Expert Systems With Applications 214 (2023) 119145

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Emergency logistics network optimization with time window assignment

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ARTICLE INFO

Keywords:
Emergency logistics
Two-echelon vehicle routing problem
Vehicle sharing
Time window assignment
Multi-objective adaptive large neighborhood search

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.

1. Introduction

The coronavirus disease 2019 (COVID-19) outbreak has affected human lives and global economic activities considerably (Cheramin et al., 2021; Mitręga 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

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https://doi.org/10.1016/j.eswa.2022.119145
Received 15 May 2022; Received in revised form 16 October 2022; Accepted 23 October 2022
Available online 31 October 2022
0957-4174/

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. Goods are transferred from DCs to the corresponding satellites in high-risk areas by semitrailer trucks, and the satellites deliver goods to customers by vehicles (Wang et al., 2020b). Centralized transfer of goods by semitrailer trucks can reduce the cross-regional quarantine inspection time when entering high-risk areas. In middle-/low-risk areas, DCs serve customers using vehicles directly.

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 are 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-EVRPTWA) 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-EVRPTWA. 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-EVRPTWA 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-EVRPTWA 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 minimization of 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-EVRPTWA.

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-EVRPTWA in detail with an example. Section 4 introduces definition and mathematical model of 2E-EVRPTWA. 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.

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., 2022). 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, Mirchandani, Agnetis, & Ghelichi, 2022; W. Wang, Wu, Wang, Zhen, & Qu, 2021d; Y. Wang et al., 2021c; Wolfinger, Gansterer, Doerner, & Popper, 2021). Several studies related to 2E-EVRPTWA in MDVRPTW, 2E-VRPTW, TWA, vS and EVRP are reviewed.

2.1. Multi-depot vehicle routing problem with time windows

Many studies have examined MDVRPTW in the past decades (Tu et al., 2014; Wang et al., 2018; Li et al., 2019; Sadati et al., 2020). Ray et al. (2014) discussed a new integer linear programming model to minimize the total cost and developed a fast heuristic algorithm on the basis of knowledge gathering to find near-optimal solutions for MDVRPTW. Masmoudi et al. (2016) proposed an adaptive large neighborhood search (ALNS) algorithm, hybrid bee algorithm with simulated annealing, and hybrid bee algorithm with deterministic annealing to address MDVRPTW; the results show that the proposed algorithms are effective in finding the optimal solution. Wang et al. (2018) constructed a multi-objective mathematical model to minimize the operating cost and number of vehicles for MDVRPTW and extended the k-means algorithm and non-dominated sorting genetic algorithm-II to solve this problem. To avoid falling into the local optimal solution, Sadati et al. (2021) proposed a variable Tabu neighborhood search algorithm that includes granular local search and Tabu shaking mechanisms to solve MDVRPTW. The algorithm allows the violation of the constraints of a particular problem in the search process and converges to a feasible

Table 1
Comparison between the relevant literature and this study.

Literature	1E/2E	1D/MD	VS	TWA	Emergency	Objective function	Approach
Cattaruzza et al. (2014)	1E	1D	√	–	–	Minimize travel time	Memetic algorithm
Moreno et al. (2016)	1E	1D	–	–	√	Minimize operating cost	Relax-and-fix and fix-and-optimize heuristic
Rivera et al. (2016)	1E	1D	√	√	–	Minimize travel time	Adaptation of Bellman–Ford algorithm
Liu et al. (2017)	2E	1D	–	–	–	Minimize operating cost	Tabu search
Subramanyam et al. (2018)	1E	1D	–	√	–	Minimize operating cost	Scenario decomposition algorithm
Zhou et al. (2018)	2E	MD	–	–	–	Minimize operating cost	Hybrid multi-population GA
Martins et al. (2019)	1E	1D	–	√	–	Minimize operating cost	Adaptive large neighborhood search
Li et al. (2019)	1E	MD	–	–	–	Minimize operating cost	Improved ant colony optimization algorithm
Breunig et al. (2019)	2E	1D	–	–	–	Minimize operating cost	LNS
He and Li (2019)	2E	1D	√	–	–	Minimize number of vehicles, cost and waiting times	Memetic algorithm
Zhen et al. (2020)	1E	MD	√	–	–	Minimize travel time	Hybrid PSO and GA
Wang et al. (2020a)	1E	MD	√	–	–	Minimize operating cost	Hybrid Tabu and ALNS
Wang et al. (2020b)	2E	MD	–	–	–	Minimize operating cost and waiting time	CW-NSGA-II and Lagrangian relaxation
Liu et al. (2021)	1E	MD	–	–	√	Minimize travel time	Multiple dynamic programming algorithm
Jalilvand et al. (2021)	1E	1D	–	√	–	Minimize operating cost	Progressive hedging algorithm
Wang et al. (2021c)	1E	MD	–	√	–	Minimize operating cost and number of vehicles	Self-learning non-dominated sorting genetic algorithm-II (SNSGA-II)
Wang et al. (2021a)	2E	MD	√	–	–	Minimize cost, waiting time and number of vehicles	Improved reference point-based NSGA -III
Wolfinger et al. (2021)	2E	MD	–	–	√	Minimize operating cost	LNS
Govindan et al. (2021)	2E	MD	–	–	√	Minimize operating cost and pollution risk	Fuzzy goal programming approach
Wang et al. (2021b)	2E	MD	√	–	√	Minimize operating cost and delivery time	CW-NSGA-II
Zhen et al. (2022)	1E	MD	–	–	–	Minimize operating cost	Column generation-based algorithm
Xue et al. (2022)	2E	1D	–	–	–	Minimize operating cost	Improved genetic algorithm-tabu search
This study	2E	MD	√	√	√	Minimize operating cost, delivery time and number of vehicles	MOALNS-SA

Abbreviations: 1E: One echelon; 2E: Two-echelon; 1D: One depot; MD: Multi-depot; VS: vehicle sharing strategy; TWA: time window assignment strategy; Emergency: emergency vehicle routing problem.

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; Sluijk et al., 2022). Grangier 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 in the two echelons. They combined an efficient island-based memetic algorithm with Lin–Kernighan local search to address 2E-VRPTW. Meanwhile, Li et al. (2020) investigated 2E-VRPTW for parcel deliveries in city transportation systems and designed an ALNS algorithm to tackle 2E-VRPTW. Yu et al. (2021) studied 2E-VRPTW in a last-mile distribution logistics network. They formulated a mixed-integer linear programming model and proposed an ALNS algorithm to tackle 2E-VRPTW.

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.

Rational customer service TWA can improve the number of sharing vehicles (Spliet and Desaulniers, 2015; Dalmeijer and Spliet, 2018; Wang et al., 2021c). TWA with VRP (TWAVRP) was introduced by Spliet and Gabor (2015), who proposed a model to assign candidate time windows to customers to minimize travel costs. Neves-Moreira, Pereira da Silva, Guimarães, Amorim, and Almada-Lobo (2018) developed a new formulation for TWAVRP based on multiple product segments and a three-stage method to solve this problem. Subramanyam et al. (2018) studied a method that adapts to continuous and discrete feasible solutions for TWA sets and a new scenario decomposition algorithm for addressing TWAVRP. Martins et al. (2019) incorporated a product-oriented time preference into the design of TWAVRP and proposed an ALNS to tackle the product-oriented TWAVRP. Jalilvand et al. (2021) proposed an optimization model for TWAVRP to minimize the operating cost and designed an efficient progressive hedging algorithm to address this problem. A robust framework based on requirement violation was

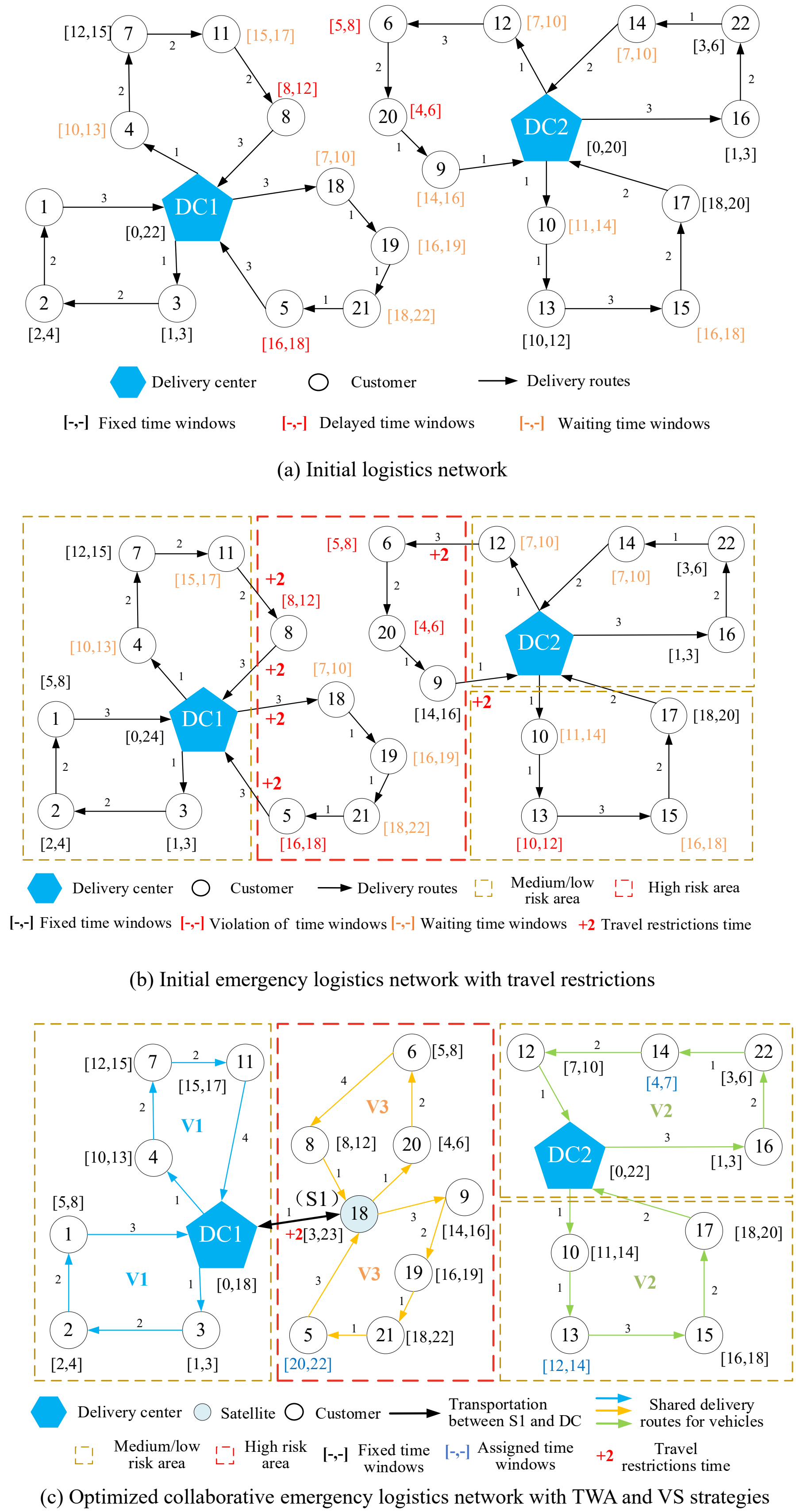


Fig. 1. An emergency logistics network in three different scenarios.

Table 2
Data sources for customers.

Customer	Demands	Customer	Demands	Customer	Demands	Customer	Demands
C1	2	C6	1	C12	2	C17	2
C2	1	C7	2	C13	3	C18	2
C3	4	C8	5	C14	4	C19	5
C4	4	C9	2	C15	1	C20	4
C5	1	C10	4	C16	2	C21	2

presented by Hoogeboom et al. (2021) to minimize travel time and the risk of time window violations in TWAVRP.

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 CO_2 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 city systems (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-Espíndola 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 ALNS 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-EVRPTWA, 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 collaborative emergency logistics networks have not been well studied. (3) Single-objective models cannot adapt to the complex situations in collaborative emergency logistics networks and maintain stable performance. (4) The algorithms for solving the multi-objective problem are not utilized to solve 2E-EVRPTWA in most studies.

3. Problem statement

Effective planning and devising of a collaborative emergency logistics network can ensure the normal operation of urban logistics when an unpredictable occurrence occurs. In this study, TWA and vS strategies are applied in a two-echelon collaborative emergency logistics network with travel restrictions to improve operational efficiency. An emergency logistics network involves several DCs, satellites, and assigned customers. Maximum utilization of limited transportation resources can be obtained through the vS strategy. Customers with irrational time windows are reassigned new time windows in the collaborative emergency logistics network through the TWA strategy. Fig. 1 shows three scenarios in the collaborative emergency logistics network, and the waiting time window means that the vehicle arrives before the customer service time window starts, and needs to wait for the time window to start for service, while the delayed service time window means that the vehicle arrives after the end of the customer service time window. In addition, the initial emergency logistics network (i.e., Fig. 1(b)) is a network that adds travel restrictions on the basis of the initial logistics network (Fig. 1(a)).

In Fig. 1 (a), DC1 and DC2 operate independently in the logistics network. Customer demands cannot be met timely due to the irrational design of delivery routes. In addition, when customers' time windows are small, more vehicle usage further reduces the total delivery time. In Fig. 1(b), the distribution area is divided into middle-/low-risk and high-risk areas in emergency modes. DC1 and DC2 are located in the middle-/low-risk areas and several customers are located in the high-risk area. Travel restrictions are constructed in the middle-/low-risk and high-risk areas to avoid cross-infection. When vehicles cross the travel restrictions to serve customers, namely, vehicles accept the cross-regional quarantine inspection, the travel restriction time is generated. For example, Customer 8 (C8) in the route (e.g., DC1 → C4 → C7 → C11 → C8 → DC1) is located in a high-risk area, and the vehicle for the route needs to cross travel restrictions, which generate four per unit travel restriction times. As travel restrictions develop, the total travel time and the number of customers whose demands cannot be served on time are increased. Therefore, efficient emergency logistics network planning is required to enhance the 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 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 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

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 (0*)	–	1200	2560
Emergency	Initial network	64	39	20	–	1525	–	6 (0*)	–	1200	2725
	Optimized network	59	–	–	9	650	90	3 (3*)	1	900	1640

*: The number of shared vehicles; NV: Number of vehicles; NS: Number of semitrailer trucks.

to $20/unit time and $10/unit time, respectively. The penalty cost for waiting and lateness can be defined as $15/unit time, and the assignment cost from the expected time windows to the assigned time windows can be set to $10/unit time. The maximal capacity for a semitrailer truck and vehicle is 15 and 10 per unit demand, respectively. The rental cost of each semitrailer truck and each vehicle can be set to $300 and $200, respectively, in one planning period. The demands of customers and the related optimization results of the emergency logistics network are shown in Tables 2 and 3.

As shown in Table 3, the two-echelon collaborative emergency logistics network with TWA and vS strategies has a lower cost ($1640) than the two other scenarios. When an emergency occurs, the delivery time is significantly increased due to travel restrictions. The number of delivery vehicles decreases from 6 to 3 when the vS strategy is adopted in the emergency logistics network. Through the TWA strategy, the sum of waiting and delayed time shows an obvious reduction that ensures the timeliness of delivery service. Therefore, the two-echelon distribution system with TWA and vS strategies is conductive to building an efficient emergency logistics network.

4. Optimization model

The limited transportation resources and the travel restrictions in areas where COVID-19 occurs may increase the operating cost and delivery time of logistics networks (Li, Zhou, Kundu, & Zhang, 2021a; Zhao et al., 2021). To mitigate the negative effect caused by COVID-19, a tri-objective optimization model with TWA and vS strategies is constructed to obtain the minimum total operating cost, delivery time, and number of vehicles in a two-echelon logistics network. Several essential and rational assumptions are considered in the design of the optimization model.

Assumption 1. *In high-risk areas, satellites are set up in areas without DCs. The DCs transport goods to the corresponding satellites, and customers are served by these satellites.*

Assumption 2. *The total demand and total supply are equal, furthermore, although the capacity of a single semitrailer truck is limited, the transportation between DC and high-risk area can be accomplished by multiple semitrailer trucks.*

Assumption 3. *In an emergency situation, the geographical location of each satellite is given by the government in the corresponding high-risk area.*

Assumption 4. *Considering the shortage of transportation resources and the risk of COVID-19 transmission in the emergency logistics network, the vS strategy is applied in each DC and each satellite, namely, vehicles in high-risk-areas can be shared within these areas and vehicles in middle-/low-risk areas can be shared within and among areas.*

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).

$$\text{Min} \quad Z_1 = TC_1 + TC_2 \tag{1}$$

$$\begin{aligned} Min\ Z_2 = & \sum_{p\in D\cup W}\sum_{q\in D\cup W}\sum_{s\in S}\left(t_{pqs}+IT\right)\times y_{pqs}+\sum_{i\in D\cup W\cup C}\sum_{j\in D\cup W\cup C}\sum_{v\in V}\sum_{k\in O_v}\sum_{a,b\in A_H} t_{ijv}\times x_{ijv}^{abk} \\ & +\sum_{i\in D\cup C}\sum_{j\in D\cup C}\sum_{v\in V}\sum_{k\in O_v}\sum_{a,b\in A_{ML}} t_{ijv}\times x_{ijv}^{abk}+\sum_{p\in D\cup W}\sum_{s\in S}Wt_{qs}+\sum_{i\in W\cup C}\sum_{v\in V}\sum_{k\in O_v}\sum_{a\in A}Wt_{iv}^{ka} \end{aligned} \tag{2}$$

$$\text{Min} \quad Z_3 = \sum_{a,b\in A_H}\sum_{v\in V}\left\{\sum_{q\in W}\sum_{j\in C}\sum_{k\in O_v}x_{qjv}^{\text{abk}},1\right\}+\sum_{a,b\in A_{ML}}\sum_{v\in V}\left\{\sum_{p\in D}\sum_{j\in C}\sum_{k\in O_v}x_{pjv}^{\text{abk}},1\right\} \tag{3}$$

In Eq. (1), Z_1 includes two components: TC_1 and TC_2. TC_1 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, $\sum_{p\in D\cup W}\sum_{q\in D\cup W}\sum_{s\in S}\left(t_{pqs}+IT\right)\times y_{pqs}$ and $\sum_{p\in D\cup W}\sum_{s\in S}Wt_{qs}$ represent the traveling and waiting times in the first echelon, $\sum_{i\in D\cup C}\sum_{j\in D\cup C}\sum_{v\in V}\sum_{k\in O_v}\sum_{a,b\in A_{ML}}t_{ijv}\times x_{ijv}^{abk}$ and $\sum_{i\in W\cup C}\sum_{v\in V}\sum_{k\in O_v}\sum_{a\in A}$ Wt_{iv}^{ka} indicate the traveling and waiting times in the second echelon. In Eq. (3), Z_3 indicates the number of vehicles in the second echelon, $\sum_{a,b\in A_H}\sum_{v\in V}\min\left\{\sum_{q\in W}\sum_{j\in C}\sum_{k\in O_v}x_{qjv}^{\text{abk}},1\right\}$ and $\sum_{a,b\in A_{ML}}\sum_{v\in V}\min\left\{\sum_{p\in D}\sum_{j\in C}\sum_{k\in O_v}x_{pjv}^{\text{abk}},1\right\}$ represent the numbers of used vehicles in high-risk and middle-/low-risk areas.

$$\begin{aligned} TC_1 = & \sum_{p\in D\cup W}\sum_{q\in D\cup W}\sum_{s\in S}S_{pq}\times U_s\times y_{pqs}\times = +\sum_{p\in D}\sum_{q\in W}\sum_{s\in S}y_{pqs}\times MC_s \\ & +\sum_{p\in D\cup W}\sum_{q\in W}\sum_{s\in S}\max\left\{e_q-at_{qs},at_{qs}-l_q,0\right\}\times y_{pqs}\times\alpha \end{aligned} \tag{4}$$

Table 4
Symbol definitions and explanations.

Set	Definition
A	Set of areas in the logistics network, $A=\{a\|a=1,2,3\ldots,\rho\}$ and ρ is the total number of areas
A_H	Set of high-risk areas in the logistics network, $A_H \subseteq A$
A_{ML}	Set of middle-/low-risk areas in the logistics network, $A_{ML} \subseteq A$
D	Set of DC, $D=\{p\|p=1,2,3\ldots,\eta\}$ and η is the total number of DCs
W	Set of satellites, $W=\{q\|q=1,2,3\ldots,\sigma\}$ and σ is the total number of satellites
C	Set of delivery customers, $C=\{i\|i=1,2,3\ldots,\lambda\}$ and λ is the total number of customers
V	Set of vehicles for delivery, $V=\{v\|v=1,2,3\ldots,\delta\}$ and δ is the total number of vehicles
S	Set of semitrailer trucks for transferring goods from DCs to satellites, $S=\{s\|s=1,2,3\ldots,\varphi\}$ and φ is the total number of semitrailer trucks
O_v	Set of delivery routes of vehicle v, $O_v=\{k\|k=1,2,3\ldots,\varepsilon\},v\in V$
Input 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_{ij}	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 s 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_s	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, $q \in W$
$[e_i,l_i]$	Time window of customer or satellite i, $i \in C \cup W$
$[ea_i,la_i]$	Candidate time window assigned to customer i, $i \in C$
$[E_p,L_p]$	Service time window of DC p, $p \in D$
α	Penalty cost for early or late arrival per unit time
β	Cost coefficient when customer's time window changes to the assigned time window per unit time
t_{ijv}	Travel time of vehicle v between entities i and j, $i, j \in D \cup W \cup C$, $v \in V$
t_{pqs}	Travel time of semitrailer truck s between entities p and q, $p, q \in D \cup W$, $s \in S$
BN	Large number
$MaxT$	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	**Definition**
dtak qv	Departure time of the kth route of vehicle v from DC or satellite q in area a, $v \in V$, $q \in D \cup W$, $k \in O_v$, $a \in A$
dt_{ps}	Departure time of semitrailer truck s from DC p, $s \in S$, $p \in D$
atak qv	Arrival time of the kth route of vehicle v at DC or satellite q in area a, $v \in V$, $q \in D \cup W$, $k \in O_v$, $a \in A$
atak iv	Arrival time of the kth route of vehicle v at customer i in area a, $v \in V$, $i \in D \cup W \cup C$, $k \in O_v$, $a \in A$
at_{qs}	Arrival time of semitrailer truck s at satellite q, $s \in S$, $q \in W$
Wtak iv	Waiting time of the kth route of vehicle v at customer i in area a, $i \in C$, $v \in V$, $k \in O_v$, $a \in A$
Wt qs	Waiting time of the semitrailer truck s at satellite q, $q \in W$, $s \in S$.
CLak qv	Load of vehicle v in the kth route when it departs from DC or satellite q in area a, $v \in V$, $k \in O_v$, $q \in D \cup W$, $a \in A$
CL_{ps}	Load of semitrailer truck s when it departs from DC q, $s \in S$, $q \in D$
xabk ijv	If the kth route of vehicle v travels from node i in area a to node j in area b, then *xabk ijv* $= 1$; otherwise, *xabk ijv* $= 0$, $i,j \in D \cup W \cup C$, $v \in V$, $k \in O_v$, $a,b \in A$
ypqs	If semitrailer truck s transports between DC or satellite p and DC or satellite q, then *y pqs* $= 1$; otherwise, *y pqs* $= 0$, $p, q \in D$, $s \in S$
τabk qiv	If vehicle v operates the kth route from DC or satellite q in area a to serve customer i in area b, then *τabk qiv* $= 1$; otherwise, *τabk qiv* $= 0$, $v \in V$, $k \in O_v$, $i \in C$, $q \in D \cup W$, $a,b \in A$
κpqs	If semitrailer truck s departing from DC p serves satellite q, *κ pqs* $= 1$; otherwise, *κ pqs* $= 0$, $s \in S$, $p \in D$, $q \in W$
CTa i	If the candidate time window is assigned to customer i in area a, *CTa i* $= 1$;otherwise, *CTa i* $= 0$, $i \in C$, $a \in A$

$$
\begin{aligned}
TC_2 = & \sum_{i\in C\cup D}\sum_{j\in C\cup D}\sum_{v\in V}\sum_{k\in O_v}\sum_{a,b\in A_{ML}} S_{ij}\times U_v \times x_{ijv}^{abk} \times = + \sum_{i\in C\cup W}\sum_{j\in C\cup W}\sum_{v\in V}\sum_{k\in O_v}\sum_{a,b\in A_H} S_{ij}\times U_v \times x_{ijv}^{abk} \times = \\
& + \left[\sum_{a,b\in A_H}\sum_{v\in V}\min\left\{\sum_{q\in W}\sum_{j\in C}\sum_{k\in O_v} x_{qjv}^{abk}, 1\right\} + \sum_{a,b\in A_{ML}}\sum_{v\in V}\min\left\{\sum_{p\in D}\sum_{j\in C}\sum_{k\in O_v} x_{pjv}^{abk}, 1\right\}\right]\times MC_v \\
& + \sum_{i\in D\cup W\cup C}\sum_{j\in C}\sum_{v\in V}\sum_{k\in O_v}\sum_{a,b\in A}\max\left\{e_j - at_{jv}^{kb}, at_{jv}^{kb} - l_j, 0\right\}\times x_{ijv}^{abk}\times\alpha \\
& + \sum_{a\in A_{ML}}\sum_{i\in C}\left[CT_i^a \min\{|e_i - ea_i|, |l_i - lt_i|\}\right]\times\beta
\end{aligned}
\tag{5}
$$

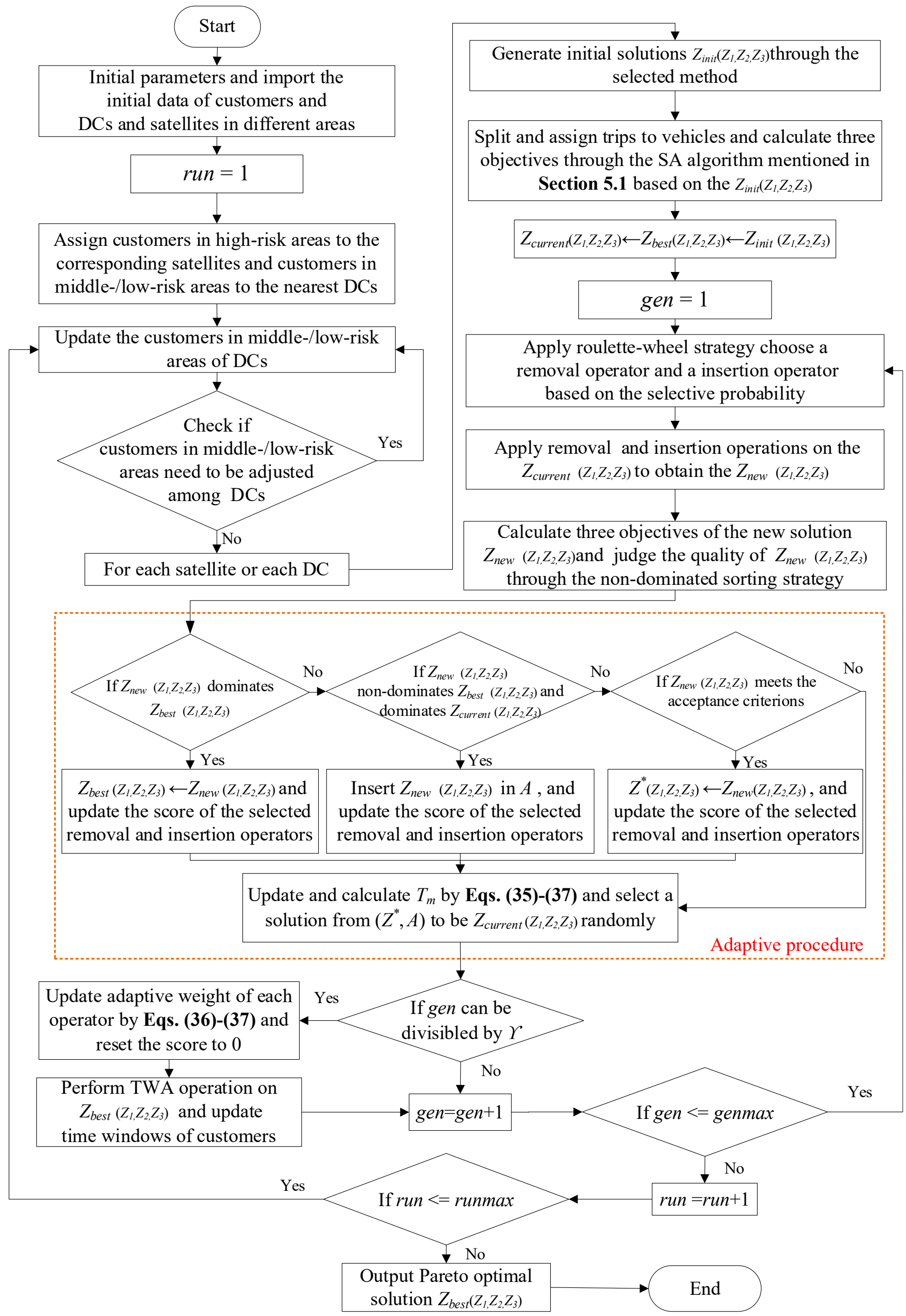


Fig. 2. Procedure of MOALNS-SA.

Constraints on satellites:

$$\sum_{p\in D}\sum_{s\in S} y_{pqs} \leqslant 1, \forall q \in W \tag{6}$$

$$\sum_{p\in D} y_{pqs} = 1, \forall q \in W, s \in S \tag{7}$$

$$\sum_{q\in W} y_{pqs} - \sum_{q\in W} y_{qgs} = 0, \forall p, g \in W \cup D, s \in S \tag{8}$$

$$\sum_{p\in D} y_{qps} = 1, \forall q \in W, s \in S \tag{9}$$

$$CL_{ps} = \sum_{q\in W} d_q \times \kappa_{pqs}, \forall s \in S, p \in D \tag{10}$$

$$CL_{ps} \leqslant Q_s, \forall p \in D, s \in S \tag{11}$$

$$dt_{ps} + IT + t_{pqs} - BN(1 - y_{pqs}) \leqslant at_{qs}, \forall p \in D, q \in W, s \in S \tag{12}$$

$$dt_{ps} + IT + t_{pqs} + BN(1 - y_{pqs}) \geqslant at_{qs}, \forall p \in D, q \in W, s \in S \tag{13}$$

$$at_{qs} + IT + t_{qm} - BN(1 - y_{qms}) \leqslant at_{ms}, \forall q \in W, m \in W \cup D, s \in S \tag{14}$$

$$at_{qs} + IT + t_{qm} + BN(1 - y_{qms}) \geqslant at_{ms}, \forall q \in W, m \in W \cup D, s \in S \tag{15}$$

$$at_{qs} + IT + t_{qps} \leqslant y_{qps} L_p, \forall q \in W, p \in D, s \in S \tag{16}$$

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 maximal 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:

$$\sum_{j\in C}\sum_{v\in V}\sum_{k\in O_v} x_{ijv}^{abk} \leqslant 1, \forall i \in W \cup D \cup C, a, b \in A \tag{17}$$

$$\sum_{i\in D\cup W}\sum_{j\in C} x_{ijv}^{abk} = 1, \forall i \in C \cup D \cup W, v \in V, k \in O_v, a, b \in A \tag{18}$$

$$\sum_{j\in C} x_{ijv}^{abk} - \sum_{j\in C} x_{jmv}^{bfk} = 0, \forall i, m \in C \cup W \cup D, v \in V, k \in O_v, a, b, f \in A \tag{19}$$

$$\sum_{j\in C}\sum_{i\in D\cup W} x_{jiv}^{bak} = 1, \forall i \in C \cup D \cup W, v \in V, k \in O_v, a, b \in A \tag{20}$$

$$CL_{qv}^{ak} = \sum_{i\in C} d_i \tau_{qiv}^{abk}, \forall v \in V, k \in O_v, q \in W \cup D, a, b \in A \tag{21}$$

$$CL_{qv}^{ak} \leqslant Q_v, \forall q \in W \cup D, v \in V, k \in O_v, a \in A \tag{22}$$

$$\sum_{s\in S} CL_{ps} + \sum_{a\in A}\sum_{v\in V}\sum_{k\in O_v} CL_{pv}^{ak} \leqslant Q_p, \quad \forall p \in D \tag{23}$$

$$\sum_{v\in V}\sum_{k\in O_v} CL_{qv}^{ak} \leqslant Q_q, \ \ \forall q \in W, a \in A_H \tag{24}$$

$$\sum_{i\in C\cup W}\sum_{k\in O_v} wt_{iv}^{ak} + \sum_{i\in C\cup W\cup D}\sum_{j\in C\cup W\cup D}\sum_{k\in O_v} x_{ijv}^{abk} \times t_{ijv} + PT \times \left| 1 - \sum_{i\in W\cup D}\sum_{j\in C}\sum_{k\in O_v} x_{ijv}^{abk} \right| \leqslant \max T, \forall v \in V, a, b \in A \tag{25}$$

$$[(1-CT_i^a)e_i + CT_i^a ea_i] \sum_{j\in C\cup W\cup D} x_{ijv}^{abk} \leqslant at_{iv}^{ak} + wt_{iv}^{ak} \leqslant [(1-CT_i^a)l_i + CT_i^a la_i] \sum_{j\in C\cup W\cup D} x_{ijv}^{abk}, \forall i\in C, v\in V, k\in O_v, a, b\in A \tag{26}$$

$$E_q \tau_{qiv}^{abk} \leqslant dt_{qv}^{ak} \leqslant L_q \tau_{qiv}^{abk}, \forall i \in C, q \in W \cup D, v \in V, k \in O_v, a, b \in A \tag{27}$$

$$E_q \tau_{qiv}^{abk} \leqslant at_{qv}^{ak} \leqslant L_q \tau_{qiv}^{abk}, \forall i \in C, q \in W \cup D, v \in V, k \in O_v, a, b \in A \tag{28}$$

$$dt_{qv}^{ak} + t_{qiv} - BN(1 - x_{qiv}^{abk}) \leqslant at_{iv}^{bk}, \forall q \in W \cup D, i \in C, v \in V, k \in O_v, a, b \in A \tag{29}$$

$$dt_{qv}^{ak} + t_{qiv} + BN(1 - x_{qiv}^{abk}) \geqslant at_{iv}^{bk}, \forall q \in W \cup D, i \in C, v \in V, k \in O_v, a, b \in A \tag{30}$$

$$at_{iv}^{ak} + wt_{iv}^{ak} + t_{ijv} - BN(1 - x_{ijv}^{abk}) \leqslant at_{jv}^{bk}, \forall i \in C, j \in C \cup W \cup D, v \in V, k \in O_v, a, b \in A \tag{31}$$

$$at_{iv}^{ak} + wt_{iv}^{ak} + t_{ijv} + BN(1 - x_{ijv}^{abk}) \geqslant at_{jv}^{bk}, \forall i \in C, j \in C \cup W \cup D, v \in V, k \in O_v, a, b \in A \tag{32}$$

$$at_{qv}^{ak} + PT - BN(1 - \tau_{qiv}^{ab(k+1)}) \leqslant dt_{qv}^{a(k+1)}, \forall q \in W \cup D, v \in V, k \in O_v, a, b \in A \tag{33}$$

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 (29) and (30) guarantee the continuous departure time of vehicles at DCs (satellites). Constraints (31) and (32) ensure the continuous arrival time of vehicles at customers, and Constraint (33) ensures the continuous departure time of shared delivery routes of each vehicle.

Binary decision:

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

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

$$\tau_{qiv}^{abk} = \{0, 1\}, \forall i \in C, q \in W \cup D, v \in V, k \in O_v, a, b \in A$$

$$\kappa_{pqs} = \{0, 1\}, \forall p \in D, q \in W, s \in S$$

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

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 (Azi 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 improved to find the Pareto optimal solutions for the multi-objective function. The procedure of MOALNS-SA is shown in Fig. 2. *run* and *runmax* indicate the number of optimization runs and the maximal number of runs, *gen* and *genmax* represent the number of iterations and the maximal number of iterations, Υ expresses the number of iterations needed to update the adaptive weight of operators and perform the TWA operation, Z_{init} (Z_1, Z_2, Z_3) indicates the initial solution, and $Z_{current}$(Z_1, Z_2, Z_3) denotes the current solution and Z_{best}(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 neighborhood 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 deconstruct 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

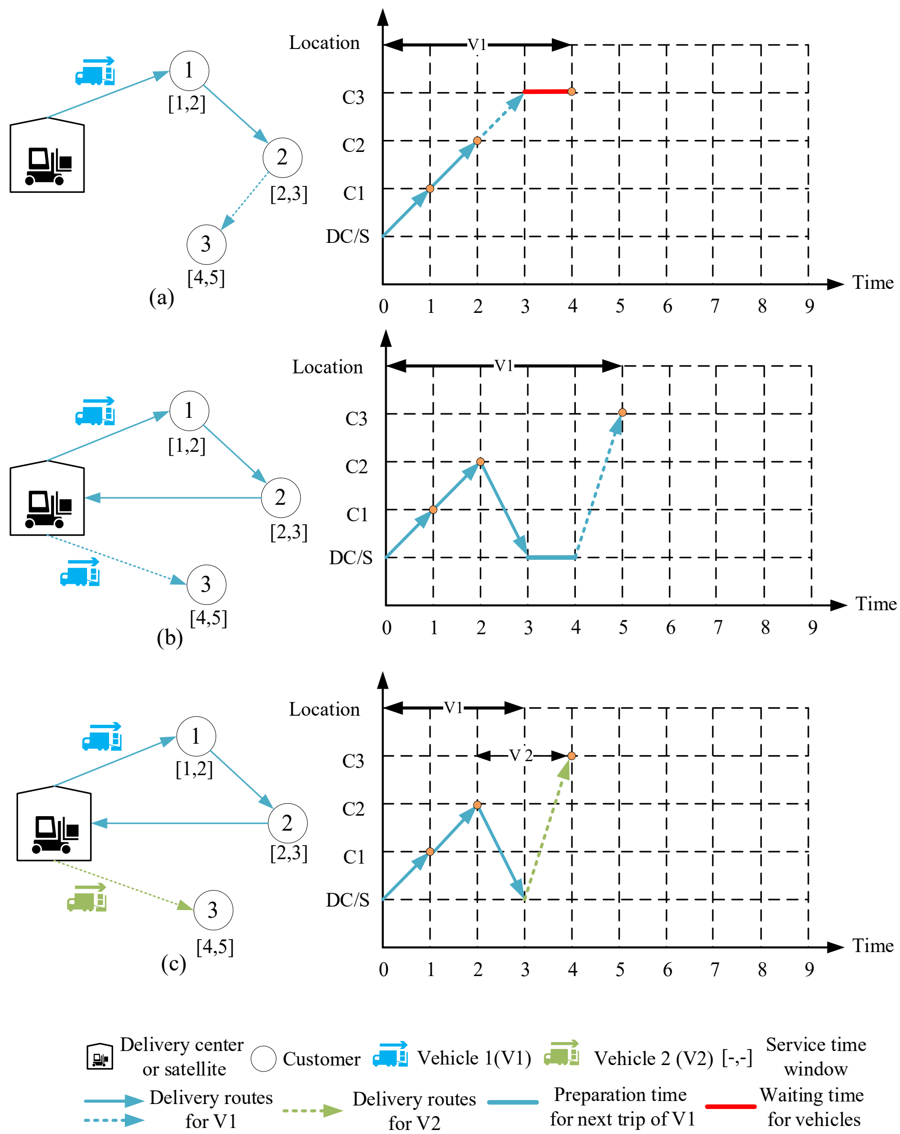


Fig. 3. Three possible trips for serving a new customer.

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 Υ

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

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)
  Generate an initial solution Z_{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)
  Initialize selective probability *sp* of removal and insertion operators
  $Z_{current}(Z_1, Z_2, Z_3) \leftarrow Z_{best}(Z_1, Z_2, Z_3) \leftarrow Z_{init}(Z_1, Z_2, Z_3)$
  For a number of iterations do
    Select a removal operator $q_x \in Q$ through roulette-wheel strategy with selective probability sp_{qx} and apply removal operation on $Z_{current}(Z_1, Z_2, Z_3)$ (Section 5.3)
    Select an insertion operator $p_y \in I$ through roulette-wheel strategy with selective probability sp_{py} and apply insertion operation on $Z_{current}(Z_1, Z_2, Z_3)$ to obtain $Z_{new}(Z_1, Z_2, Z_3)$ (Section 5.4)
    Calculate objective function (Z_1, Z_2, Z_3) of Z_{new} through the SA (Section 5.1)
    If (Z_{new} (Z_1, Z_2, Z_3) dominates $Z_{best}(Z_1, Z_2, Z_3)$ (Section 5.2)) then
      Set Z_{best} (Z_1, Z_2, Z_3) $\leftarrow$ $Z_{new}(Z_1, Z_2, Z_3)$ and add score μ_1(Section 5.6) to the selected operators q_x and p_y
    else if (Z_{new} (Z_1, Z_2, Z_3) non-dominates Z_{best} (Z_1, Z_2, Z_3) and dominates $Z_{current}(Z_1, Z_2, Z_3)$ (Section 5.2)) then
      Insert Z_{new} (Z_1, Z_2, Z_3) to A and add score μ_2 (Section 5.6) to the selected operators q_x and p_y
    else
      if (Z_{new} (Z_1, Z_2, Z_3) meets the acceptance criterions (Section 5.5)) then
        Set $Z^* \leftarrow Z_{new}$ (Z_1, Z_2, Z_3) and add score μ_3(Section 5.6) to the selected operators q_x and p_y
      End
    End
    Update and Calculate T_m by Eqs. (35)-(37) (Section 5.5)
    Randomly select a solution from (Z^*, A) to be $Z_{current}(Z_1, Z_2, Z_3)$
    If iterations reach the jth Υ iterations
      Update the adaptive weight of each operator by Eqs. (38)-(39)
      Set all scores to zero
      If the area is the middle-/low-risk area then
        Apply TWA strategy to assign *ctw* to customers with irrational time windows based on Z_{best} (Z_1, Z_2, Z_3) and update Z_{best} (Z_1, Z_2, Z_3) (Section 5.7)
      End
    End
  End
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, labels for n nodes include the trip assignments. Each label has $(\delta + 5)$ elements, and δ represents the number of vehicles. The first δth elements express the time to get ready to start the next trip for the δth 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 δ, speed of vehicle v, distance of nodes $dist$

Output: Label with trips and objectives

$Labellist_1 = (\underbrace{0,\ldots,0},0,0,0,0,0)$, $Labellist_{current} \leftarrow Labellist_1$
$current = 0$
While $current < |S|$ do
  $succ = current + 1$
  $load = d_{succ}$
  $label_{current} = \emptyset$
  For all $L \in Labellist_{current}$
    For $k = 1 \rightarrow 2{*}Z_3$
      For $f = 1{:}2$ (Value help to split trips)
        If $f == 1$
          time $= 2{*}dist_{0,current}/v$
          $L' = L$, $L'_k = L'_k +$ time, $L'_{\delta+4} = load$
          $L'_{\delta+1} = Z_1$, $L'_{\delta+2} = Z_2$, $L'_{\delta+3} = Z_3$
          $L'_{\delta+5} = current$, $label_{current} \leftarrow label_{current} \cup L'$
        else
          time $= dist_{current-1,current} + dist_{0,current}/v - dist_{0,current-1}$
          $L' = L$, $L'_k = L'_k +$ time, $L'_{\delta+4} = L_{\delta+4} + load$
          $L'_{\delta+1} = Z_1$, $L'_{\delta+2} = Z_2$, $L'_{\delta+3} = Z_3$
          $L'_{\delta+5} = current$, $label_{current} \leftarrow label_{current} \cup L'$
        End
      End
    End
    For $k = 2{*}Z_3{+}1$
      time $= 2{*}dist_{0,current}/v$
      $L' = L$, $L'_k = L'_k +$ time, $L'_{\delta+4} = load$
      $L'_{\delta+1} = Z_1$, $L'_{\delta+2} = Z_2$, $L'_{\delta+3} = Z_3$
      $L'_{\delta+5} = current$, $label_{current} \leftarrow label_{current} \cup L'$
    End
    Perform non-dominated sorting and remain elite label $label_{current\text{-}elite}$
    $Labellist_{current} \leftarrow label_{current\text{-}elite}$
  End
End
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 nth node in turn in accordance with the sequence S through SA, and the

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(*C*2) and is served by the used Vehicle 1 (V1). When V1 has finished the delivery service of C1 and *C*2 at time two, it travels from *C*2 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 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.

5.2. 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.

Input: Labels(solutions) with all objectives ($Z_1, Z_2 \ldots Z_m$)
Output: Pareto optimal labels(solutions)

```
Rank = 0
While all labels(solutions) are assigned rank do
    Rank = Rank +1
    For each label(solution) i do
        k = 1(Value help to assigned rank)
        For each label(solution) j (except label i) do
            For n = 1:m
                If any objectives (Z1, Z2…Zm) of label i is inferior objectives (Z1, Z2…Zm) of label j then
                    k = 0
                    Break
                End
            End
            If k == 1 then
                Rank of label(solution) i ← Rank
            End
        End
    End
End
```

directly. Therefore, $(2{*}Z_3 + 1)$ 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

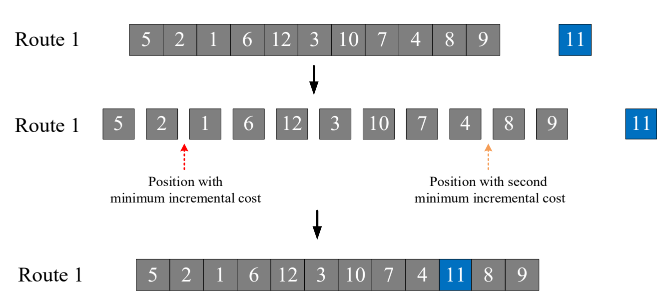


Fig. 4. Example of SI.

In Algorithm 3, each label (solution) is compared with all the other labels (solutions) on the basis of objectives. The Pareto optimal labels (solutions) retained to perform the next operation. In the adaptive score adjustment procedure, only three solutions need to be compared through the non-dominated sorting strategy. For example, when generating a new solution $Z_{new}(Z_1, Z_2 \ldots Z_m)$ with m objectives, it should be compared with $Z_{best}\,(Z_1, Z_2 \ldots Z_m)$ and $Z_{currrent}\,(Z_1, Z_2 \ldots Z_m)$ based on m objectives to obtain a dominant relationship among them.

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.

Table 5
Performance comparison of the CPLEX and MOALNS-SA algorithm for small-scale instances.

Number of customers: 30							
No.	Solution by CPLEX				Solution by proposed approach		*GAP_CL*(%)
	UB ($)	*LB* ($)	*GAP_UL*(%)	Time (s)	Cost ($)	Time (s)	
1	882.1	882.1	0	782.1	882.1	31.9	0
2	908.5	908.5	0	865.2	911.8	34.3	0.36
3	927.6	927.6	0	883.9	929.5	27.6	0.20
4	863.7	863.7	0	749.6	863.7	30.1	0
5	934.2	934.2	0	916.4	934.2	39.8	0
6	925.1	925.1	0	897.3	925.1	37.7	0
7	920.2	920.2	0	961.2	923.3	41.5	0.34
8	866.8	866.8	0	817.8	866.8	33.2	0
9	973.3	973.3	0	998.5	973.3	40.8	0
10	986.7	986.7	0	1016.7	989.9	43.4	0.32
Average	918.8	918.8	0	936.2	920.0	36.0	0.13
Number of customers: 60							
No.	Solution by CPLEX				Solution by proposed approach		*GAP_CL*(%)
	UB ($)	*LB* ($)	*GAP_UL*(%)	Time (s)	Cost ($)	Time (s)	
11	1565.1	1565.1	0	4875.2	1565.1	65.7	0
12	1583.7	1583.7	0	4737.1	1587.3	67.2	0.23
13	1573.8	1573.8	0	4908.5	1573.8	59.5	0
14	1621.5	1621.5	0	5123.6	1621.5	63.4	0
15	–	1759.3	–	6000	1767.4	68.6	0.46
16	1627.6	1627.6	0	5207.5	1632.9	55.3	0.33
17	1618.2	1618.2	0	5169.3	1618.2	47.1	0
18	1695.3	1672.5	1.3	6000	1679.3	51.2	0.41
19	1761.8	1724.4	2.1	6000	1724.4	68.7	0
20	–	1756.3	–	6000	1765.2	62.5	0.51
Average	–	1650.2	–	5402.1	1653.5	60.9	0.19

Input: Current solution $Z_{current}(Z_1, Z_2, Z_3)$, number of customers to be removed $N_{removed}$
Output: Partiality removal solution Z_p, removal list L
1 Initialize removal list ($L \leftarrow \emptyset$), partiality removal solution $Z_p \leftarrow Z_{current}(Z_1, Z_2, Z_3)$
2 While $|L| < N_{removed}$ do
3 Apply remove operation, find customer i (or customers in route i) to remove
4 $L \leftarrow L \cup i$
5 Remove customer i (or customers in route i) from Z_p
6 End

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 partiality-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 $Z_{current \setminus \{i\}}(Z_1, Z_2, Z_3)$ 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 $Z_{current \setminus \{i\}}(Z_1, Z_2, Z_3)$; 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):

$$R_{ij} = \psi_1 \times \frac{S_{ij}}{\max\limits_{i,j \in C} S_{ij}} + \psi_2 \times \frac{|d_i - d_j|}{\max\limits_{i \in C} d_i - \min\limits_{i \in C} d_i} + \psi_3 \times \frac{|at_i - at_j|}{\max\limits_{i \in C} at_i - \min\limits_{i \in C} at_i} + \psi_4 \times l_{ij} \tag{34}$$

In Eq. (34), ψ_1-ψ_4 are normalized weights. In the first component, S_{ij} represents the distance between customers i and j, $\max\limits_{i,j \in C} S_{ij}$ denotes the

Table 6
Settings of instances.

Instance	No.	NHA	NMLA	ND	NC	VC	Instance	No.	NHA	NMLA	ND	NC	VC
pr01	1	1	1	4	48	200	pr06	16	1	1	4	288	175
	2	2	2	4	48	200		17	2	2	4	288	175
	3	2	3	4	48	200		18	2	3	4	288	185
pr02	4	1	1	4	96	195	pr07	19	1	1	6	72	200
	5	2	2	4	96	195		20	2	2	6	72	200
	6	2	3	4	96	195		21	2	3	6	72	200
pr03	7	1	1	4	144	190	pr08	22	1	1	6	144	190
	8	2	2	4	144	190		23	2	2	6	144	190
	9	2	3	4	144	190		24	2	3	6	144	190
pr04	10	1	1	4	192	185	pr09	25	1	1	6	216	180
	11	2	2	4	192	185		26	2	2	6	216	180
	12	2	3	4	192	185		27	2	3	6	216	180
pr05	13	1	1	4	240	180	pr10	28	1	1	6	288	170
	14	2	2	4	240	180		29	2	2	6	288	170
	15	2	3	4	240	180		30	2	3	6	288	170

maximum distance of customers. In the second component, d_i is the demand of customer i. In the third component, at_i 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 $Z_{current}(Z_1, Z_2, Z_3)$ to avoid wasting the delivery time of vehicles.

6. Worst load route removal

This operator removes routes with low load from the current solution $Z_{current}(Z_1, Z_2, Z_3)$. 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 $Z_{current}(Z_1, Z_2, Z_3)$.

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.

Input: Partiality removal solution Z_p, removal list L
Output: New solution $Z_{new}(Z_1, Z_2, Z_3)$

```
The new solution Z_new ← Z_p
While isempty |L|
    For (each customer i in removal list L) do
        Insert customer i in the new solution Z_new
        Remove customer i from L
    End
End
```

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

Table 8
Results of the three algorithms.

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(s)	Z_1	Z_2(min)	Z_3	CT
1	**1257**	**582**	**2**	**533**	1350	625	2	602	1419	604	3	641	1304	594	2	598
2	**1302**	**562**	**3**	**542**	1488	607	3	622	1552	598	4	686	1394	580	3	607
3	**1581**	**573**	**4**	**575**	1900	594	5	615	1983	592	5	617	1630	584	4	641
4	**1977**	**902**	**4**	**992**	2156	990	4	1205	2325	1058	4	1307	2207	998	4	1145
5	**1932**	**882**	**4**	**1005**	2200	950	5	1226	2598	1130	5	1311	2467	941	5	1197
6	**2244**	**884**	**5**	**1018**	2654	969	6	1224	2776	1058	6	1327	2640	1072	6	1248
7	**2615**	**1254**	**5**	**1422**	3007	1287	6	1799	3794	1687	7	1884	2984	1297	6	1756
8	**2701**	**1198**	**6**	**1465**	3076	1258	7	1809	3477	1604	7	1890	3107	1260	7	1846
9	**2997**	**1154**	**7**	**1491**	3288	1289	8	1816	3575	1559	8	1908	3347	1209	8	1897
10	**3458**	**1587**	**7**	**1874**	3958	1798	8	1985	4184	1987	8	2084	3841	1785	8	1948
11	**3648**	**1548**	**8**	**1898**	4156	1763	9	1994	4476	1850	10	2135	4209	1847	9	2005
12	**3669**	**1490**	**8**	**1917**	4213	1692	10	2088	4387	1807	10	2200	4313	1803	9	2068
13	**5367**	**2278**	**12**	**2154**	5911	2489	13	2572	6073	2648	13	2684	5675	2364	13	2506
14	**5499**	**2299**	**12**	**2184**	6134	2507	14	2697	6692	2774	15	2709	6291	2577	14	2689
15	**5572**	**2107**	**13**	**2249**	6197	2498	14	2887	6379	2548	15	2781	6470	2647	15	2527
16	**6150**	**2680**	**13**	**2533**	6750	2985	14	2962	6819	2994	15	3141	6698	3007	14	2987
17	**6102**	**2662**	**13**	**2542**	6788	2977	14	2992	6802	2988	15	3186	6821	2942	15	3069
18	**6311**	**2663**	**14**	**2575**	6805	2964	15	2995	6983	2962	16	3217	6847	3016	15	3147
19	**1657**	**780**	**3**	**733**	1980	885	4	962	2219	904	4	1001	2046	942	4	947
20	**1592**	**762**	**3**	**742**	1908	877	4	992	2152	898	4	1016	2247	937	5	991
21	**1741**	**736**	**4**	**775**	2180	864	5	1005	2283	862	5	1017	2305	921	5	1025
22	**2657**	**1095**	**5**	**1433**	3450	1585	6	1862	3619	1704	7	1941	3142	1498	6	1807
23	**2762**	**992**	**6**	**1427**	3388	1507	6	1892	3592	1698	7	1986	3098	1450	6	1846
24	**2731**	**980**	**6**	**1475**	3600	1484	8	1905	3783	1662	8	2017	3246	1403	7	1951
25	**4332**	**2106**	**8**	**1897**	5056	2285	10	2162	5097	2304	10	2341	4973	2288	10	2243
26	**4418**	**1997**	**9**	**1895**	4988	2207	10	2192	5228	2298	11	2386	5047	2256	11	2231
27	**4375**	**1963**	**9**	**1990**	4995	2140	11	2205	5182	2274	11	2317	5136	2207	11	2204
28	**6109**	**2874**	**12**	**2208**	6648	2948	14	2662	6861	3089	14	2341	6378	2978	13	2998
29	**6177**	**2892**	**12**	**2196**	6870	2936	15	2692	6902	3048	15	2486	6809	3075	14	2954
30	**6289**	**2807**	**13**	**2214**	6870	2936	15	2705	7027	2992	16	2517	6984	3004	14	3008
Average	3641	1576	8	1598	4132	1736	9	1910	4341	1873	10	1969	4122	1783	9	1936
t-test					−14.25	−7.20			−16.53	−9.13			−12.22	−8.02		
p-value					1.3E-14	6.2E-08			2.7E-16	5E-10			5.9E-13	7.7E-09		

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.

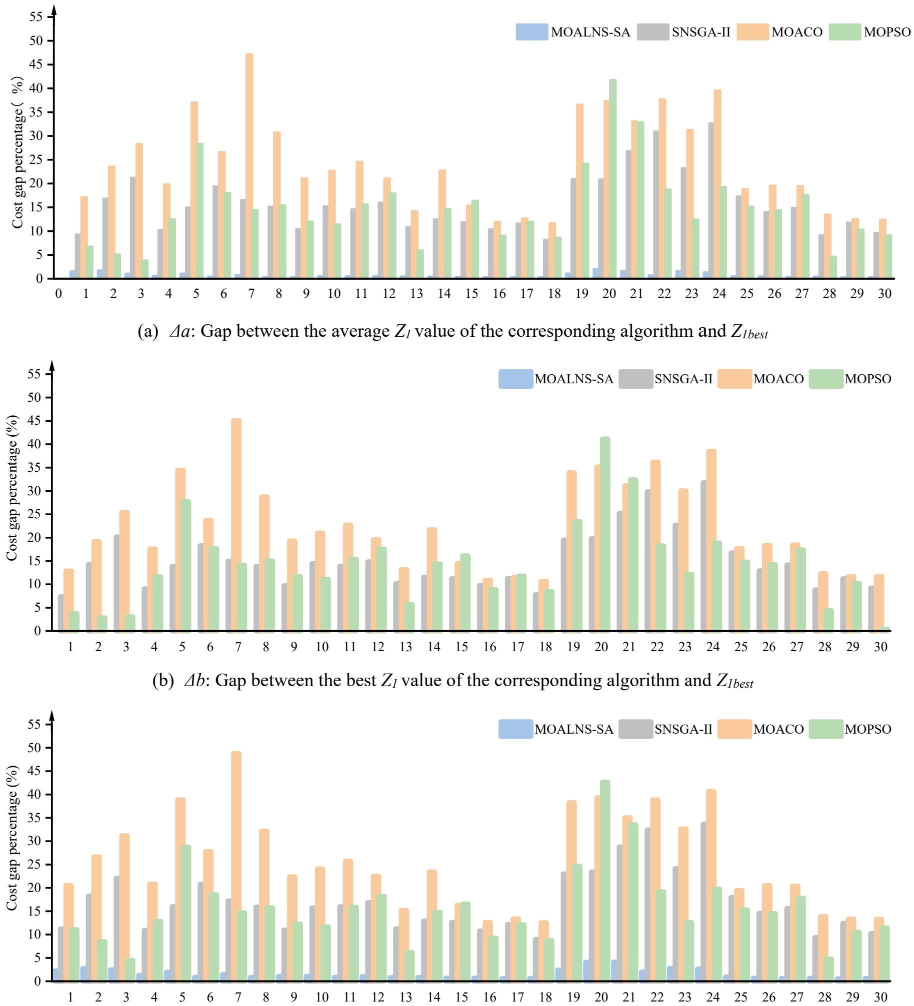
2. K-regret insertion

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

Input: Partiality removal solution Z_p, removal list L, the current cost $Z_{current}$

Output: New solution $Z_{new}(Z_1, Z_2, Z_3)$

The new solution $Z_{new} \leftarrow Z_p$
While isempty $|L|$
  For (each customer i in removal list L) do
    Find the insert position of each customer i with minimum incremental cost based on
    the new solution Z_{new}
    Insert customer i to the position and generate the new solution Z_{new}
    Remove customer i from L
  End
End



(a) Δa: Gap between the average Z_1 value of the corresponding algorithm and Z_{1best}

(b) Δb: Gap between the best Z_1 value of the corresponding algorithm and Z_{1best}

(c) Δw: Gap between the worst Z_1 value of the corresponding algorithm and Z_{1best}

Fig. 5. Comparison of the results of Z_1.

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 $f_{i,n}$ be the insertion cost of the nth potential insertion position for customer i. The minimum insertion cost $f_{i,\min}$ and the second minimum insertion cost $f_{i,second\text{-}\min}$ are determined. The regret value of customer i is $\Delta f_i = f_{i,second\text{-}\min} - f_{i,\min}$. In each iteration, the customer with maximum regret values is selected and inserted in partiality removal solution Z_p. This step is repeated until all customers in removal list L are inserted in partiality removal solution Z_p and $Z_{new}(Z_1, Z_2, Z_3)$ 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_{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 φ as calculated in Eqs. (35)–(37).

$$T_{n-start} = -\frac{0.05}{\ln 0.5} {}^{*}Z_{n,0} \tag{35}$$

$$T_n = T_{n-start} \times c^{iteration} \tag{36}$$

$$\varphi = \frac{\sum_{n=1}^{m} e^{\frac{-(Z_{n,new} - Z_{n,current})}{T_n}}}{m} \tag{37}$$

In Eq. (35), $Z_{n,0}$ and $T_{n\text{-}start}$ are the initial value and initial temperature of nth objectives, respectively. In Eq. (36), the temperature of nth 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, $Z_{n,new}$ and $Z_{n,current}$ represent the new and current values of nth 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

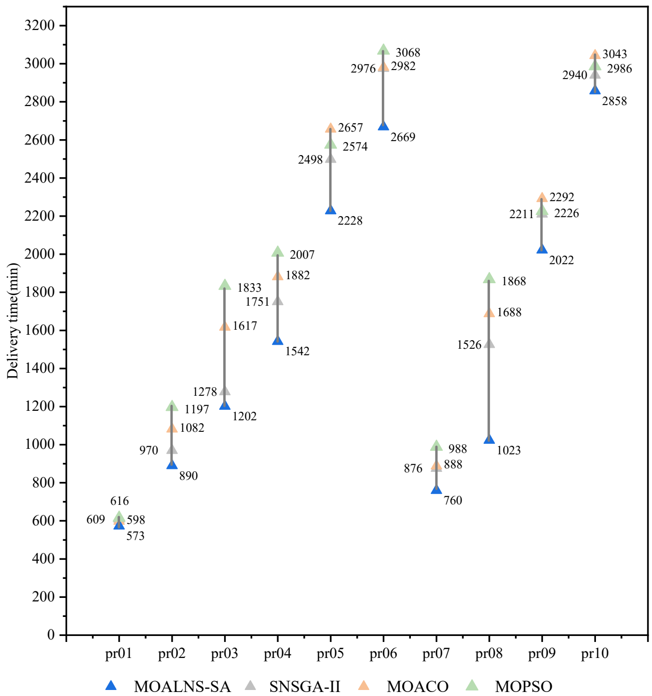


Fig. 6. Average delivery time of each instance in three situations.

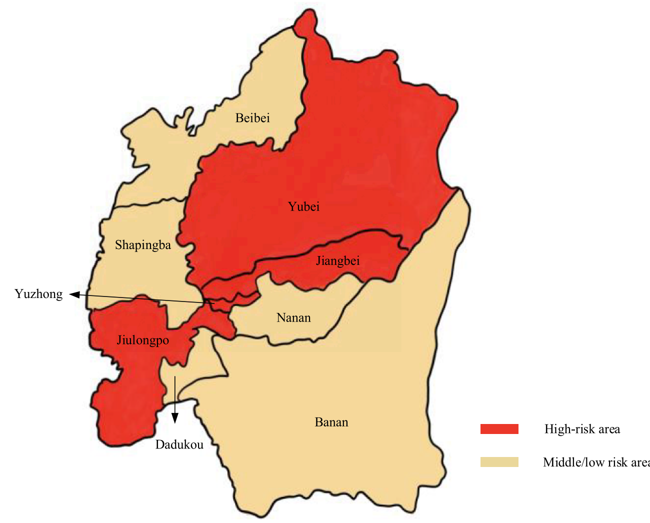


Fig. 7. Risk levels of each area.

Table 9
Distribution of persons injected with COVID-19.

Area	Number of persons infected with COVID-19	Risk levels	Area number
Yuzhong	20	High	A1
Dadukou	7	Middle/ low	A2
Jiangbei	28	High	A3
Jiulongpo	21	High	A4
Nanan	15	Middle/ low	A5
Beibei	0	Middle /low	A6
Yubei	17	High	A7
Banan	6	Middle/ low	A8
Shapingba	9	Middle/ low	A9
Total	123		

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 ($Z_{1,\ new}$, $Z_{2,\ new}$, …, $Z_{m,new}$) are superior to the *m* objectives of the current best solution ($Z_{1,\ best}$, $Z_{2,\ best}$, …, $Z_{m,best}$), that is, the new solution dominates over the current best solution, the score will be increased by μ_1.

Category 2: If the *m* objectives of the new solution ($Z_{1,new}$, $Z_{2,new}$,…, $Z_{m,new}$) do not dominate over the *m* objectives of the current best solution ($Z_{1,\ best}$, $Z_{2,\ best}$, …, $Z_{m,best}$) but dominate over those of the current solution ($Z_{1,current}$, $Z_{2,current}$, …, $Z_{m,current}$), the score will be increased by μ_2.

Category 3: If the *m* objectives of the new solution ($Z_{1,\ new}$, $Z_{2,\ new}$, …, $Z_{m,new}$) are inferior to those of the current solution ($Z_{1,\ current}$, $Z_{2,\ current}$, …, $Z_{m,current}$), and the new solution is accepted through the acceptance criterion, the score will be increased by μ_3.

Given Υ 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).

$$\begin{cases} w_{i,j+1} = w_{i,j}, O_{ij} = 0 \\ w_{i,j+1} = (1-\omega)w_{i,j+1} + \dfrac{\omega^{*}score_{i,j}}{O_{i,j}}, O_{ij} \neq 0 \end{cases} \tag{38}$$

$$sp_{i,j+1} = \frac{w_{i,j+1}}{\sum_{i=1}^{n} w_{i,j+1}} \tag{39}$$

In Eq. (38), the adaptive weight *w* of each operator is calculated. O_{ij} is the number of times that operator *i* is selected, and $Score_{i,j}$ is the total score of operator *i* during the *j*th Υ iterations. ω controls the inertia in the weight-update quotation; when ω 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 ω is min{(0.002*j-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.

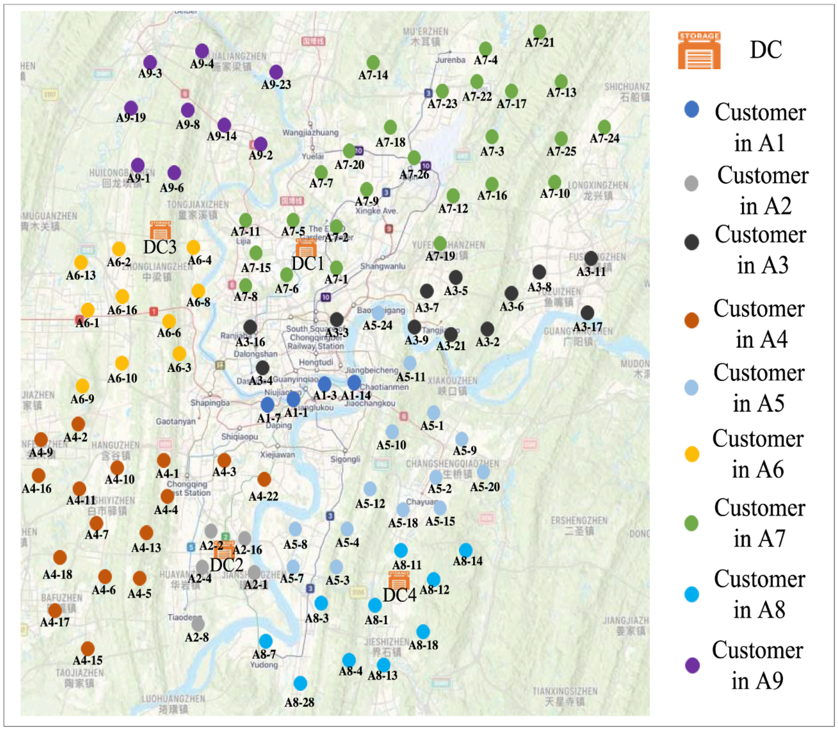


Fig. 8. Spatial distribution of customers and DCs.

Input: Candidate time windows *ctw*, initial time windows of customers *itw*, arrival time at customers *at*, current time windows of customers *current-tw*
Output: Assigned time windows of customers *atw*

For each customer do
  atw←*current-tw*
  If *at* not in the *current-tw* then
    If *at* in the *itw* then
      Recover the *itw* to the customer
      Update the *itw* in *atw* of the customer
    elseif *at* in the *ctw* then
      Assign the *ctw* to the customer
      Update the *ctw* in *atw* of the customer
    End
  End
End

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. In this

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

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_s	Maximum capacity of a semitrailer truck	600
Q_v	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_s	Usage cost of a semitrailer truck (dollar/km)	0.75
U_v	Usage cost of a vehicle (dollar/km)	0.5
MC_s	Maintenance cost for semitrailer truck *s* in one planning period	300
MC_v	Maintenance cost for vehicle *v* in one planning period	200
α	Penalty cost for early or late arrival (dollar/hour)	30
β	Assignment cost (dollar/hour)	15
v	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
$=$	The working days in one planning period	5
$genmax$	Maximum number of iterations	1500
$runmax$	Maximum number of optimization runs	300
$N_{removed}$	The number of customers need to removed	10
ψ_1	First Shaw parameters	0.5
ψ_2	Second Shaw parameters	0.2
ψ_3	Third Shaw parameters	0.1
ψ_4	Fourth Shaw parameters	0.2
μ_1	New best solution score	5
μ_2	Dominant current solution score	3
μ_3	Deterioration solution score	1
c	Cooling rate	0.99975
ctw_1	First candidate time window	[120,200]
ctw_2	Second candidate time window	[240,320]
ctw_3	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**

study, customers in middle-/low-risk areas accept the TWA strategy.

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,

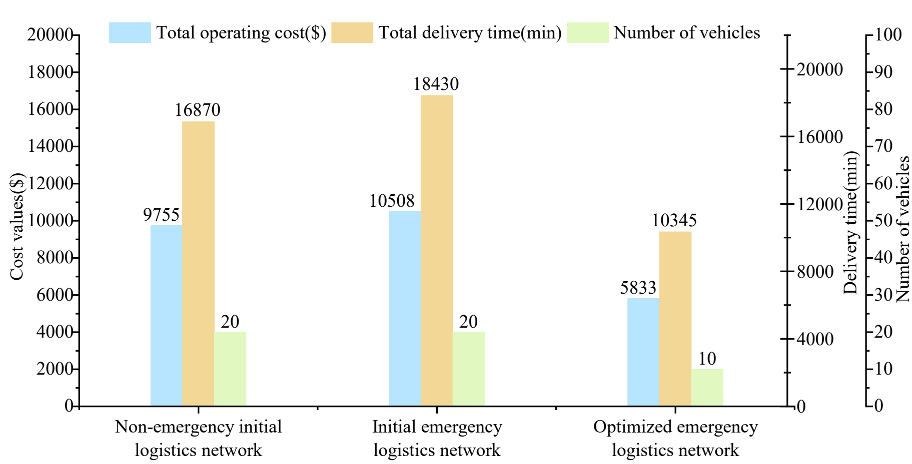


Fig. 9. Comparison of three objectives in three scenarios.

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
		S1 → A1-20 → A1-4 → A1-3 → A1-13 → A1-15 → A1-14 → A1-16 → A1-11 → A1-18 → A1-19 → S1
A3	V2	S2 → A3-7 → A3-5 → A3-18 → A3-6 → A3-8 → A3-15 → A3-11 → A3-17 → A3-2 → A3-21 → A3-9 → S2
		S2 → A3-13 → A3-16 → A3-14 → A3-4 → A3-12 → A3-19 → A3-10 → A3-20 → A3-22 → A3-3 → A3-1 → S2
A4	V3	S3 → A4-1 → A4-10 → A4-7 → A4-19 → A4-17 → A4-15 → A4-5 → A4-21 → A4-4 → A4-3 → A4-22 → A4-8 → S3
		S3 → A4-13 → A4-6 → A4-18 → A4-20 → A4-12 → A4-9 → A4-16 → A4-2 → A4-14 → A4-11 → S3
A7	V4	DC1 → A7-11 → A7-15 → A7-8 → A7-6 → A7-1 → DC1
		DC1 → A7-19 → A7-27 → A7-12 → A7-16 → A7-10 → A7-25 → A7-24 → A7-13 → A7-17 → A7-3 → DC1
		DC1 → 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
A6&A9	V5	DC3 → A6-5 → A6-4 → A6-15 → A6-3 → A6-14 → A6-8 → A6-11 → A9-7 → A9-24 → A9-9 → **A9-18***→DC3
		DC3 → **A6-2***→A6-13 → A6-1 → A6-21 → A6-9 → A6-10 → A6-12 → A6-19 → **A6-20***→**A6-6***→A6-7 → A6-22 → A6-18 → DC3
	V6	DC3 → A9-6 → A9-13 → A9-14 → A9-8 → A9-10 → A9-1 → A9-21 → A6-17 → A6-23 → **A6-16***→A6-24 → DC3
		DC3 → A9-17 → A9-5 → A9-2 → A9-12 → A9-20 → **A9-23***→**A9-15***→**A9-16***→A9-4 → A9-22 → A9-11 → A9-3 → A9-19 →DC3
A2&A5&A8	V7	DC2 → A2-7 → A2-11 → A2-17 → A2-23 → A5-8 → A5-6 → **A5-4***→A5-15 → A8-11 → A8-15 → A8-9 → **A8-25*** →DC2
		DC2 → A2-15 → A2-9 → A2-5 → A8-7 → A8-5 → A8-27 → A5-13 → A5-18 → **A5-2***→**A5-10***→A5-14 → A5-22 → A5-12 → A2-19 → A2-13 → DC2
	V8	DC4 → A8-3 → A5-21 → A2-3 → A2-1 → A2-21 → **A8-17***→A8-13 → A8-23 → **A8-19*** →A8-21 → A8-1 → DC4
	V9	DC4 → A8-20 → A5-5 → A5-7 → A2-12 → **A2-16***→**A2-18***→A2-6 → A2-20 → A2-14 → **A5-16***→A5-3 → **A8-10***→DC4
		DC4 → A8-4 → A8-28 → A8-18 → A8-8 → A8-6 → A8-16 → A8-2 → **A5-19***→**A5-17*** →A5-25 → A2-2 → A2-4 → A2-22→ A2-8 → A2-10 → DC4
	V10	DC4 → A5-24 → A5-23 → A5-11 → A5-1 → A5-9 → A5-20 → A8-26 → **A8-14***→A8-22 → A8-12 → A8-24 → DC4

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; Asghari 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_1, total delivery time Z_2, number of vehicles Z_3, 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 three other algorithms, demonstrating the good performance of the proposed MOALNS-SA. The gaps in total operating cost Z_1 in the three types are shown in Fig. 5. In Fig. 5, Δa indicates the gap between the average Z_1 value of the corresponding algorithm and Z_{1best}, Δb indicates the gap between the best Z_1 value of the corresponding algorithm and Z_{1best}, and Δw indicates the gap between the worst Z_1 value of the corresponding algorithm and Z_{1best}.

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_{1best} 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 areas. 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

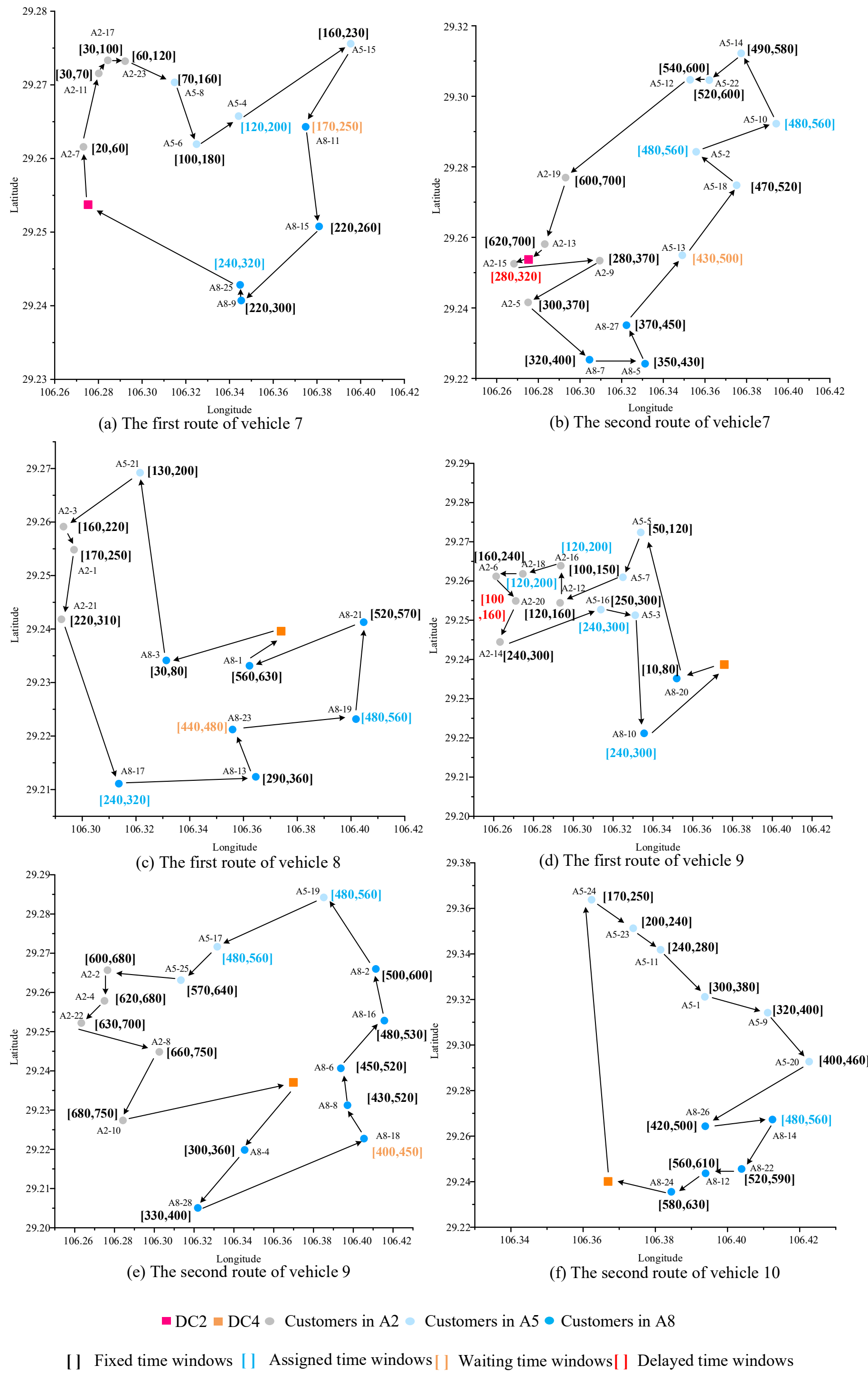


Fig. 10. Optimized delivery routes in A2, A5, and A8.

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 semitrailer 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.

Table 16
Labels associated with customers in A1 during the split procedure.

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

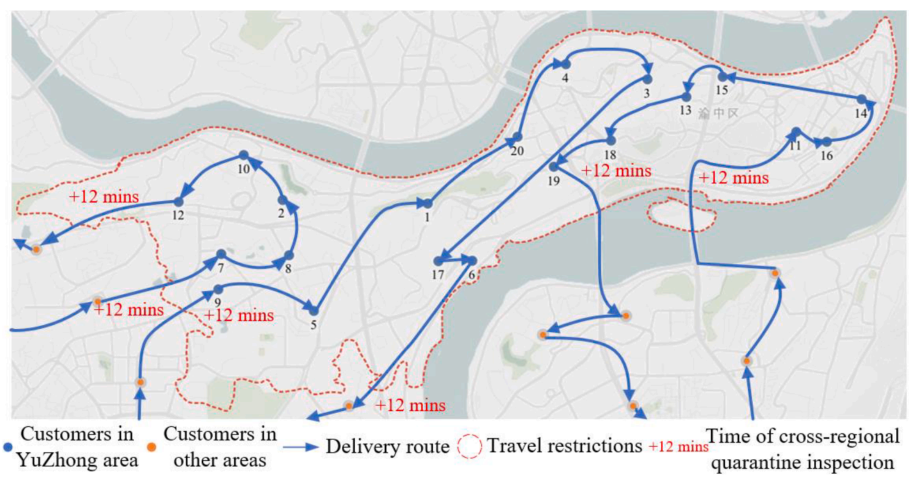


Fig. 11. Initial emergency delivery routes for A1.

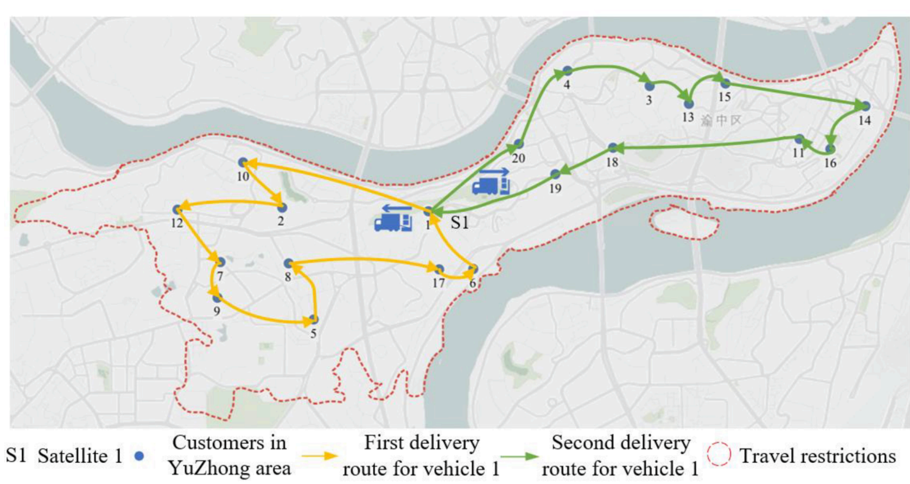


Fig. 12. Optimized emergency delivery routes for A1.

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

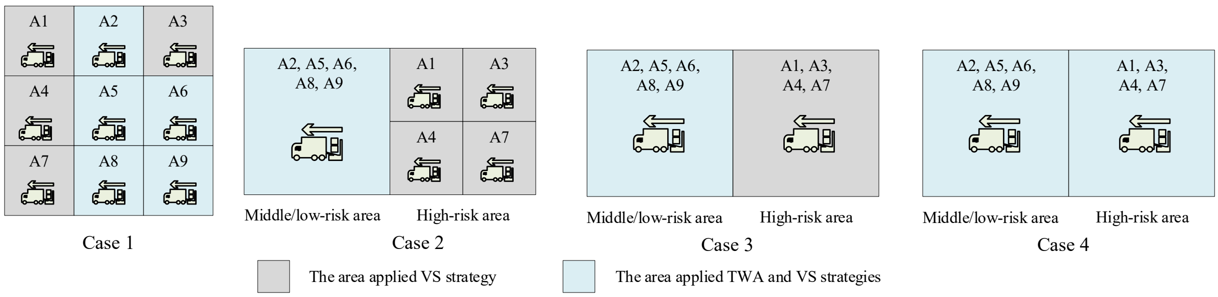


Fig. 13. TWA and vS strategies in four cases.

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	375	10,840	2310	1500
Case 2	**6465**	**10,345**	**10**	**3**	**325**	**9575**	**770**	**1300**
Case 3	7714	13,535	14	–	470	13,535	–	1880
Case 4	7619	12,865	14	–	605	12,865	–	2420

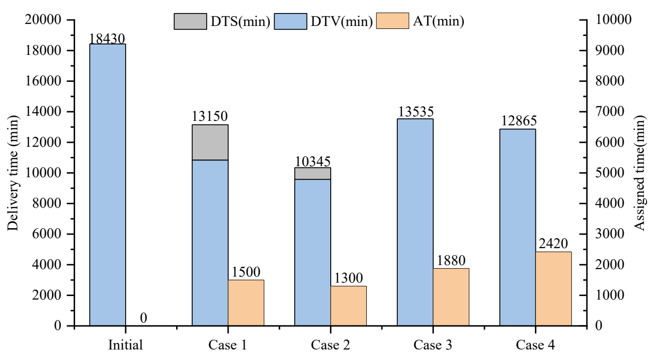


Fig. 14. Comparison of the total delivery time and assigned time among five cases.

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.

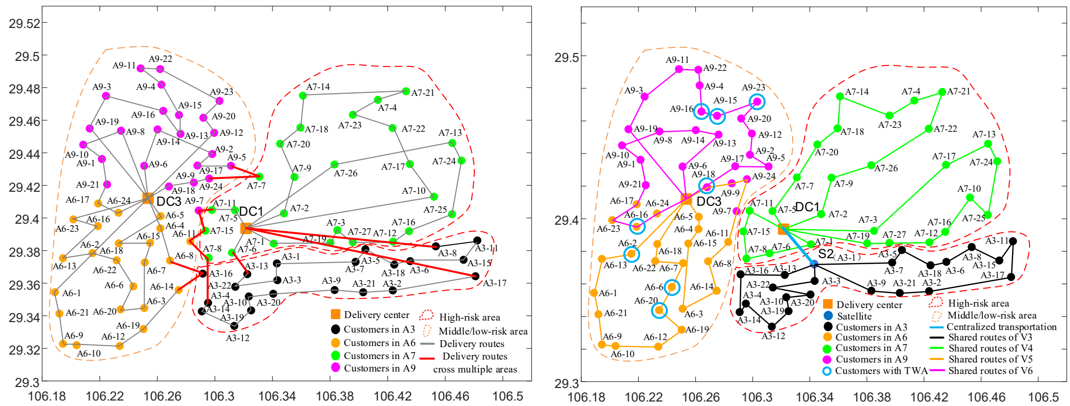
As indicated in Table 14, ten vehicles perform 19 delivery routes in the real-world case. Each high-risk area is closed and independent. Four vehicles performing nine trips depart from DC1, S1, S2, and S3 to serve customers in high-risk areas. Customers in the middle-/low-risk areas are assigned and 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 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	–	–	20(0*)	–	215	26
Case 2	DC1	1012	1565	290	1275	93	–	–	1(3*)	1	27	1
	DC2	1404	1560	480	1080	85	250	63	1(2*)	2	27	2
	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.



(a) The initial vehicle routes in DC1 and DC3 (b) The optimized vehicle routes in DC1 and DC3

Fig. 15. Initial and optimized vehicle routes in DC1 and DC3 in the emergency mode.

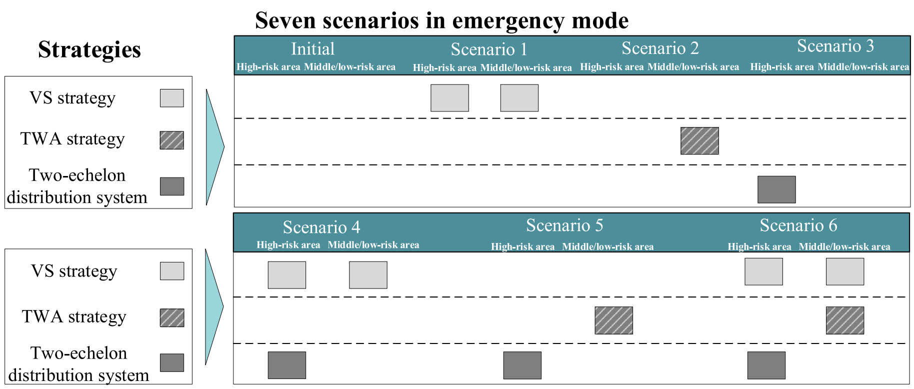


Fig. 16. Seven scenarios in the emergency mode.

Table 19
Results of the seven scenarios.

Scenario	TC ($)	DT (min)	NV	NS	DTV (min)	DTS (min)	AC ($)
Initial	10,508	18,430	20	–	18,430	–	–
Scenario 1	8525	15,340	16	–	15,430	–	–
Scenario 2	9793	15,940	19	–	15,940	–	380
Scenario 3	9726	14,515	19	3	13,745	770	–
Scenario 4	7737	12,745	13	3	11,975	770	–
Scenario 5	9644	13,735	18	3	12,965	770	435
Scenario 6	**6465**	**10,345**	**10**	**3**	**9574**	**770**	**325**

"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 vector of Vehicle Time is greater than zero (67.48 min), that is, one vehicle performs A1′s delivery service in 67.48 min. Z_2 consists of the travel time and preparation time of the vehicle for the next route. The values $213.87 and 55.48 min in the last label refer to the total operating cost and total delivery time of the vehicle, respectively. The Prepoint column in each label indicates the last service point of the vehicle. 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 →

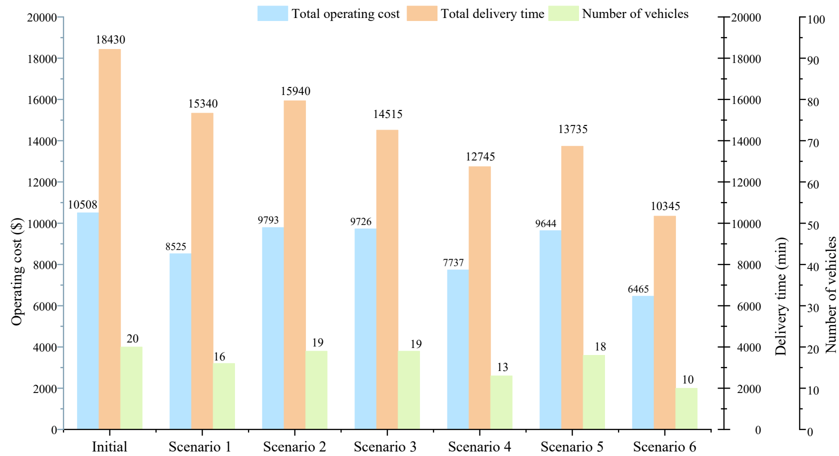


Fig. 17. Result comparison of the seven scenarios.

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), and assigned time (AT) are shown in Table 17 and Fig. 14.

As indicated in Table 17, TWA and vS strategies decrease the cost in the emergency logistics network. The number of used vehicles is reduced greatly through the vS strategy, thus decreasing the maintenance cost of vehicles. The lowest operating cost of $6465 is obtained in **Case 2**, indicating a reduction of $4043 compared with **Initial case**. In Fig. 14, the total delivery time consisting of the delivery time of vehicles and the delivery time of semitrailer trucks is plotted on the first bar chart. The difference between **Initial case** and **Case 2** in terms of the total delivery time of vehicles is large. In **Case 2**, satellites are established and vehicles are shared in each area. Decreased cross-regional transportation results in a considerable reduction in cross-regional quarantine inspection time, thus reducing the total delivery time of vehicles. However, the centralized transportation among satellites increases, which means the delivery time of semitrailer trucks increases. In **Case 3** and **Case 4**, vehicles are shared in high-risk and middle-/low-risk areas, respectively. The lack of satellites in **Case 3** and **Case 4** results in an increase in cross-regional quarantine inspection time, thus increasing the total delivery time. Hence, the establishment of satellites in high-risk areas is conducive to the reduction of the total delivery time.

Given the infectivity of COVID-19, vehicles that are not shared between high-risk areas can effectively prevent cross-infection. **Case 4** consumes less total delivery time than **Case 3**, but the difference is not significant, which means the benefit of applying the TWA strategy to customers in the high-risk areas is not obvious. From a humanitarian point of view, vehicles serving customers in high-risk areas within the expected time windows contribute to the satisfaction of customers and sustainable development of the enterprise (Balcik et al., 2008). Compared with **Case 3** and **Case 4**, **Case 2** has a shorter delivery time of semitrailer trucks and an appropriate delivery time of vehicles in the emergency logistics network. These results show that applying TWA and vS strategies in **Case 2** benefits the cost-saving and response speed of the emergency logistics network. The results of **Initial case** and **Case 2** on the total operating cost (TC), total delivery time (DT), 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 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 to share vehicles in different DCs and satellites (**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 vS 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-EVRPTWA 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.

Acknowledgments

The authors would like to express our sincere appreciation for the valuable comments made by two anonymous reviewers, which helped us to improve the quality of this paper. This research is supported by National Natural Science Foundation of China (Project No. 71871035, 71971036, 71831008), Key Science and Technology Research Project of Chongqing Municipal Education Commission (KJZD-K202000702), Natural Science Foundation of Chongqing in 2022 (CSTB2022NSCQ-MSX0535, CSTB2022NSCQ-MSX0394), Chongqing Liuchuang Plan Innovation Project (cx2021038), Team Building Project for Graduate Tutors in Chongqing (JDDSTD2019008), Chongqing Bayu Scholar Youth Project (YS2021058).

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