → A4-17 → A4-15 → A4-5 → A4-21 → A4-4 → A4-3 → A4-22 → A4-8 → S5 |
| A5   | V5 S5 → A5-13 → A5-6 → A5-18 → A5-20 → A5-12 → A5-9 → A5-4 → A5-23 → A5-16 → A5-14 → A5-11 → A5-3 → A5-19 → A5-20 → A5-26 → A5-6 → A5-7 → A5-22 → A5-13 → A5-3 |
| A6 & A9 | V6 DC3 → A6-5 → A6-4 → A6-15 → A6-3 → A6-14 → A6-8 → A6-11 → A9-7 → A9-24 → A9-9 → A9-18* → DC1 |
| A7   | V7 DC5 → A7-5 → A7-7 → A7-20 → A7-18 → A7-14 → A7-23 → A7-4 → A7-21 → A7-22 → A7-26 → A7-9 → A7-2 → DC1 |
| A8   | V8 DC7 → A8-21 → A8-3 → A8-23 → A8-24* → A8-19 → A8-16* → A8-26* → A8-6 → A8-22 → A8-15 → A8-3 |
| A9   | V9 DC9 → A9-7 → A9-5 → A9-12 → A9-20 → A9-23* → A9-15* → A9-16* → A9-9 → A9-22 → A9-11 → A9-3 → A9-19 → A9-20 |
| A10  | V10 DC10 → A10-1 → A10-2 → A10-12 → A10-7 → A10-9 → A10-5 → A10-3 → A10-11 → A10-2 |

A*: Customers with time window assignment.

Table 15
Number of customers with time window assignment.

| Candidate time windows | The number of customers with time window assignment |
|------------------------|--------------------------------------------------|
| [120,200]             | 3                                                |
| [240,320]             | 7                                                |
| [480,560]             | 11                                               |

14, 16, and 17. Moreover, CPLEX can obtain a lower bound but no feasible solutions for instances 15 and 20, and only obtain feasible solutions with gaps of about 2% for instances 18 and 19. These results show that the proposed MOALNS-SA algorithm achieves stability and robustness in addressing the MDVRPTW. Therefore, the proposed MOALNS-SA algorithm outperforms the CPLEX solver by obtaining good feasible solutions for small-scale instances using short computing times.

6.2. Algorithm comparison and analysis

To further test the performance of MOALNS-SA, the self-learning non-dominated genetic algorithm-II (SNSGA-II), multi-objective ant colony optimization algorithm (MOACO), and multi-objective particle swarm optimization algorithm (MOPSO) are compared with the proposed algorithm (Goh et al., 2010; Bezerra et al., 2013; Ashghari and Al-e-hashem, 2020). Ten instances from the work of Vidal et al. (2012) are extended to 30 instances to verify the capability of the proposed algorithm. The settings of the instances are shown in Table 6. The number of high-risk areas (NHA), the number of middle-/low-risk areas (NMLA), the number of depots (ND), the number of customers (NC), and vehicle capacity (VC) are also given in Table 6.

The related parameters of SNSGA-II, MOACO, and MOPSO are shown in Table 7. Each instance is run 10 times by each algorithm. The parameters of MOALNS-SA and the associated costs are similar to those the same as in Section 6.4. Table 8 compares the three algorithms’ results, including total operating cost $Z_t$, total delivery time $Z_d$, number of vehicles $Z_v$, and computation time (CT).

Table 8 illustrates the results of the proposed algorithm when compared with those of SNSGA-II, MOACO, and MOPSO. According to the t-test value and p-value, significant differences exist in the results of the four algorithms. In all instances, MOALNS-SA achieves lower operating cost, shorter delivery time, smaller number of vehicles, and less computation time than the other three algorithms, demonstrating the good performance of the proposed MOALNS-SA. The gaps in total operating cost $Z_t$ in the three types are shown in Fig. 5. In Fig. 5, $\Delta a$ indicates the gap between the average $Z_t$ value of the corresponding algorithm and $Z_{best}$. $\Delta b$ indicates the gap between the best $Z_t$ value of the corresponding algorithm and $Z_{best}$. $\Delta w$ indicates the gap between the worst $Z_t$ value of the corresponding algorithm and $Z_{best}$.

Fig. 5 shows that the difference among the three gaps of MOALNS-SA is small, that is, the stability of finding the Pareto optimal solution for addressing 2E-EVRPTWA is high. In most instances, the results of MOACO, MOPSO, and SNSGA-II are far from $Z_{best}$ in three aspects. The average delivery time of each instance in three situations is shown in Fig. 6.

Fig. 6 indicates that MOALNS-SA has the smallest average delivery time in each instance. The maximum average delivery time gap is 665 min in pr08. In pr08, the average delivery time of MOACO and MOALNS-SA is 1688 and 1023 min, respectively. Hence, the proposed algorithm has clear advantages in solving the medium- or large-scale MDVRP.

6.3. Data sources

In this section, a real-world case in Chongqing City, China, is studied to verify the validity of the 2E-EVRPTWA model and the efficiency of MOALNS-SA. The distribution of persons infected with COVID-19 and the risk levels of central urban areas in Chongqing in February 2020 are shown in Table 9 and Fig. 7, respectively. Central urban areas in Chongqing are divided into nine areas. A total of 123 confirmed COVID-19 cases are distributed in different areas. When the number of persons infected with COVID-19 exceeds 15 in an area, the area is judged to be a high-risk area. Areas where the number of persons infected with COVID-19 is less than or equal to 15 are judged as a middle-/low-risk area. In Fig. 7, four areas in red are high-risk areas and five areas in pale yellow are middle-/low-risk areas.

The logistics network consists of four DCs (DC1, DC2, DC3, DC4) and 215 delivery customers (A1-1, A1-2, A1-3...A9-24). Three satellites (S1, S2, S3) are set in three high-risk areas. The number of customers consists of the area number and customer number. For example, A1-1 represents the first customer in A1. The distribution and number of DCs, satellites, and customers in each area are shown in Fig. 8, Table 10, and Table 11, respectively. In addition, the geographical location of a satellite is set to be the same as that of the first customer in the high-risk area without DC.

6.4. Relevant parameter settings

The relevant parameters adopted in the computational experiment are from Li’s and Wang’s studies (Li, Wang, Chen, & Bai, 2020; Wang et al., 2021d; Y. Wang et al., 2021c) and are shown in Tables 12, The
time windows of DCs and satellites for customers are distributed within [0,720]. The candidate time windows are selected based on the real situation.

6.5. Effectiveness of the formulation and algorithm

The real-world case with 215 customers is solved by MOALNS-SA. The results of three scenarios in one working period, namely, the non-emergency initial logistics network, initial emergency logistics network, and optimized emergency logistics network, are shown in Table 13 and Fig. 9. The non-emergency initial logistics network and initial emergency logistics network are non-optimal logistics networks, and the initial emergency logistics network is a network that adds travel restrictions on the basis of the non-emergency initial logistics network. In other words, vehicle sharing does not exist in the non-emergency initial logistics network and initial emergency logistics network. Six results are compared: total delivery time (DT), number of vehicles (NV), number of trailer trucks (NS), operating cost in the first echelon (OC1), operating cost in the second echelon (OC2), and total operating cost (TC).

Table 13 indicates that the total operating cost of the optimized emergency logistics network is the smallest among the compared values.
When the travel restrictions are applied in the areas, the total delivery time of vehicles is increased from 16,870 min in the non-emergency initial logistics network to 18,430 min in the initial emergency logistics network. In the optimized emergency logistics network, a two-echelon collaborative logistics network is established, and TWA and vS strategies are applied. Customers are divided into different areas with

| Number | Customer | Vehicle Time | $Z_1$($) | $Z_2$(min) | $Z_3$ | Load | Prepoint |
|--------|----------|--------------|----------|------------|-------|------|----------|
| 1      | A1-10    | (11.82,0,0,0,0) | 202.955  | 11.82      | 1     | 40   | S1       |
| 2      | A1-2     | (12.5,0,0,0,0)  | 203.125  | 12.5       | 1     | 50   | 10       |
| 3      | A1-12    | (16.64,0,0,0,0) | 204.16   | 16.64      | 1     | 70   | 2        |
| 4      | A1-7     | (18.6,0,0,0,0)  | 204.65   | 18.6       | 1     | 110  | 12       |
| 5      | A1-9     | (19.93,0,0,0,0) | 204.9825 | 19.93      | 1     | 120  | 7        |
| 6      | A1-5     | (24.02,0,0,0,0) | 206.005  | 24.02      | 1     | 160  | 9        |
| 7      | A1-8     | (26.24,0,0,0,0) | 206.56   | 26.24      | 1     | 190  | 5        |
| 8      | A1-17    | (28.58,0,0,0,0) | 207.145  | 28.58      | 1     | 220  | 8        |
| 9      | A1-6     | (29.36,0,0,0,0) | 207.34   | 29.36      | 1     | 250  | 17       |
| 10     | A1-1     | (41.36,0,0,0,0) | 207.34   | 29.36      | 1     | 280  | 6        |
| 11     | A1-20    | (47.12,0,0,0,0) | 208.78   | 35.12      | 1     | 20   | S1       |
| 12     | A1-4     | (52.49,0,0,0,0) | 210.1225 | 40.49      | 1     | 40   | 20       |
| 13     | A1-3     | (55.36,0,0,0,0) | 210.84   | 43.36      | 1     | 70   | 4        |
| 14     | A1-13    | (56.54,0,0,0,0) | 211.135  | 44.54      | 1     | 100  | 3        |
| 15     | A1-15    | (57.51,0,0,0,0) | 211.3775 | 45.51      | 1     | 130  | 13       |
| 16     | A1-14    | (62.58,0,0,0,0) | 212.645  | 50.58      | 1     | 160  | 15       |
| 17     | A1-16    | (63.76,0,0,0,0) | 212.94   | 51.76      | 1     | 190  | 14       |
| 18     | A1-11    | (64.5,0,0,0,0)  | 213.125  | 52.5       | 1     | 220  | 16       |
| 19     | A1-18    | (66.33,0,0,0,0) | 213.5825 | 54.33      | 1     | 230  | 11       |
| 20     | A1-19    | (67.48,0,0,0,0) | 213.87   | 55.48      | 1     | 270  | 18       |
different risk levels and served by the corresponding DCs or satellites to minimize the impact of travel restrictions on delivery time. As shown in Fig. 9, the values of the three objective functions are obviously reduced by the proposed method. The number of vehicles is reduced from 20 to 10 through the vS strategy. Therefore, the proposed method can improve the emergency response speed, the utilization of vehicles, and the operational efficiency of the emergency logistics network. The optimized delivery routes for this case and the number of customers with TWA are shown in Tables 14 and 15, respectively. The optimized delivery routes in A2, A5, and A8 are shown in Fig. 10.

As indicated in Table 14, ten vehicles perform 19 delivery routes in the real-world case. Each high-risk area is closed and independent. Four vehicles performing nine trips depart from DC1, S1, S2, and S3 to serve customers in high-risk areas. Customers in the middle-/low-risk areas are assigned and served by the nearest DC. Vehicles 5 and 6 start from DC3 to serve customers in A6 and A9. Vehicle 7 starts from DC2, and Vehicles 8, 9, and 10 begin from DC4 to serve customers in A2, A5, and A8. As presented in Table 15, the TWA strategy assigns candidate time windows to 21 customers in middle-/low-risk areas. More than 50 % of the customers accept the candidate time window [480,560]. Three customers accept assigned time window [120,200], seven customers accept assigned time window [240,320], eleven customers accept assigned time window [480,560]. Fig. 10 shows six delivery routes in A2, A5, and A8. In addition, Vehicles 7 and 9 are shared in A2, A5, and A8 and perform four trips. The trips for A1 are explained in detail below to elaborate how SA assigns trips to vehicles to achieve the vS strategy.

The best trips for A1 are split by SA in one working day, and the procedure is shown in Table 16. Each line expresses the label of the corresponding customer. Each element in “Vehicle Time” represents the time to get ready to start the next trip for the corresponding vehicle.

Table 17
Results of five scenarios.

| Case   | TC ($) | DT (min) | NV | NS | AC ($) | DTV (min) | DTS (min) | AT (min) |
|--------|--------|----------|----|----|--------|-----------|-----------|----------|
| Initial| 10,508 | 18,430   | 20 | –  | 18,430 | –         | –         | –        |
| Case 1 | 10,058 | 13,150   | 12 | 7  | 10,840 | 2310      | 1500      | –        |
| Case 2 | 6465   | 10,345   | 10 | 3  | 9575   | 770       | 1300      | –        |
| Case 3 | 7714   | 13,535   | 14 | –  | 13,535 | –         | 1880      | –        |
| Case 4 | 7619   | 12,865   | 14 | –  | 12,865 | –         | 2420      | –        |

Table 18
Comparison of the results of Initial case and Case 2.

| Case   | Facility | TC ($) | DT (min) | DTS (min) | DTV (min) | PC ($) | AT (min) | AC ($) | NV | NS | NSC | NTA |
|--------|----------|--------|----------|-----------|-----------|--------|----------|--------|----|----|-----|-----|
| Initial| DC1      | 2196   | 3605     | –         | 3605      | 560    | –        | 4(0*) | 49 | 8  | –   | –   |
|        | DC2      | 3768   | 7055     | –         | 7055      | 695    | –        | 7(0*) | 68 | 12 | –   | –   |
|        | DC3      | 2365   | 3750     | –         | 3750      | 637    | –        | 5(0*) | 48 | 4  | –   | –   |
|        | DC4      | 2179   | 4020     | –         | 4020      | 505    | –        | 4(0*) | 50 | 2  | –   | –   |
|        | Total    | 10,508 | 18,430   | –         | 18,430    | 2395   | –        | 220(0*)| 215| 26 | –   | –   |

| Case 2 | DC1      | 1012   | 1565     | 290       | 1275      | 93     | –        | 1(3*) | 1   | 27 | 1   | 1   |
|        | DC2      | 1404   | 1560     | 480       | 1080      | 85     | 250      | 63     | 1(2*)| 2   | 27  | 1   |
|        | DC3      | 1305   | 2355     | –         | 2355      | 197    | 600      | 150    | 2(4*)| –   | 48  | –   |
|        | DC4      | 1679   | 3065     | –         | 3065      | 232    | 450      | 112    | 3(4*)| –   | 49  | –   |
|        | S1       | 269    | 275      | –         | 275       | –      | –        | 1(2*) | –   | –   | 20  | –   |
|        | S2       | 390    | 735      | –         | 735       | 13     | –        | 1(2*) | –   | –   | 22  | –   |
|        | S3       | 406    | 790      | –         | 790       | 17     | –        | 1(2*) | –   | –   | 22  | –   |
|        | Total    | 6465   | 10,345   | 770       | 9575      | 637    | 1300     | 325    | 10(19*)| 3  | 215 | 3   |

*: Number of delivery routes of vehicles.
"Load" represents the loading of the vehicle when a customer is added to this trip. "Prepoint" indicates the predecessor node that helps output vehicle routes.

Table 16 presents 20 optimal labels selected and retained by the non-dominated sorting strategy. In the last label, only one member in the vehicle routes.

For example, the Prepoint of the label of customer A1-20 is S1, which means the vehicle finishes the last trip and starts a new trip from S1 to serve customer A1-20. The Load label of customers A1-1 and A1-19 are 280 and 270, respectively, indicating the total load capacity of two trips. A1’s initial and optimized delivery routes in the emergency logistics network are shown in Figs. 11 and 12, respectively.

Fig. 11 indicates that customers in A1 are served by three vehicles departing from different DCs. Each vehicle enters the high-risk area A1 and crosses the travel restrictions twice, namely, they are required to undergo the cross-regional quarantine inspection twice. Each cross-regional quarantine inspection last for 12 min, and the total time of the cross-regional quarantine inspection in A1 is 72 min. Hence, effective measures are needed to optimize the delivery time of the vehicle and reduce the impact of cross-regional quarantine inspection on delivery time. A1’s optimized delivery routes in the emergency logistics network are shown in Fig. 12.

As indicated in Fig. 12, a two-echelon distribution system is constructed to minimize the impact of travel restrictions. Satellite 1 (S1) is established based on the geographical location of the first customer A1-1. The demands of customers in A1 are transferred to S1 by centralized transportation. When TWA and vs strategies are adopted in the second echelon, 20 customers in A1 are served by Vehicle 1 (V1), which departs from and returns to S1. V1 performs the first trip (S1 → A1-10 → A1-2 →
A1-12 → A1-7 → A1-9 → A1-5 → A1-8 → A1-17 → A1-6 → A1-1 → S1) and second trip (S1 → A1-20 → A1-4 → A1-3 → A1-13 → A1-15 → A1-14 → A1-16 → A1-11 → A1-18 → A1-19 → S1). V1 does not undergo cross-regional quarantine inspection because V1 does not leave A1.

6.6. Analysis and discussion

6.6.1. Comparison of the results of TWA and vS strategies adopted in different areas

According to the optimized results in Section 6.5, TWA and vS strategies can considerably improve the operational efficiency and reduce the number of used vehicles in the second echelon. The results obtained by TWA and vS strategies vary with the scope where time windows are assigned and vehicles are shared (Wang et al., 2021a). To obtain the optimal application of TWA and vS in real-world cases, TWA and vS strategies are applied in different areas, and four cases are discussed in the emergency logistics network, as shown in Fig. 13.

Case 1: In the nine areas, five satellites are established to serve customers in A1, A3, A4, A5, and A9, and the other areas are served by the DCs within them. Vehicles that start from each satellite or DC are shared in each area independently, and the TWA strategy is applied in the middle-/low-risk areas.

Case 2: In the four high-risk areas, three satellites are established to serve customers in A1, A3, and A4. Customers in A7 are served by DC1, and vehicles are shared in each high-risk area independently. In the five middle-/low-risk areas, the TWA strategy is applied and vehicles are shared in each DC, namely, each DC can serve customers in several areas; then, vehicles can be shared by several areas.

Case 3: In the four high-risk areas, vehicles are shared in each DC. In the five middle-/low-risk areas, the TWA strategy is applied, and vehicles are shared in each DC.

Case 4: On the basis of Case 3, the TWA strategy is applied in the high-risk areas.

The results of five scenarios in terms of the total operating cost (TC), total delivery time (DT), number of vehicles (NV), number of semitrailer trucks (NS), time window assignment cost (AC), delivery time of vehicles (DTV), delivery time of semitrailer trucks (DTS), penalty cost (PC), time window assignment cost (AC), assigned time (AT), number of vehicles (NV), number of semitrailer trucks (NS), number of times across multiple areas (NTA), and number of served customers (NSC) are shown in Table 18. The initial and optimized vehicle routes of DC1 and DC3 are shown in Fig. 15.

As indicated in Table 18, the total operating cost decreases from $10,508 in Initial case to $6465 in Case 2. In Case 2, satellites are established in the high-risk areas, and the number of times that multiple areas are crossed is reduced through centralized transportation, thereby reducing delivery time of vehicles. In addition, the number of used vehicles decreases from 20 to 10 when the vS strategy is adopted, and the utilization of vehicles is greatly increased. Through the TWA strategy, the waiting and delayed times of vehicles are decreased, resulting in a low PC. Fig. 15(a) shows the initial vehicle routes performed by night vehicles. DC1 and DC3 serve customers in two middle-/low-risk areas and two high-risk areas. In the emergency situation, four vehicles cross the high-risk areas 12 times, and the delivery time of vehicles increases by 720 min in one working period. Fig. 15(b) presents the optimized delivery routes performed by four vehicles. Satellite 2 (S2) is established in A3, and the demands of the customers in A3 are transported from DC1.

Fig. 17. Result comparison of the seven scenarios.
to S2 to reduce the delivery time of vehicles.

6.6.2. Result comparison in different scenarios

TWA and vS strategies are implemented in different scenarios with and without the two-echelon distribution system to demonstrate the efficiency of the proposed methods. Seven scenarios with travel restrictions in the emergency mode are shown in Fig. 16.

In Fig. 16, seven scenarios are presented as follows. (1) In the emergency initial logistics network, each DC operates independently (Initial scenario). (2) On the basis of the Initial case, the vS strategy is adopted for each DC (Scenario 1). (3) On the basis of the Initial, the TWA strategy is applied to customers in middle-/low-risk areas (Scenario 2). (4) On the basis of the Initial case, a two-echelon distribution network is constructed, and satellites are established in high-risk areas without DCs (Scenario 3). (5) Based on Scenario 3, the vS strategy is adopted in the second echelon and the TWA strategy is applied to customers in middle-/low-risk areas (Scenario 4). (6) On the basis of Scenario 3, the TWA strategy is applied to customers in middle-/low-risk areas (Scenario 5). (7) On the basis of Scenario 3, the vS strategy is adopted in the second echelon, and the TWA strategy is applied to customers in middle-/low-risk areas (Scenario 6). The results of the seven scenarios in terms of the total operating cost (TC), total delivery time (DT), number of vehicles (NV), number of semitrailer trucks (NS), delivery time of vehicles (DTV), delivery time of semitrailer trucks (DTS), and time window assignment cost (AC) are shown in Table 19 and Fig. 17.

In Table 19, the total operating cost, total delivery time, and number of vehicles can be decreased by TWA and vS strategies in the two-echelon emergency logistics network. When the vS strategy is adopted, the number of vehicles decreases from 20 in the Initial scenario to 16 in Scenario 1. The time windows of several customers are adjusted by the TWA strategy, which results in changes in the logistics network, thus improving the operational efficiency and reducing the operating cost in Scenario 2. Although three semitrailer trucks are used in the two-echelon distribution system, the total delivery time is greatly reduced in Scenario 3. Fig. 17 shows that adopting the vS or TWA strategies on the basis of the two-echelon distribution system can considerably reduce the total operating cost, total delivery time, and number of vehicles in Scenarios 4 and 5. The minimum values of the three objectives (i.e., $6465, 10,345$ min, and 10) are obtained when the proposed methods are adopted in Scenario 6. Therefore, the speed of the emergency response, the utilization of vehicles, and operational efficiency exhibit a remarkable improvement through the two-echelon distribution system with TWA and vS strategies.

6.7. Management insights

The outbreak of COVID-19 was unexpected, and governments and enterprises in the world were unprepared for it. Although containment and closure policies are effective in some regions, the transportation of daily life supplies for residents in closed areas has become a problem. Therefore, this study recommends several strategies that should be helpful in designing an emergency logistics network to ensure the transportation of essential supplies. The insights derived from the strategies are as follows:

(1) The two-echelon collaborative distribution system that considers the risk of infection in each area can efficiently improve the speed of emergency response and ensure uninterrupted operation in emergency mode. In the presence of containment and closure policies, vehicles that perform delivery services among different areas are subject to travel restrictions, and they are required to undergo cross-regional quarantine inspections. On the basis of collaboration between DCs and satellites, centralized transportation between DCs and satellites can reduce the impact of travel restrictions on the total delivery time and the risk of cross-regional COVID-19 transmission. The vehicles of each area deliver goods only within the area to avoid long-distance transportation and ensure timely delivery. Thus, the two-echelon distribution system helps cope with emergencies and establish an efficient collaborative emergency logistics network.

(2) TWA and vS strategies can reallocate transportation resources, and enhance the utilization of vehicles and the operational efficiency of emergency logistics networks. Compared with normal logistics networks, emergency logistics networks have fewer available vehicles (e.g., the number of available drivers decreased during the outbreak of COVID-19). To avoid cross-regional transmission and increase the utilization of vehicles, vehicles are only shared in each DC or satellite in the two-echelon distribution system. Unreasonable time windows from customers may result in low delivery efficiency and high penalty costs. The TWA strategy assigns appropriate time windows to customers with unreasonable time windows in middle-/low-risk areas in the two-echelon distribution system. TWA and vS strategies contribute to an efficient emergency logistics network and promote the sustainable development of emergency logistics networks.

(3) Emerging technologies facilitate the development of emergency logistics networks. When natural disasters or accidents occur, emerging technologies, such as big data, cloud computing, and the Internet of Things, can assist the government and logistics enterprises in building an emergency logistics network with fast response. In addition, innovative tools can be applied to reduce the risk of transmission by contact and enhance the efficiency of emergency logistics networks. For example, automatic inspection and quarantine equipment that can perform quarantine operations for vehicles traveling between different risk areas accelerate the process in two-echelon emergency logistics networks.

7. Conclusions

This study aims to design an efficient collaborative emergency logistics network during the outbreak of COVID-19. To tackle this problem, a tri-objective optimization model is formulated to minimize the total operating cost, total delivery time, and number of vehicles under different operating modes. On the basis of the number of confirmed COVID-19 cases, the service areas are divided into high-risk and middle-/low-risk areas, and a two-echelon emergency logistics network is established to reduce the cross-regional transportation. The MOALNS-SA algorithm is used to assign trips to vehicles and candidate time windows to customers to find the Pareto optimal solution. The performance of MOALNS-SA is compared with the CPLEX solver through 20 small-scale instances and those of the SNSGA-II, MOACO, and MOPSO through 30 benchmarks, and the results indicate that MOALNS-SA has advantages in solving 2E-EVRPTWA.

A real-world case in Chongqing, China, is solved by MOALNS-SA, which results in a total operating cost of $6465, total delivery time of 10,345 min, and 10 vehicles in a working period. In addition, four scenarios are proposed to optimize the application scheme of TWA and vS strategies. Other scenarios where TWA and vS strategies are operated in each high-risk area and between middle-/low-risk areas are considered. The results of the four scenarios indicate that TWA and vS strategies implemented differently in Case 2 can reduce the risk of transmission and maximize the utilization of vehicles. The importance of the two-echelon distribution system and TWA and vS strategies in addressing 2E-EVRPTWA is discussed in the Initial scenario and the following six scenarios. The result comparison among seven scenarios shows that the delivery time and number of vehicles are reduced, and the operational efficiency is improved when TWA and vS strategies are adopted in the two-echelon emergency logistics network.

Analysis and discussion in Section 6.6 show that the proposed method is very effective in optimizing the emergency logistics networks. In a critical case like the COVID-19 lock-down, traditional distribution logistics network design methods cannot construct a less contagious and
flexible logistics network (Mondal and Roy, 2021; Govindan et al., 2021). However, the proposed methods can establish a two-echelon emergency logistics service network quickly. Satellites are constructed in high-risk areas to reduce the impact of travel restrictions and maintain the uninterrupted operation of the logistics network. With limited transportation resources in the emergency mode, the implementation of v5 strategy in different areas can improve the utilization of vehicles and reduce the risk of cross-regional COVID-19 transmission. Furthermore, the TWA strategy is used to assign appropriate time windows to customers in the middle-/low-risk areas, which can effectively improve the response speed and operational efficiency of the two-echelon emergency logistics networks. Therefore, this study contributes to developing intelligent and efficient logistics systems and promoting the sustainable development of emergency logistics networks.

Although this study has achieved the emergency logistics network optimization with TWA, the following extensions based on this study should be considered in the future. (1) Exact algorithms and meta-heuristics for 2E-EVRPTWTA can be pursued to improve the solution quality. (2) The delivery priority of customers can be adjusted based on the urgency of customer demands in emergency logistics networks. (3) The characteristics of other emergency scenarios, such as flood and earthquake disasters, can be considered in the proposed model to extend the adoption scenarios of the proposed model. (4) On the basis of this study, future work could consider dynamic customer demands in real-world emergency logistics networks.

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.

Data availability

Data will be made available on request.

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