https://doi.org/10.1016/j.knosys.2021.107041

Emergency logistics network design based on space–time resource configuration

Yong WANG[a], Shouguo PENG[b,*], Min XU[b,*]

([a]*School of Economics and Management, Chongqing Jiaotong University, Chongqing 400074, China)*

([b]*Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hung Hom, Hong Kong)*

E-mail: yongwx6@gmail.com; shouguo.peng@polyu.edu.hk*; min.m.xu@polyu.edu.hk*

*Corresponding author

Abstract: The occurrence of natural disasters or accidents causes the obstruction or interruption of road traffic connectivity and affects the transportation of essential materials, especially for cross-regional delivery under emergency situations. Affected by COVID-19, government administrators establish cross-regional quarantine roadblocks to reduce the risk of virus transmission caused by cross-regional transportation. In this study, we propose an emergency logistics network design problem with resource sharing under collaborative alliances. We construct a state–space–time network-based multi-objective mixed integer programming model to optimize the vehicle routes in order to meet customer demands for essential materials with the lowest cost and highest emergency response speed under limited transportation resources. A two-stage hybrid heuristic algorithm is then proposed to find good-quality solutions for the problem. Clustering results are obtained using a 3D *k*-means clustering algorithm with the consideration of time and space indices. The optimization of the initial population generated by the improved Clarke and Wright saving method and improved nondominated sorting genetic algorithm-II with elite retention strategy provides stable and excellent performance for the searching of Pareto frontier. The cost difference of the entire emergency logistics network before and after collaboration, i.e., the profit, is fairly allocated to the participants (i.e., logistics service providers) through the Shapley value method. A real-world case in Chongqing City, China is used to validate the effectiveness of the proposed model and algorithm. This study contributes to smart transportation and logistics system in emergency planning and has particular implications for the optimal response of existing logistics system to the current COVID-19 pandemic.

Keywords: Emergency logistics; resource sharing; state–space–time network; collaboration; Shapley value method

1. Introduction

The construction of an emergency logistics network is a necessary and crucial task for government officials and managers to protect the residents' normal life in the occurrence of some natural disasters or accidents (Shin et al., 2019). At the end of 2019, the outbreak of COVID-19 has caused many countries in the world to enter a state of emergency. Several countries have imposed some strict traffic control policies, including the policy of closing cities, to deal with the high infectivity and mortality of the new coronavirus. On the one hand, measures, such as road traffic restrictions, including cross-regional quarantine inspection of transportation vehicles and prohibition of residents from purchasing materials across regions, reduce the risk of virus transmission, thereby ensuring the health of residents. On the other hand, ensuring the accessibility and timeliness of transportation of the living supplies is an important issue that must be addressed by logistics service providers and governors when transportation resources are limited and transportation is blocked.

Compared with the logistics networks under a non-emergency mode, more factors, such as emergency response time, limited transportation resources, and high transportation costs, need to be considered in emergencies (Duque et al., 2016; Oruc and Kara, 2018). Sudden disasters, such as earthquakes, epidemic outbreaks, and other emergencies, usually have a series of adverse effects on logistics delivery activities, such as the lengthened travel time, the shortage of transportation resources, and the obstruction of cross-regional delivery operations. However, the timely and safe delivery of living materials to urban residents is vital to ensuring social stability. As a government manager, increasing the response speed to material delivery under emergency conditions with limited resources is necessary to ensure the normal delivery for residents. From an enterprise's perspective, logistics service providers need to optimize delivery networks under various policy constraints to ensure the normal operation of their enterprises with a relatively low cost. Therefore, an optimization strategy that considers multiple decision goals is needed to achieve a holistic design of the delivery network in an emergency.

1.1. Literature review

The design of emergency logistics network for living materials plays a vital role in maintaining normal social order and ensuring residents' daily lives when emergencies or unexpected disasters such as earthquakes and epidemics occur (Hamacher and Tjandra, 2001; Sheu, 2007). The occurrence of an emergency involves the research and exploration of the following issues: transportation supplies of living materials, formulation of evacuation plans, placement and transfer of casualties, and the location of emergency logistics facilities (Balcik and Beamon, 2008; Rath and Gutjahr, 2014; Rancourt et al., 2015; Osman and Ram, 2017). In the past, research on emergency logistics and discussions and analyses for actual disasters are very limited due to the accidental and the low-frequency characteristics of disasters (Holguin-Veras et al., 2012; Ozguven, and Ozbay, 2012). Recently, with the increasing awareness of humanitarian and human fate community, more and more academic experts and decision-makers of enterprises have focused on the research on emergency logistics (Galindo and Batta, 2013; Huang et al., 2015). For example, in 2020, with the impact of COVID-19, the time and cost of cross-regional transportation are inevitably increased to avoid the risk of virus transmission caused by cross-regional contact due to quarantine, epidemic prevention, and other policies (Zhang et al., 2020). Therefore, designing a safe and reliable emergency logistics network in face of the traffic interruption, such as the increase in travel time or costs for some sections of cross-regional transportation is of vital importance to social stability (Cleophas et al., 2019; Gansterer and Hartl, 2020; Santos et al., 2020).

Emergency logistics network design has focused on the optimization of relief routing in previous literature, especially on the quick and safe transfer of people who have experienced disasters to a predetermined refuge after a disaster (Zhang et al., 2017; Bayram and Yaman, 2018). The study of emergency logistics network design aims to find an effective solution for distributing life supplies to customers in need. Some researchers considered an emergency logistics network design in a deterministic environment with objectives of minimizing total delivery time (Campbell et al., 2008; Ozkapici et al., 2016). In response to emergency situations that may cause road damage such as natural disasters, Yan and Shih (2009) added emergency road maintenance considerations to solve a combined emergency logistics network optimization problem. In addition, delivery efficiency and operational cost should be taken into consideration when designing the emergency logistics network to ensure fairness (Camacho-Vallejo et al., 2015). However, for the possible road interruptions after disasters, such as the blocking of roads by debris in the emergency logistics network, many scholars focused on removing road barriers with minimum cost or minimum cleaning time to ensure the connectivity and reachability of the emergency delivery network (Celik et al., 2015; Sahin et al., 2016; Berktas et al., 2016; Akbari and Salman, 2017). The research on how to satisfy the daily customer demands on the basis of existing accessible roads through multi-facility collaboration needs further exploration. Therefore, we consider the design of the emergency logistics network based on the feasible transportation network, and establish a collaborative delivery mode to meet the delivery demands of customers while ensuring the economic benefits of the logistics enterprises.

However, all the aforementioned studies focused on the logistics network design problem for one logistics company only. They did not consider the possible collaboration and resource sharing among multiple logistic service providers, although it is important especially in an emergency. Through the formation of collaborative alliances, we can achieve a win-win solution for both customers and enterprises themselves. In the previous literature, the importance of coordination or allocation of limited resources, especially for multi-facility cross-regional collaborative delivery, has been largely ignored (Karlaftis et al., 2007; Duque and Sörensen, 2011; Wang et al., 2018). Many studies on resource allocation focused on route optimization only within a logistics company to achieve transportation accessibility (Huang et al., 2013; Balcik, 2017). Delays or undeliverable phenomena may occur in some cross-regional long-distance deliveries due to road traffic obstruction and non-collaborative logistics operation modes.

Moreover, most studies considered only one objective function, i.e., minimizing the total delivery cost. However, in an emergency, other aspects are also important. For example, the speed of emergency response, especially the timeliness of emergency delivery of blood, medical resources, daily necessities, etc., is crucial to the lives of residents. Zhou et al. (2017) proposed a multi-period emergency resource scheduling problem that aims to minimize the risk of unmet needs and the choice of damaged roads. Shin et al. (2019) proposed a comprehensive optimized scheduling strategy for maintenance personnel and rescue vehicles after a disaster, with the goal of minimizing the service completion time of the total demands. Although the timeliness of transportation or delivery after disasters or emergencies is extremely important, especially disasters that may cause casualties, such as earthquakes and hurricanes (Zhou et al., 2017; Shin et al., 2019), multiple objectives, such as emergency response time, delivery costs, and the efficiency of the used transportation resources (e.g., transportation trucks or vehicles) under emergency conditions are required to be considered simultaneously (Oruc et al., 2018). Therefore, we consider addressing a multi-objective optimization problem that takes into account the logistics cost of the enterprise, the satisfaction of customer demands, and the limitation of social available resources to alleviate or improve the possible conflicts in the emergency situation.

Therefore, reducing cross-regional conditions through collaborative logistics operations while satisfying the demand of existing customers is another important issue for emergency logistics network optimization. Most of the previous logistics delivery issues concerning collaboration only considered the vehicle routing optimization through the collaborative operations between multiple facilities in the entire static or dynamic situation rather than the particularity of emergency situations, such as the increase in travel time or costs for some sections of cross-regional transportation (Cleophas et al., 2019; Gansterer and Hartl, 2020; Santos et al., 2020).

1.2. Objectives and contributions

To close the above research gaps, we design an emergency logistics network based on a collaborative mode with resource sharing from multiple perspectives, including the cost, the emergency response time, and the effective utilization of transportation resources. The change in cross-regional travel time due to unexpected conditions is considered when calculating the objective functions of the entire delivery network cost and response time. Designing a relatively closed regional collaborative delivery network reduces the transportation time, including quarantine time when transportation trucks perform delivery tasks across regions. The logistics cost of independent operation under noncollaborative mode is also reduced, thereby ensuring the timeliness of delivery services and accessibility of cargo transportation under an emergency situation. The cost difference due to collaboration, that is, the additional profit can be fairly allocated by comparing the total logistics cost under the optimized delivery strategy and the original delivery mode to promote the formation of the collaborative relationship and maintain its stability and sustainability.

Compared with previous research on the optimization of emergency logistics networks, this study has the following innovations: (i) we propose a collaborative emergency logistics strategy among multiple logistics facilities based on state–space–time network using existing road resources to fulfill the delivery demands rather than the independent operations among different logistics facilities or enterprises; (ii) we consider multiple objectives, including the total logistics delivery costs, the total time, and the number of used vehicles, to get the lowest cost and highest emergency response speed while using limited transportation resources, thus achieving the Pareto optimality under multiple objectives; (iii) we adopt a two-stage heuristic algorithm to validate the advantages of the collaborative delivery strategy in an emergency in terms of total delivery cost, total time, and used transportation resources in a real case in Chongqing City, China.

The remainder of the paper is organized as follows. Section 2 presents the problem statement. Section 3 introduces the mathematical model formulation for the investigated problem, including the assumptions and notations. Section 4 proposes a two-stage heuristics algorithm by combining the Clarke and Wright (CW) saving method and improved nondominated sorting genetic algorithm-II (NSGA-II). Section 5 conducts the numerical experiments in Chongqing City, China. Section 6 summarizes the conclusions.

2. Problem statement

Taking the conventional logistics delivery network in a non-emergency mode as a reference, we explain the superiority of a collaborative emergency logistics network based on resource sharing when an unexpected event occurs. The state–space–time network is used to describe and analyze the emergency response speed and logistics cost between the non-emergency and emergency modes (Mahmoudi and Zhou, 2016). Compared with the traditional delivery network optimization, delivery activities are regarded as single logistics delivery operations that only consider the delivery destination. The stocking operations of these delivery goods are ignored, and the initial state of these delivery trucks is defaulted to be fully loaded. However, such a process may make the potential risk of untimely stocking in emergency conditions due to the shortage of resources and the increase in demand. Therefore, this study transforms the delivery operation into a pickup and delivery problem with paired origin and destination. Fig. 1 shows the optimized delivery network without driving restrictions under a noncollaborative non-emergency mode.

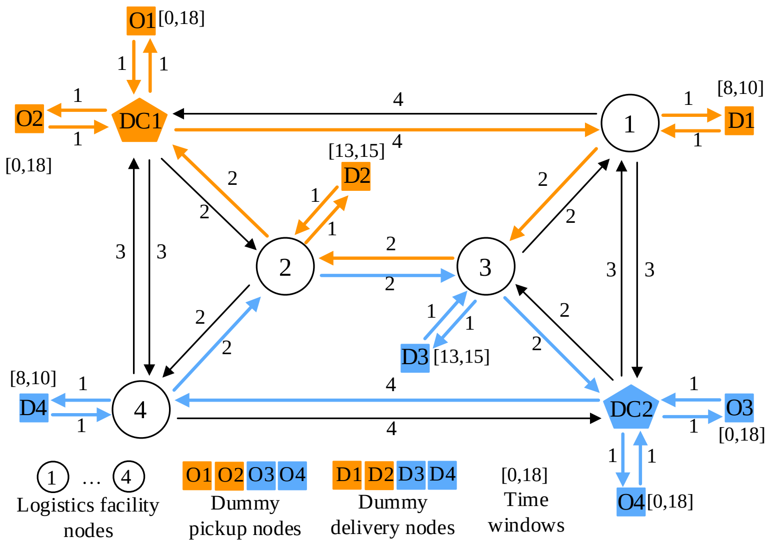

Fig. 1 Optimized delivery network without driving restrictions under a noncollaborative mode

In Fig. 1, two trucks (k_1 and k_2) departing from two delivery centers (DC1 and DC2) independently complete the delivery tasks for the given customer demands along the optimized shortest path. Considering the stocking operations of these goods to be delivered, delivery operations are defined as pickup and delivery operations with specific origin and destination (O–D), that is, a paired O–D pickup and delivery problem. Under the non-emergency condition, the two delivery centers complete the delivery tasks in a relatively independent service mode. The shortest path with visiting sequence (O,1,DC1,1,2,S1,2,4,3,S2,3,1,O) in truck k_1's state–space–time network is shown in Fig. 2.

Fig. 2 Shortest path with visiting sequence (O,1,DC1,1,2,S1,2,4,3,S2,3,1,O) in truck k_1's state–space–time network

In Fig. 2, the state of the truck at any time and any place can be known for information acquisition and flexible deployment of the truck. At the same time, the pickup and delivery states are represented by green and blue lines, respectively, and 0 and 1 in square brackets (e.g., [0 0], [0 1]), respectively, indicate whether the storage space is empty or full. The network optimization results in non-emergency mode can then be obtained by summarizing the operating costs and delivery time of all independent facilities. However, the original independently operated optimized network may have difficulty in meeting the existing demands with low costs and less delivery time when an emergency occurs and the road traffic conditions change. Therefore, we designed a collaborative emergency logistics network based on resource sharing as shown in Fig. 3.

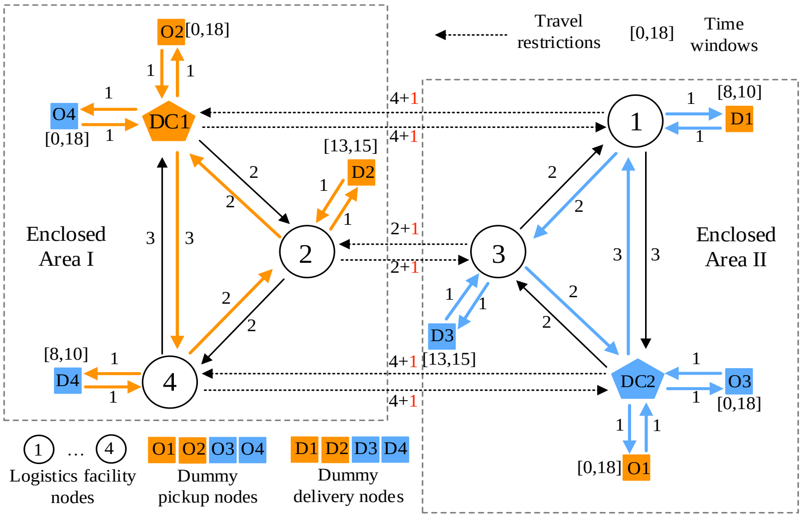

Fig. 3 Optimized delivery network with driving restrictions under a collaborative mode

In Fig. 3, we designed a delivery service network in a relatively enclosed area centered on DC1 and DC2 because of the formation of collaboration between DC1 and DC2 and as the travel restrictions. Customer service can then be shared by collaborative logistics facilities, thereby minimizing total cost and delivery time while maximizing resource utilization based on the customers' geographic locations, demands, and time windows in an emergency logistics network. Similarly, the shortest path with visiting sequence (O,1,DC1,1,5,S4,5,3,S2,3,1,O) in truck k_1's state–space–time network under a collaborative mode is shown in Fig. 4.

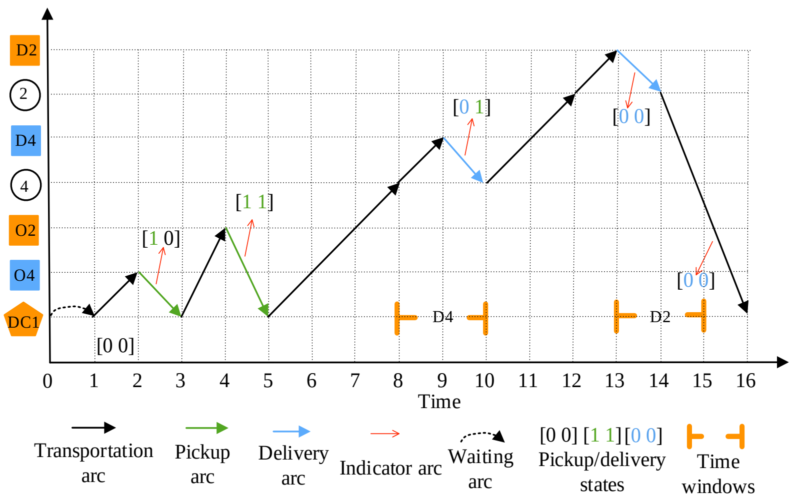

Fig. 4 Shortest path with visiting sequence (O,1,DC1,1,5,S4,5,3,S2,3,1,O) in truck k_1's state–space–time network

We explain the superiority of the collaborative emergency logistics network based on resource sharing in terms of the total cost, total time, and the number of used trucks. Without loss of generality, the unit transportation cost in transportation or service arcs using a truck can be set to $30/h, and the unit penalty cost for waiting or late can be defined as $40/h. Trucks waiting in the depot (i.e., logistics center) should not be imposed with the waiting costs because resources are not unnecessarily occupied. Therefore, the total cost and related optimization results of the noncollaborative and collaborative networks in accordance with the shortest paths and the above definitions are shown in Table 1.

Table 1 Result comparison between noncollaborative and collaborative logistics networks

Scenario	Case	Delivery time (h)	Waiting time (h)	Transportation cost ($)	Penalty cost ($)	Rental cost ($)	Total cost ($)	Total time (h)	Number of trucks
Non-emergency	Non-collaborative network	36	0	1080	0	400	1480	36	2 (0*)
Emergency	Non-collaborative network	40	2	1200	80	400	1680	42	2 (0*)
	Collaborative network	30	0	900	0	400	1300	30	2 (2*)

*: The number of shared trucks.

As shown in Table 1, the collaborative emergency logistics network shows a remarkable superiority from the perspectives of cost and timeliness of the delivery operation. Logistics companies are faced with high transportation costs across distant regions due to the obstruction of road traffic. The total cost of the noncollaborative network under an emergency condition is $1,680, which is higher than a collaborative network (i.e., $1,300). At the same time, the timeliness of delivery is greatly affected because of the increase in the cross-regional travel time, and the waiting cost should be paid additionally for the violation of the time window. The rental cost based on the number of used trucks should be paid for delivering the living materials. Therefore, the collaborative emergency logistics network based on resource sharing has potential advantages in responding to unexpected situations, improving emergency response speed, and reducing logistics operating costs.

3. Optimization model

The shortage of transportation resources and the extended travel time for quarantine in emergency conditions may cause the increase in waiting time and logistics operating costs of logistics companies during the delivery process. Therefore, a multi-objective optimization model with the consideration of emergency response speed and transportation resource sharing is conducted to study the design of emergency logistics network, thus to achieve the optimization of total logistics operating costs, waiting time, and transportation resources.

3.1. Assumptions and notations

In emergencies, such as earthquakes, epidemics, etc., which may cause extended travel time across regions, therefore, we consider reducing the logistics delivery costs and reduce the situation of untimely or even unable to deliver due to emergencies by first delimiting collaborative delivery areas and then optimizing routes in the enclosed delivery areas. Before the construction of the mathematical model, several necessary and reasonable assumptions are as follows.

- Under an emergency situation, customer demands remain relatively stable and known in advance with the government's allocation of resources and macro-control (e.g., restricted purchase policy).

- Delivery goods should be transferred from the delivery centers to the delivery satellites by trucks in the first echelon and be delivered to the customers by vehicles in the second echelon.
- To improve the emergency response to unexpected events (e.g., epidemic or earthquake), the government usually adopts financial subsidies to promote the formation of collaborative alliances, thereby ensuring the timeliness and accessibility of delivery.

Based on the assumptions, we design a state–space–time-based two-echelon collaborative emergency logistics network in accordance with the actual operational mode of logistics delivery enterprises. The first-echelon network is composed of logistics center facilities (i.e., logistics delivery centers, $l \in L$) and satellite facilities (i.e., delivery satellites, $s \in S$), and the second-echelon network is composed of satellite facilities $s \in S$ and customers $d \in D$. In the first echelon, truck $k \in K$ is used to transport living materials between logistics delivery centers and delivery satellites. Correspondingly, transportation cost $c_{(i,j,t,t',\omega,\omega',k)}$ should be paid when truck *k* travels from node *i* at time *t* in state ω and arrives at node *j* at time *t'* in state ω'. Similarly, in the second echelon, vehicle $v \in V$ is used to deliver living materials from delivery satellites to customers. Transportation cost $c_{(p,q,\tau,\tau',w,w',v)}$ when vehicle *v* travels from node *p* at time *t* in state *w* and arrives at node *q* at time *t'* in state w'. Compared with the independent operation mode of each logistics facility under the traditional emergency mode in the past, we introduce variable θ_l to explore the influence of a collaboration strategy on the delivery cost, emergency response time and resource usage. If delivery center *l* joins in the collaborative alliance, θ_l=1; otherwise θ_l=0. All the other notations and explanations used in the whole study are listed in the appendix. The multi-facility collaboration and resource sharing in emergency logistics network design, as well as the multiple objectives consideration in the formulation, are explored in this paper.

3.2. Model formulation

As one of the most important factors to maintain the operation of logistics enterprises, the total cost, which is composed of the transportation cost in the two-echelon emergency logistics network and the maintenance cost of trucks, vehicles, and facilities, is formulated as our first objective function. Then, to reduce the possible excessive waiting time caused by cross-regional transportation and guarantee the delivery timeliness, we consider minimizing the total delivery time as the second objective function for the improved emergency response speed. In addition, with the consideration of shortage for transportation resources in emergencies, we apply the minimum number of shared vehicles in the second echelon as the third objective function to improve the utilization rate of transportation resources. Therefore, we construct a mixed-integer programming model with multiple objectives, including the minimum of the total logistics operating cost, the total delivery time of the entire transportation network, and the number of vehicles used to complete customer services.

We establish a mixed-integer programming multi-objective optimization model considering state-space-time to design a collaborative emergency logistics network. The mathematical model is established as follows. Eqs. (1) – (3) express the three objectives including the minimum of the total logistics operating cost f_1, the total delivery time f_2, and the number of vehicles f_3, respectively. The total logistics operating cost is composed of the total cost of the first echelon TC_1 and the total cost of the second echelon TC_2.

$$\min f_1 = TC_1 + TC_2 \tag{1}$$

$$\min f_2 = \sum_{k\in K}\sum_{(i,j,t,t',\omega,\omega')\in\phi_k} Tt_{ijk}\cdot x_{(i,j,t,t',\omega,\omega',k)} + \sum_{v\in V}\sum_{(p,q,\tau,\tau',w,w')\in\phi_v} Tt_{pqv}\cdot y_{(p,q,\tau,\tau',w,w',v)} + \sum_{k\in K}\sum_{j\in L\cup S} Wt_j^k + \sum_{v\in V}\sum_{q\in S\cup D} Wt_q^v \quad (2)$$

$$\min f_3 = \sum_{s\in S} N_s^v \cdot \sum_{(p,q,\tau,\tau',w,w')\in\phi_V, p=s} y_{(p,q,\tau,\tau',w,w',v)} \quad (3)$$

$$TC_1 = \sum_{k\in K}\sum_{(i,j,t,t',\omega,\omega')\in\phi_k} c_{(i,j,t,t',\omega,\omega',k)}\cdot x_{(i,j,t,t',\omega,\omega',k)} + \sum_{l\in L}\sum_{k\in K} m_k\cdot N_l^k + \sum_{l\in L} m_l + \sum_{l\in L}(c_l-\lambda_l)\cdot\theta_l \quad (4)$$

$$TC_2 = \sum_{v\in V}\sum_{(p,q,\tau,\tau',w,w',v)\in\phi_v} c_{(p,q,\tau,\tau',w,w',v)}\cdot y_{(p,q,\tau,\tau',w,w',v)} + \sum_{s\in S}\sum_{v\in V} m_v\cdot N_s^v + \sum_{s\in S} m_s \quad (5)$$

In Eq. (4), different from the cost under the conventional non-collaborative emergency mode (i.e., the transportation cost of the trucks, the maintenance cost of the trucks and facilities), two additional cost components, including collaborative cost and financial subsidy from gorvenment, are supplemented in TC_1 induced by the establishment of collaborative alliances. In practice, as an additional quantity-based cost c_l, when the logistics company l serves customers initially affiliated to other collaborative company l', collaborative cost should be added to the total cost. In additon, to compensate for the collaborative cost of logistics company l and promote the formation of collaborative alliances under emergency, a quantity-based financial subsidy is deducted from the total cost as a cost compensation. Since collaborative cost and financial subsidy have been considered in the first echelon, in Eq. (5), the total cost of the second echelon TC_2 only includes the transportation cost of the vehicles, the maintenance cost of the vehicles and facilities.

Subject to

- The constraints in the first echelon.

$$\sum_{(i,j,t,t',\omega,\omega')\in\phi_k} x_{(i,j,t,t',\omega,\omega',k)} = 1, \qquad i\in L, t = Dt_i^k, \omega=\omega'=\omega_0, k\in K \quad (6)$$

$$\sum_{(i,j,t,t',\omega,\omega')\in\phi_k} x_{(i,j,t,t',\omega,\omega',k)} = 1, \qquad j\in L, t' = At_j^k, \omega=\omega'=\omega_0, k\in K \quad (7)$$

$$\sum_{(i,j,t,t',\omega,\omega')\in\phi_k} x_{(i,j,t,t',\omega,\omega',k)} - \sum_{(j,i',t',t'',\omega',\omega'')\in\phi_k} x_{(j,i',t',t'',\omega',\omega'',k)} = 0, \qquad k\in K, i\neq i' \quad (8)$$

$$\sum_{k\in K} x_{(i,j,t,t',\omega,\omega',k)} = 1, \qquad j\in L, (i,j,t,t',\omega,\omega',k)\in\phi_k \quad (9)$$

$$\sum_{(i,j,t,t',\omega,\omega')\in\phi_k} Q_j^k\cdot x_{(i,j,t,t',\omega,\omega',k)} \le Q_k, \qquad k\in K \quad (10)$$

$$\sum_{v\in V}\sum_{(i,j,t,t',\omega,\omega')\in\phi_v} Q_j^k\cdot x_{(i,j,t,t',\omega,\omega',k)} \le Q_l, \qquad l\in L \quad (11)$$

$$Et_j\cdot x_{(i,j,t,t',\omega,\omega',k)} \le At_j^k \le Lt_j\cdot x_{(i,j,t,t',\omega,\omega',k)}, \qquad (i,j,t,t',\omega,\omega')\in\phi_k, k\in K \quad (12)$$

$$Dt_i^k + Tt_{ijk} + Wt_j^k - M\cdot(1-x_{(i,j,t,t',\omega,\omega',k)}) \le At_j^k, \qquad (i,j,t,t',\omega,\omega')\in\phi_k, k\in K \quad (13)$$

$$Dt_i^k + Tt_{ijk} + Wt_j^k + M\cdot(1-x_{(i,j,t,t',\omega,\omega',k)}) \ge At_j^k, \qquad (i,j,t,t',\omega,\omega')\in\phi_k, k\in K \quad (14)$$

$$\sum_{j\in S}\sum_{i\in S} x_{(i,j,t,t',\omega,\omega',k)} \le |S_k| - 1 \qquad S_k\subset S\cup L, 2\le|S_k|\le n-1 \quad (15)$$

$$\sum_{(i,j,t,t',\omega,\omega')\in\phi_k}\sum_{k\in K} Q_j^k\cdot x_{(i,j,t,t',\omega,\omega',k)} \Big/ Q_k \le \sum_{(i,j,t,t',\omega,\omega')\in\phi_k}\sum_{k\in K} x_{(i,j,t,t',\omega,\omega',k)}, \qquad i\in L \quad (16)$$

$$c_l = \alpha_1 \cdot \sum_{l' \in L, l' \neq l} Q_{ll'} + \alpha_2 \cdot \sum_{s \in S, s' \neq s} Q_{ss'}, \qquad l \in L \tag{17}$$

$$\lambda_l = \beta_1 \cdot \sum_{l' \in L, l' \neq l} Q_{ll'} + \beta_2 \cdot \sum_{s \in S, s' \neq s} Q_{ss'}, \qquad s \in S \tag{18}$$

Eqs. (6) – (8) express the flow balance at truck k's origin, destination, and intermediate vertex, respectively. Eq. (9) indicates that the satellite demand in the first echelon can and only served by one truck. Eq. (10) indicates that the delivery service can only be completed within the maximum capacity of trucks. Eq. (11) represents the maximum service capacity of the logistics delivery centers. Eq. (12) indicates that the delivery service in the first echelon must be completed by trucks within the time window of the logistics delivery satellites. Eqs. (13) – (14) ensure the delivery service continuity of trucks in the first echelon. Eq. (15) is the constraint for eliminating subtours in the first echelon. Eq. (16) shows the number of trucks within shared utilization between multiple logistics facilities in the first echelon under emergency logistics mode. Eqs. (17)–(18) express the collaborative cost and financial subsidy from the government, respectively. Generally, to promote and sustain the formation of collaborative alliances, the subsidy coefficient should be slightly higher than the collaborative coefficient by 10%-20% (Govindan et al, 2014; Wang et al., 2020). The constraints in the second echelon.

$$\sum_{(p,q,\tau,\tau',w,w') \in \phi_v} y_{(p,q,\tau,\tau',w,w',v)} = 1, \qquad p \in S, \tau = Dt_p^v, w = w' = w_0, v \in V \tag{19}$$

$$\sum_{(p,q,\tau,\tau',w,w') \in \phi_v} y_{(p,q,\tau,\tau',w,w',v)} = 1, \qquad q \in S, \tau' = At_q^v, w = w' = w_0, v \in V \tag{20}$$

$$\sum_{(p,q,\tau,\tau',w,w') \in \phi_v} y_{(p,q,\tau,\tau',w,w',v)} - \sum_{(q,p',\tau',\tau'',w',w'') \in \phi_v} y_{(q,p',\tau',\tau'',w',w'',v)} = 0, \qquad v \in V, p \neq p' \tag{21}$$

$$\sum_{v \in V} y_{(p,q,\tau,\tau',w,w',v)} = 1, \qquad q \in S, (p,q,\tau,\tau',w,w') \in \phi_v \tag{22}$$

$$\sum_{(p,q,\tau,\tau',w,w') \in \phi_v} Q_q^v \cdot y_{(p,q,\tau,\tau',w,w',v)} \leq Q_v, \qquad v \in V \tag{23}$$

$$\sum_{v \in V} \sum_{(p,q,\tau,\tau',w,w') \in \phi_v} Q_q^v \cdot y_{(p,q,\tau,\tau',w,w',v)} \leq Q_s, \qquad s \in S \tag{24}$$

$$Et_q \cdot y_{(p,q,\tau,\tau',w,w',v)} \leq At_q^v \leq Lt_q \cdot y_{(p,q,\tau,\tau',w,w',v)}, \qquad (p,q,\tau,\tau',w,w') \in \phi_v, v \in V \tag{25}$$

$$Dt_p^v + Tt_{pqv} + Wt_q^v - M \cdot (1 - y_{(p,q,\tau,\tau',w,w',v)}) \leq At_q^v, \qquad (p,q,\tau,\tau',w,w') \in \phi_v, v \in V \tag{26}$$

$$Dt_p^v + Tt_{pqv} + Wt_q^v + M \cdot (1 - y_{(p,q,\tau,\tau',w,w',v)}) \geq At_q^v, \qquad (p,q,\tau,\tau',w,w') \in \phi_v, v \in V \tag{27}$$

$$\sum_{q \in D_v} \sum_{p \in D_v} x_{(p,q,\tau,\tau',w,w',v)} \leq |D_v| - 1 \qquad D_v \subset D \cup S, 2 \leq |D_v| \leq m - 1 \tag{28}$$

$$\sum_{(p,q,t,t',\omega,\omega') \in \phi_v} \sum_{v \in V} Q_q^v \cdot x_{(p,q,t,t',\omega,\omega',v)} \Big/ Q_v \leq N_p^v, \qquad p \in S \tag{29}$$

$$N_p^v \leq \sum_{v \in V} y_{(p,q,\tau,\tau',w,w',v)}, \qquad (p,q,\tau,\tau',w,w') \in \phi_v, p \in S \tag{30}$$

$$x_{(i,j,t,t',\omega,\omega',k)} = \{0,1\}, \qquad (i,j,t,t',\omega,\omega') \in \phi_k, k \in K$$

$$y_{(p,q,\tau,\tau',w,w',v)} = \{0,1\}, \quad (p,q,\tau,\tau,w,w') \in \phi_v, v \in V$$

$$\theta_l = \{0,1\}, \qquad l \in L$$

Eqs. (19) – (21) express the flow balance at vehicle *v*'s origin, destination, and intermediate vertex, respectively. Eq. (22) indicates that the customer demand in the second echelon can and only served by one vehicle. Eq. (23) indicates that the delivery service can only be completed within the maximum capacity of vehicles. Eq. (24) represents the maximum service capacity of the logistics delivery satellites. Eq. (25) indicates that the delivery service in the second echelon must be completed by vehicles within the time window of customers. Eqs. (26) – (27) ensure the delivery service continuity of vehicles in the second echelon. Eq. (28) is the constraint for eliminating subtours in the second echelon. Eqs. (29) – (30) show the number of vehicles within shared utilization between multiple logistics facilities in the second echelon under emergency logistics mode.

4. Solution methods

To solve the proposed mathematical model with multiple objectives and two echelons based on the emergency logistics network, we design a two-stage solution algorithm, including a 3D *k*-means clustering algorithm based on the enclosed area of the customers' geographic locations and service time windows and an improved NSGA-II algorithm. We use the 3D *k*-means clustering algorithm to divide an enclosed collaborative delivery area. The geographic location and service time window of logistics facilities and customers will be used as input parameters, and then the service clusters can be obtained by using the 3D *k*-means clustering method based on time and space indices. Then an improved NSGA-II algorithm is used to optimize the delivery routes in the enclosed area with the lowest cost, the minimum delivery time, and the maximum utilization of transportation resources. Details can be found in the next subsections.

4.1. 3D k-means clustering algorithm

3D *k*-means clustering algorithm is an improved clustering algorithm used to reduce the computation complexity by dividing a large-scale network into multiple subnetworks in accordance with certain indicators. The basic procedure of the algorithm is shown in Algorithm 1. Specifically, we increase the time dimension on the basis of the traditional *k*-means clustering algorithm and use the customers' time windows and geographic locations as the common indicator to achieve the division of logistics facility service area. The closed emergency logistics network is optimized by reducing the cost of over-distance transportation caused by cross-regional transportation, and the potential for untimely delivery caused by cross-regional operations is avoided. The comparison of clustering results between the traditional *k*-means clustering algorithm and the improved 3D *K*-means clustering algorithm is illustrated in Fig. 5.

Algorithm 1: 3D *k-means clustering algorithm based on time and space indices*

Input: Customer data (i.e., customers' geographical coordinates and time windows); Cluster parameters (e.g., number of clusters, satellite facilities).

Output: Cluster data for emergency deliveries.

//Clustering center initialization.

Randomly select *k* clustering centers for customers;

//3D distance calculation.

Calculate the 3D distance between each customer and the clustering center in accordance with the customers' geographical coordinates and time windows;

Determine and mark the affiliation of customer d in accordance with the minimum distance between each customer d to clustering center i;

//Update

Update customers affiliations until the clustering center no longer change;

Determine the customers' affiliation in accordance with the distance between the calculated clustering center and actual k satellite facilities as the output cluster data.

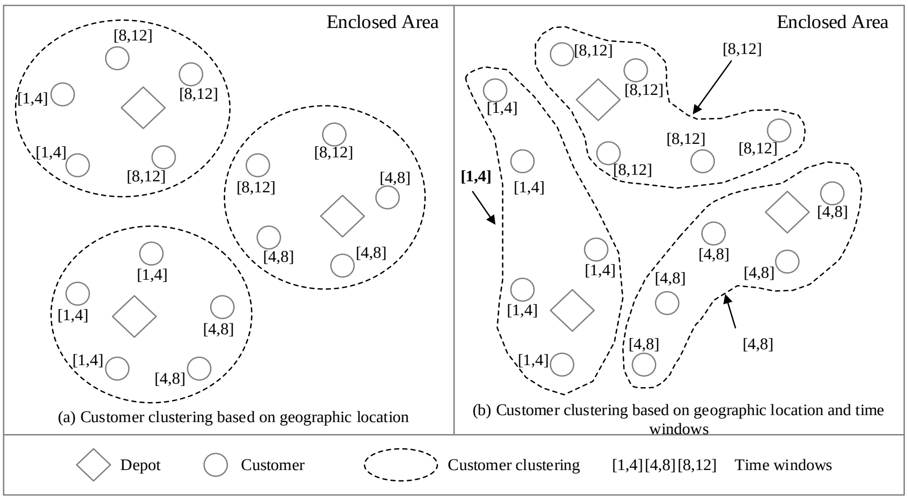

Fig. 5 Algorithm comparison between the traditional K-means and 3D k-means clustering

In Fig. 5(a), the time index is normally ignored in the traditional k-means clustering algorithm. Thus, customers whose time window differences are extremely large, such as customers with [1,4] and [8,12] time windows are clustered together, resulting in excessive waiting or delay. In Fig. 5(b), clustering based on time windows and geographic locations may result in extremely concentrated service times and demands for many transportation vehicles when the time index is included in the clustering parameters. The total number of vehicles can be reduced due to the vehicle sharing mode at different time periods and different service facilities in the enclosed area.

4.2. Improved NSGA-II with CW saving algorithm

Improved NSGA-II with CW saving algorithm is used to obtain the optimal routes in the enclosed areas. The basic procedure of the algorithm is shown in Algorithm 2. The clustering results of customers and their service facilities in the enclosed area obtained by Algorithm 1 are used as the input data of Algorithm 2 for the next optimization of the delivery network. In Algorithm 2, we optimize the generation of the initial population and elite retention and iteration using the traditional NSGA-II to improve the stability and global search ability of the algorithm. The CW saving algorithm optimizes the randomly generated initial population through the distance saving value to obtain initial individuals with excellent genes (Clarke and Wright, 1964). With the consideration of time and space, the distance in the CW saving algorithm adopts an improved Manhattan distance, that is, $D_{sd} = |x_s - x_d| + |y_s - y_d| + \chi \cdot |t_s - t_d|$, as shown in Fig. 6.

Algorithm 2: Improved NSGA-II

Input: Each cluster data; Parameters of the constructed emergency logistics delivery network (e.g., maintenance cost for each vehicle); Parameters used in the algorithm (e.g., population size, number of generations, number of runs).

Output: The total logistics operating cost, the total delivery time of the entire transportation network, and the number of vehicles used in the second echelon.

//**Population initialization.**

Generate the initial population (i.e., parent) P_t with N individuals using the CW saving algorithm based on cluster data;

Calculate distance D_{sd} between satellite s and customer d;

Calculate distance $D_{sd'}$ between satellite s and customer d';

Calculate the distance savings by $Ds = (D_{sd}+D_{sd'})-D_{dd'}$;

Stop calculating when all customer nodes are considered;

Obtain N optimization solutions (individuals) by sorting the distance savings;

Calculate the fitness of the initial population;

//**Genetic operation.**

Perform binary tournament selection, order crossover (OX), and polynomial mutation operators to generate the children population Q_t;

//**Elite retention strategy.**

Combine the parent population P_t and child population Q_t, $R_t=P_t \cup Q_t$;

//Non-dominated sorting and crowding distance comparison.

Perform non-dominated sorting to determine the non-dominated ranking, $(F_1,F_2,\cdots, F_i)$=nondominated (R_t);

Repeat

$P_{t+1}= \cup F_i$;

Until the number of individuals in P_{t+1} exceeds N;

Perform crowding distance comparison operator to select the last individuals for obtaining the next generation population with N individuals;

Repeat the genetic operation, elite retention strategy, nondominated sorting, and crowding distance comparison until the iteration criteria can be satisfied and the Pareto frontier of a multi-objective problem can be obtained.

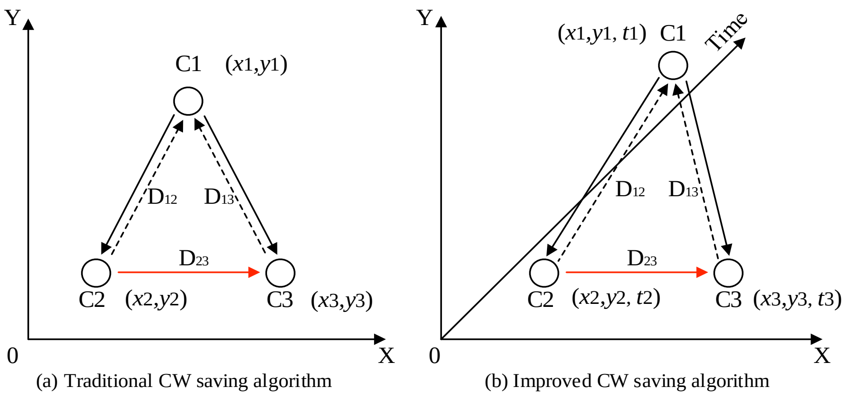

Fig. 6 Algorithm comparison between traditional and improved CW saving algorithm

On the basis of the optimized initial population P_t generated by the improved CW saving algorithm, we adopted genetic operators including binary tournament selection, OX, and polynomial mutation operators, to generate children population Q_t. The elite retention mechanism through the combination of parent and offspring populations guarantees the maximum retention of the population's genes, as shown in Fig. 7.

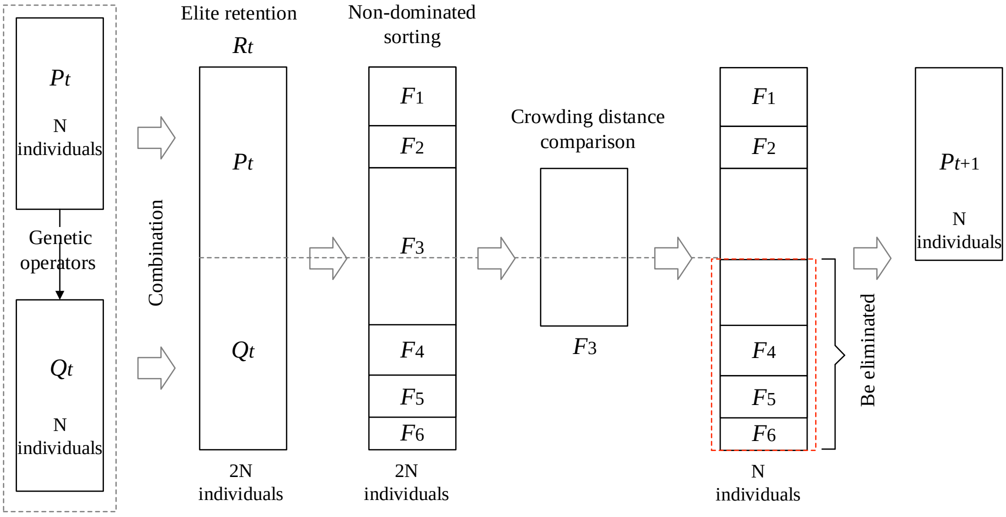

Fig. 7 Improved NSGA-II with elite retention strategy

In Fig. 7, the merging of the parent and offspring populations allows the excellent genes to be retained, but the number of individuals in the population becomes twice higher than that of the original population. Therefore, two operators, namely, fast non-dominated sorting and crowding distance comparison, are used to obtain the Pareto rank and screen for good individuals. The next-generation population with excellent genes is then obtained. The Pareto frontier is obtained after multiple iterations through repeated genetic operation, elite retention strategy, non-dominated sorting and crowding distance comparison.

4.3. Profit allocation and strictly monotonous path (SMP)

The cooperative game theory states that the cost or profit of a collaborative alliance should be fairly allocated to all participants when multiple participants form a collaborative alliance (Lozano et al., 2013; Kumoi and Matsubayashi, 2014; Chen et al., 2019). The fairness of cost or profit allocation is a crucial factor that determines whether the collaborative alliance can exist stably. Shapley (1953) proposed the Shapley value method to allocate the cost or profit through the marginal contributions of each collaborative members, which has many favorable properties in terms of efficiency, symmetric, and monotonicity, etc. (Cruijssen et al, 2010; Wang et al., 2020). On the basis of the basic premise of the Shapley value method, that is, a collaborative member will not participate in other forms of collaboration if it does not participate in a collaborative alliance, the profit allocated to collaborative participant l can be expressed as follows:

$$\psi_l(G,\upsilon)=\sum_{T\subset G,l\in T}\frac{|T|!(|G|-|T|-1)}{|G|!}\cdot(\upsilon(T\cup l)-\upsilon(T)) \tag{31}$$

Where υ represent the cost or profit to be shared, and the allocated profit for participant l is summarized in accordance with the product of the collaborative probability of participating alliance T and its marginal contribution $(\upsilon(T\cup l)-\upsilon(T))$. When a collaborative member receives additional profit for participating in a collaborative alliance, this part of the profit will serve as the incentive for the concerned member to maintain the collaboration because it offsets part of the original cost.

Particularly, the percentage of cost reductions obtained by collaborative member l from an alliance is given by

$$\zeta\left(l,\pi,\kappa\right)=\frac{\psi_l\left(\bigcup_{\pi(\omega)\le\kappa}\omega,\upsilon\right)}{C_0\left(l\right)},\kappa\ge\pi\left(l\right) \tag{32}$$

where the denominator is the original cost when the member l does not participate in collaborative alliance T, i.e., the cost of independent operation; the numerator represents the profit allocation value in collaborative sequence π when member l joins the collaborative alliance as the ω-th collaborative member; and κ represents the total number of cooperative members, i.e., $\kappa=|T|$. On the basis of the cost reduction percentage of each member in the alliance, we can then obtain a feasible collaboration sequence through a principle named strictly monotonous path (SMP), which denotes that when a new member takes part in the collaborative alliance, the members in the original collaborative alliance and the newly joined member simultaneously obtain an increasing cost reduction percentage (Cruijssen et al., 2010; Chen et al., 2019).

For the profit allocation problem under the traditional classic mode, the additional profit generated by the collaboration is usually taken as a part of the coordination cost of the collaboration organizer. This part of the profit is characterized by the coordination coefficient σ (Baruah et al., 2016). However, the organizer of a collaborative alliance in emergencies is usually a functional department, such as the government or a public welfare organization. They usually act as a public welfare organizer to coordinate all resources in response to emergencies. The value of this coefficient is thus set to zero. In other words, all additional profits are used to promote the profit allocation for achieving the formation and stable existence of collaborative alliances. At the same time, when the total cost in the emergency logistics network under collaboration is higher than the total cost under noncollaboration, the government uses a compensation mechanism to promote the formation of cooperation, i.e., the financial subsidy when a logistics facility joining a collaborative delivery.

$$\upsilon\left(T\right)=\left(1-\sigma\right)\max\left\{\sum_{l\in T}C_0\left(l\right)-C\left(T\right),0\right\} \tag{33}$$

where the coordination coefficient σ is set to zero for ensuring the maximum allocation of collaborative profit. The excess is the additional profit and is allocated to the participants in the collaborative alliance when the original cost of all members under noncollaboration is greater than the total cost of the collaborative alliance. On the contrary, the excess costs are compensated by the government when high costs are incurred by the collaboration to ensure the formation of collaboration in an emergency and the smooth delivery of life materials.

5. Empirical analyses

5.1. Algorithm comparison

The effectiveness and stability of the improved INSGA-II with elite strategy are verified in searching the Pareto frontier of the multi-objective problem. We obtain an improved Solomon dataset by replacing the coordinates in the original Solomon dataset (Solomon, 1987) with geographic coordinates based on the actual network. We compare and analyze the performance with the traditional NSGA-II (Deb et al., 2002) and multi-objective harmony search algorithm (MOHSA) (Alikar et al., 2017) in solving multi-objective problems from the perspective of the computation time, the total cost, and the total number of used vehicles. All three heuristic algorithms are executed on a personal computer with an Intel (R) Core (TM) i5-8565 1.8 GHz CPU and 8 GB RAM and on MATLAB. The three algorithms are executed under the same parameter settings with the same samples, and the relevant parameters are designed as follows: the number of generations (*NoGs*) is set as 200, and the number of populations (*NoPs*) is set to 100. The probabilities of crossover (*Pc*) and mutation (*Pm*) are initialized to 0.8 and 0.2, respectively. The specific calculation results, including the total cost (Cost), the number of used vehicles (Vehicle), and the total computing time (Time), *t*-test value and *p*-value are shown in Table 2.

Table 2 Best solutions obtained by the three heuristic algorithms with adjusted Solomon datasets

Instance	Proposed algorithm			NSGA-II			MOHSA		
	Cost	Vehicle	Time	Cost	Vehicle	Time	Cost	Vehicle	Time
C1_2_1	11293.4	11	187.34	12479.6	12	199.8	11479.6	12	213.3
C1_2_2	13121.6	13	189.49	13121.6	13	178.5	13739.9	13	201.2
C1_2_3	12378.2	11	203.66	13231.3	11	183.5	13361.3	11	203.1
C1_2_4	14028.3	14	185.89	15231.2	14	183.8	14028.3	14	188.2
C1_2_5	13836.4	15	194.9	13836.3	15	185.4	13836.4	15	199.9
C1_2_6	12697.7	15	189	13452.5	15	182.3	13366.7	15	199.2
C1_2_7	13052.3	16	191.2	14537.9	16	172.5	13052.3	16	189.2
C1_2_8	14023.2	13	199.6	15241.0	14	189.5	15242.4	14	200.1
C1_2_9	12931.7	16	207.5	12931.7	16	288.8	12481.5	16	221.2
C1_2_10	12037.8	14	201.5	12971.6	15	203.7	12971.6	15	211.2
C2_2_1	28204.1	19	226.6	29964.7	20	208.7	30304.1	21	240.2
C2_2_2	22361.2	20	243.6	22361.2	20	185.7	24333.4	20	273.1
C2_2_3	25335.5	22	266.3	26206.7	22	275.7	25335.5	22	244.2
C2_2_4	30608.3	24	235.7	31342.2	24	239.1	30608.3	24	239.1
C2_2_5	26235.7	23	244.1	26235.7	23	198.6	27732.7	23	278.2
C2_2_6	30113.2	21	234.9	30113.2	22	244.0	30113.2	21	291.2
C2_2_7	28805.7	26	267.5	29239.1	26	273.3	29239.1	26	249.1
C2_2_8	27957.4	28	268.4	30134.2	29	281.9	30134.2	29	277.1
C2_2_9	27240.2	23	254.8	27240.2	23	265.1	27240.2	23	258.1
C2_2_10	30579.5	27	245.2	31023.1	27	259.6	33234.2	27	265.2
Average	20342.07	18.55	221.859	21044.75	18.85	219.975	21091.75	18.85	232.105
t-test	-	-	-	-4.74	-	-	-3.69	-	-
p-value	-	-	-	1.43E-4	-	-	1.55E-03	-	-

Table 2 shows the best solutions for each improved Solomon dataset in five runs. From the perspective of cost optimization, the proposed algorithm frequently performs better than the traditional NSGA-II and MOHSA. In terms of the number of used vehicles, the results calculated by the traditional NSGA-II and MOHSA have the same optimization effectiveness but display worse results than the proposed algorithm. The improved NSGA-II algorithm is slightly inferior to the traditional NSGA-II in terms of calculation time because of the addition of tailored components, such as the generation of the initial population by the CW saving method. However, for the calculation example from C1_2_1 to C2_2_10 with 200 customers, the calculation time gap between the proposed algorithm and the traditional NSGA-II is less than 1% but it is still better than the MOHSA. Therefore, the improved NSGA-II algorithm has strong robustness and computational efficiency in calculating medium or large-scale multi-objective vehicle routing optimization problems. The 20 sets of test data are significantly uncorrelated from the t-test and p-value, thereby demonstrating the performance of the proposed algorithm on any case.

5.2. Data and parameter settings

To verify the effectiveness of the established model and designed algorithm for the emergency logistics network design problem. We select Chongqing's delivery network when COVID-19 broke out in early 2020 as the research object to verify the advantages of the emergency logistics strategy proposed in this paper in terms of cost, emergency response time, and resource utilization, as shown in Fig. 8. Fig. 8 shows the geographic locations of customers (i.e., C1,⋯, C210) and related logistics service facilities, including logistics delivery centers (i.e., DC1,⋯, DC6) and logistics delivery satellites (i.e., S1,⋯, S12) within the main city of Chongqing, China. In a non-emergency situation, each logistics center satisfies its affiliated customers' demands through the two-echelon logistics service network of "logistics delivery center–logistics delivery satellite–customers" under a relatively independent logistics operation mode. More specifically, the customers from C46 to C81 and delivery satellites S1 and S2 indicated by the black five-pointed star belong to the logistics delivery center DC1. Trucks with loading life materials are dispatched from DC1 to S1 and S2, and vehicles are used to complete delivery service for customers. Customer C50 whose geographical location is far from DC1 are still served by DC1, although an S12 is found in its vicinity that can provide the delivery service. When the COVID-19 occurred, many cross-regional roads are prolonged due to quarantine inspection. The customer's delivery service is severely affected by long-distance transportation when an emergency occurs. On the contrary, road traffic in the enclosed area is not affected because no risks of cross-regional contact are found. In this case, we optimize the design of the urban delivery network to complete the rapid, high-contingency, low-cost delivery of living supplies with limited transportation resources, such as transportation trucks or vehicles.

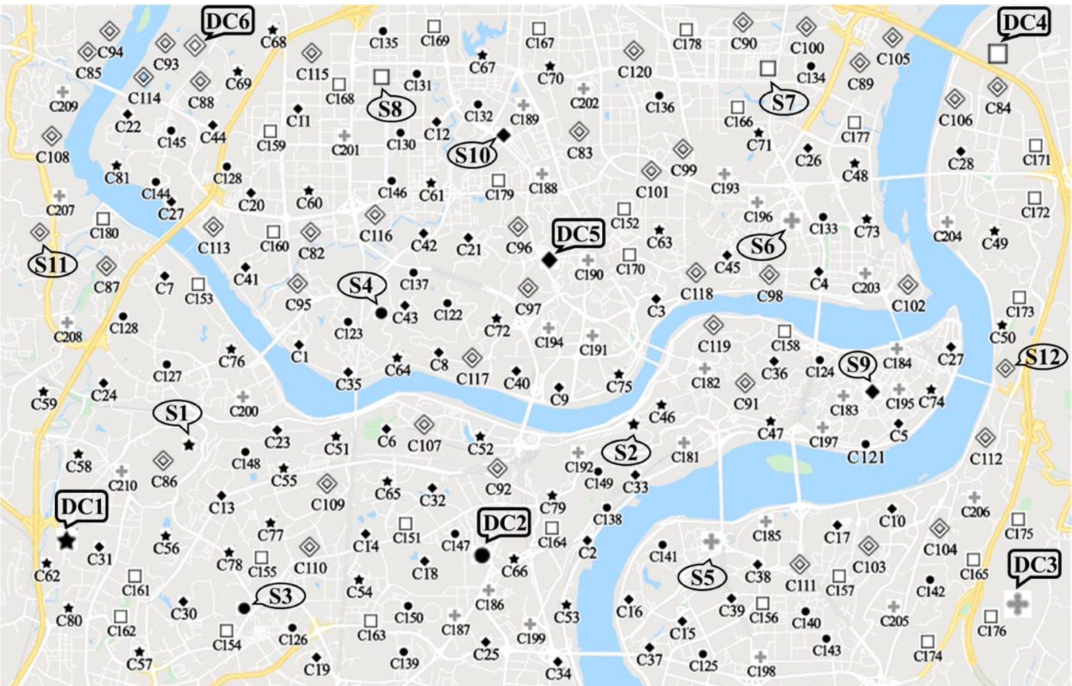

Fig. 8 Spatial distribution of customers and logistics facilities

In accordance with the actual logistics operating mode of logistics enterprises, combined with the parameter design of literature (Govindan et al, 2014; Wang et al., 2020), we set the input parameters as follows: maintenance cost for each truck $m_k = 1500$, maintenance cost for each vehicle $m_v = 200$, maintenance cost of facilities $m_{S1} = 990$, $m_{S2} = 840$, $m_{S3} = 510$, $m_{S4} = 780$, $m_{S5} = 1230$, $m_{S6} = 1320$, $m_{S7} = 1140$, $m_{S8} = 720$, $m_{S9} = 1590$, $m_{S10} = 780$, $m_{S11} = 1980$, $m_{S12} = 1260$, cost coefficient $\alpha_1 = 0.3$, $\alpha_2 = 0.1$, subsidy coefficient $\beta_1 = 0.5$, $\beta_2 = 0.2$, the number of running times *NoRs*=5, *NoGs*=500, *NoPs*=100, crossover probability *Pc*=0.8, and mutation probability *Pm*=0.2.

5.3. Results comparison to a non-emergency scenario

On the basis of the proposed emergency logistics strategy with state–space–time resource configuration, we list the customers and their corresponding service facilities before and after optimization in Table 3. The customer's delivery demands can be satisfied through the redesigned emergency logistics network based on the shared state–space–time collaborative network.

Table 3 Affiliation comparison of emergency and non-emergency scenarios

Optimized affiliation under emergency situations	DC1	S1	C13,C23,C24,C31,C55,C58,C59,C76,C86,C127,C148,C200,C200,C210
		S3	C6,C14,C18,C19,C30,C32,C51,C54,C56,C57,C62,C65,C77,C78,C80,C107,C109,C110,C126,C139,C150,C151,C154,C155,C161,C162,C163
	DC2	S2	C2,C25,C33,C34,C46,C52,C53,C66,C79,C92,C138,C147,C149,C164,C181,C186,C192,C199
		S9	C5,C27,C36,C47,C74,C91,C119,C121,C124,C158,C182,C183,C184,C195,C197
	DC3	S5	C15,C16,C17,C37,C38,C39,C103,C111,C125,C140,C141,C143,C156,C157,C185
		S12	C10,C50,C104,C112,C142,C165,C173,C174,C175,C176,C205,C206
	DC4	S6	C3, C4,C9,C40,C45,C73,C75,C97,C98,C102,C118,C133,C191,C194, ,C196,C203
		S7	C26,C28,C48,C49,C71,C84,C89,C90,C100,C105,C106,C134,C166,C171,C172,C177,C204
	DC5	S4	C1,C8,C35,C41,C42,C43,C64,C72,C82,C95,C116,C117,C122,C123,C137,C160
		S10	C12,C21,C63,C67,C70,C83,C96,C99,C101,C120,C132,C136,C152,C167,C170,C178,C179,C188,C189,C190,C193,C202
	DC6	S8	C11,C20,C44,C60,C61,C68,C69,C88,C113,C115,C128,C130,C131,C135,C146,C159,C168,C169,C201
		S11	C7,C22,C27,C81,C85,C87,C93,C94,C108,C114,C128,C144,C145,C153,C180,C207,C208,C209
Original affiliation under non-emergency situations	DC1	S1	C46,C47,C48,C49,C50,C51,C52,C53,C54,C55,C56,C57,C58,C59,C60,C61,C62,C63
		S2	C64,C65,C66,C67,C68,C69,C70,C71,C72,C73,C74,C75,C76,C77,C78,C79,C80,C81
	DC2	S3	C121,C122,C123,C124,C125,C126,C127,C128,C129,C130,C131,C132,C133,C134,C135,C136
		S4	C137,C138,C139,C140,C141,C142,C143,C144,C145,C146,C147,C148,C149,C150
	DC3	S5	C181,C182,C183,C184,C185,C186,C187,C188,C189,C190,C191,C192,C193,C194
		S6	C195,C196,C197,C198,C199,C200,C201,C202,C203,C204,C205,C206,C207,C208,C209,C210
	DC4	S7	C151,C152,C153,C154,C155,C156,C157,C158,C159,C160,C161,C162,C163,C164,C165
		S8	C166,C167,C168,C169,C170,C171,C172,C173,C174,C175,C176,C177,C178,C179,C180
	DC5	S9	C1,C2,C3,C4,C5,C6,C7,C8,C9,C10,C11,C12,C13,C14,C15,C16,C17,C18,C19,C20,C21,C22,C23,C24,C25
		S10	C26,C27,C28,C29,C30,C31,C32,C33,C34,C35,C36,C37,C38,C39,C40,C41,C42,C43,C44,C45
	DC6	S11	C82,C83,C84,C85,C86,C87,C88,C89,C90,C91,C92,C93,C94,C95,C96,C97,C98,C99,C100
		S12	C101,C102,C103,C104,C105,C106,C107,C108,C109,C110,C111,C112,C113,C114,C115,C116,C117,C118,C119,C120

The optimized second-echelon emergency logistics network based on the optimized affiliation under emergency situations is shown in Fig. 9. In each enclosed area, each customer can be served by an adjacent delivery satellite in this area. At the same time, the delivery satellite can be served by its neighboring delivery center in accordance with the affiliation in Table 3. Vehicles belonging to the same delivery center can be shared and used at different time periods to transport living materials for customers.

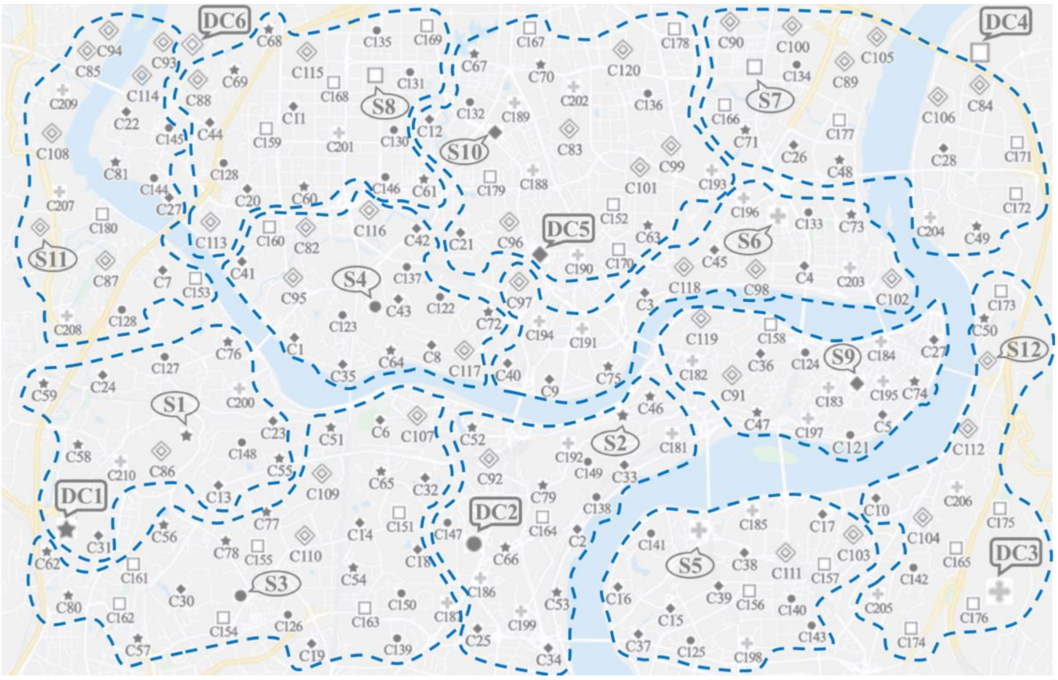

Fig. 9 Optimized logistics delivery network under the emergency scenario

In Fig. 9, the logistics delivery network is redesigned to reduce the risk of virus spread that potentially caused by cross-regional transportation. In the redesigned emergency logistics network, customers can be served by their relatively adjacent facilities in the enclosed area. Cross-regional transportation which requires a large amount of travel time due to the mandatory quarantine requirement and road traffic restrictions has been improved. To further demonstrate the merits of establishing collaborative alliances, we compare the travel time of logistics delivery operation in a non-collaborative mode and collaborative mode under the emergency situation, using DC1 in Fig. 9 as an example for ease of illustration. Specifically, Figs. 10 and 11 respectively show the shortest path from the DC1 under cross-regional non-collaborative and intra-regional collaborative scenarios. Table 4 lists the specific travel time of trucks under non-emergency non-collaborative (T.T.N) and emergency collaborative (T.T.E) scenarios.

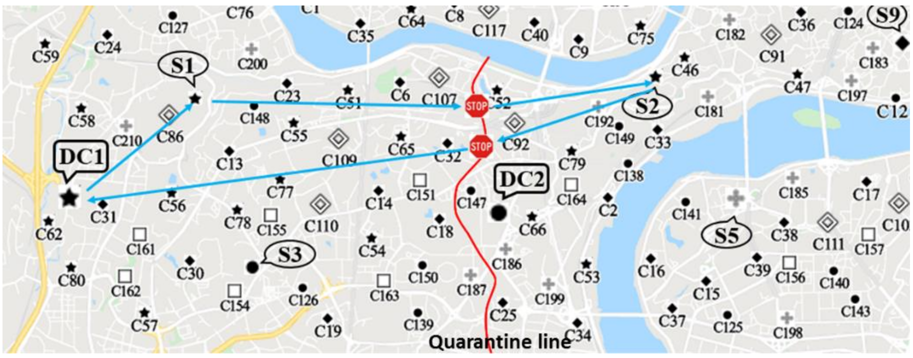

Fig. 10 The shortest delivery path from the DC1 under cross-regional and non-collaborative scenario

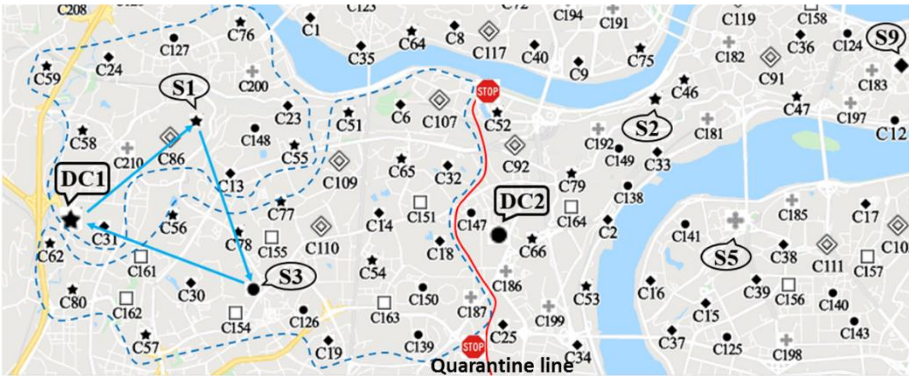

Fig. 11 The shortest delivery path from the DC1 under intra-regional and collaborative scenario

In Fig. 10 and 11, the red line is a quarantine boundary established in accordance with the administrative division, and necessary quarantine or inspection is imposed when trucks or vehicles travel across it. In Fig. 10, due to the lack of collaborative alliance between DC1 and other logistics facilities, trucks have to be dispatched to serve the satellite S1 and S2 independently, thereby resulting in an additional quarantine time when trucks travel from S1 to S2 and from S2 back to DC1. However, in Fig. 11, if collaborative alliances are established between DC1 and other logistics facilities, trucks are only dispatched from DC1 to serve the enclosed area close to it according to the optimized affiliation in Table 3, instead of undergoing the cross-regional transportation under a non-collaborative mode with a longer travel time as shown in Table 4.

Table 4 Travel time comparison of the truck from delivery centers to satellites under non-emergency (T.T.N) and emergency (T.T.E) scenarios (unit: h)

From / To	DC1		DC2		DC3		DC4		DC5		DC6	
	T.T.N	T.T.E	T.T.N	T.T.E	T.T.N	T.T.E	T.T.N	T.T.E	T.T.N	T.T.E	T.T.N	T.T.E
S1	**0.20**	**0.20**	0.38	0.47	0.57	0.73	0.67	0.92	0.47	0.55	0.40	0.48
S2	**0.52**	0.60	0.22	**0.22**	0.38	0.47	0.48	0.65	0.28	0.45	0.53	0.70
S3	0.22	**0.22**	**0.23**	0.32	0.43	0.60	0.68	0.93	0.55	0.63	0.50	0.58
S4	0.38	0.47	**0.32**	0.40	0.48	0.65	0.55	0.63	0.23	**0.23**	0.38	0.47
S5	0.58	0.75	0.33	0.42	**0.30**	**0.30**	0.50	0.58	0.33	0.50	0.62	0.87
S6	0.60	0.68	0.50	0.58	**0.38**	0.47	0.25	**0.25**	0.18	0.26	0.50	0.67
S7	0.67	0.83	0.45	0.53	0.42	0.50	**0.32**	**0.32**	0.20	0.28	0.45	0.62
S8	0.50	0.58	0.38	0.55	0.53	0.70	**0.50**	0.58	0.25	0.33	0.33	**0.33**
S9	0.53	0.62	0.33	**0.33**	0.40	0.48	0.42	0.50	**0.32**	0.48	0.62	0.78
S10	0.58	0.67	0.37	0.45	0.47	0.63	0.50	0.58	**0.18**	**0.18**	0.33	0.42
S11	0.33	0.42	0.53	0.70	0.57	0.73	0.62	0.78	0.48	0.57	**0.30**	**0.30**
S12	0.73	0.90	0.53	0.62	0.18	**0.18**	0.32	0.40	0.48	0.65	**0.65**	0.90

In accordance with the initial and optimized affiliations in Table 3, the travel time from each DC to its affiliated satellites under non-emergency and emergency scenarios are highlighted in bold. It can be seen that from the non-emergency mode to the emergency mode, most of the travel times increase due to quarantine or road restrictions. For example, the travel time from DC1 to its affiliated satellite S2 increases from 0.52 to 0.60 when an emergency occurs. On the contrary, in our designed optimized collaborative emergency logistics network, the travel times from DC1 to its new affiliated satellites S1 and S3 still maintain the lowest values for collaboration and the trucks will travel in an enclosed area rather than across regions.

In this case, the government promotes collaboration between different transportation companies through subsidies and other incentives, redistributed the delivery area, and reassigned resources to meet and stabilize customer demands by sharing customer service in relatively enclosed areas. Thus, the risk of virus transmission caused by cross-regional contact is reduced while increasing the speed of emergency logistics in the case of limited transportation resources and reducing the operating cost for logistics enterprises. In accordance with the optimization results, the shortest paths based on the state–space–time network for DC3-centered closed delivery are illustrated in Fig. 12.

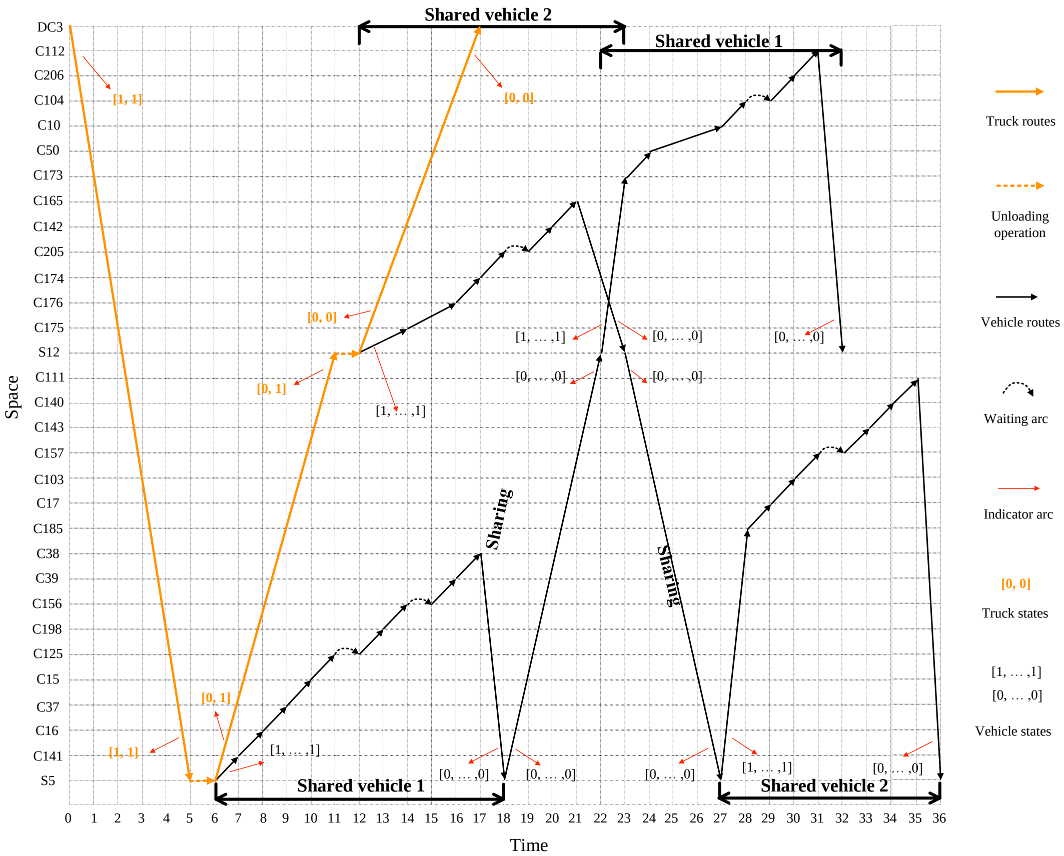

Fig. 12 Shortest paths in the state–space–time network of one truck and two vehicles

In Fig. 12, the orange line shows that in the first-echelon network, a truck full of living materials with the state of [1,1] departs from DC3, transports these living materials to S5 and S2, and returns to DC3 with the state of [0,0]. Given that the truck only serves two satellite facilities, the state is [1,1] when the truck is fully loaded, and the state becomes [0,0] after the delivery is completed. Similarly, the black line represents the process where living materials are delivered from the delivery satellite to the customers in the second-echelon network. The vehicle's state changes from 1 to 0 when the customer delivery task is completed. [1,⋯,1] denotes that the vehicle is full of a series of customers' demand, and [0,⋯,0] indicates that all customer demands are satisfied. The number of used service vehicles changes from three to two because of the sharing mode in different service periods and the sharing of vehicles in the enclosed area. In accordance with the affiliation of delivery services under emergency and non-emergency situations, we calculate the total cost, the total transportation time, and the number of used vehicles under collaborative and non-collaborative networks respectively, as shown in Table 5.

Table 5 Result comparison between non-emergency and emergency scenarios

Scenario	Case	Delivery time (h)	Waiting time (h)	Transportation cost ($)	Penalty cost ($)	Rental cost ($)	Total cost ($)	Total time (h)	Number of vehicles
Non-emergency	Non-collaborative network	45.8	4.5	32539.2	3381.1	6000	41920.3	50.3	30 (0*)
Emergency	Non-collaborative network	49.6	14.5	38317.3	10853.3	6800	55970.6	64.1	34 (0*)
	Collaborative network	40.3	4.1	30779.5	3069.9	4000	**37849.4**	**44.4**	**20 (18*)**

*: The number of shared vehicles.

In an emergency scenario, adopting a collaborative strategy can effectively improve the emergency response speed (i.e., 44.4h) at a low cost (i.e., $37,849.4) while reducing the number of used vehicles (i.e., 20 vehicles) with 18 shared vehicles. We can easily speculate that in a non-emergency scenario, the collaborative mode can perform better in cost savings, delivery timeliness, and resource utilization by comparing the total cost, the total time, and the total number of vehicles used. However, this collaborative mode is rarely used in the actual operation of logistics enterprises. Therefore, we conduct a comparative analysis of the cost before and after optimization under emergency and non-emergency situations to explore the formation of the collaborative alliances and the influencing factors of their stabilities. Fig. 13 shows the cost comparison of 63 collaborative alliances that may be formed through the cooperation of six members.

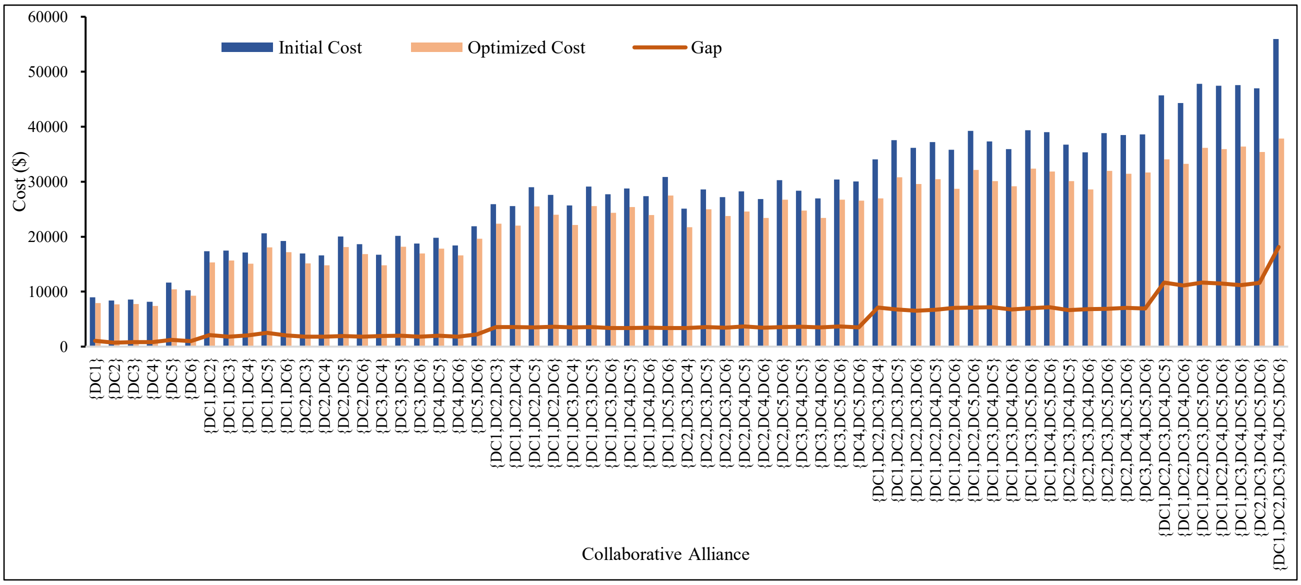

Fig. 13 Cost comparison of 63 possible collaborative alliances

As shown in Fig. 13, the cost gap before and after optimization gradually increases under an emergency situation with the increase of the number of alliance members until they form a grand collaborative alliance to achieve the maximum cost savings, $18,121.2. For the entire logistics delivery network, the adoption of a collaborative delivery mode can reduce the high transportation costs caused by unreasonable transportation, such as excessive transportation.

5.4. Results comparison to non-shared vehicle scenario

According to the optimized results shown in Fig. 12 and Table 5 in Section 6.2, we find that using shared vehicles in the second-echelon logistics network reduces the demand for transportation resources with a fixed cost for using additional vehicles. Fig. 14 clearly shows the state–space–time-based shortest paths of the truck and vehicles when the customer service can be shared in the delivery process but the vehicles cannot be shared between different satellite facilities.

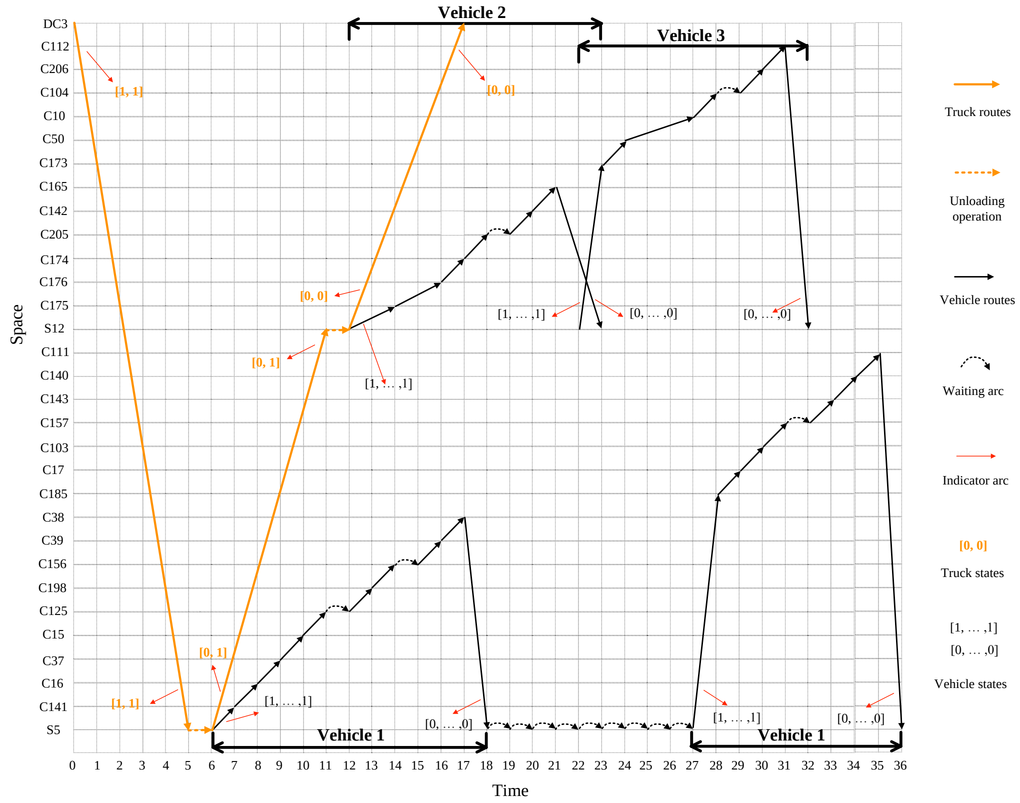

Fig. 14 Shortest paths in the state–space–time network of one truck and three vehicles

In Fig. 14, vehicles are needed to wait in the satellite facility or additionally dispatch from the delivery satellite for new delivery tasks because of the non-shared vehicles. Therefore, the number of vehicles changes from two shared vehicles to three non-shared delivery vehicles. Vehicle 1 is in a waiting state for a long time. In an emergency situation where transportation resources are relatively scarce, such idle transportation resources evidently have great disadvantages. We then compare the difference between modes with shared and non-shared vehicles in terms of travel time, waiting time, and other aspects.

Table 6 Result comparison between shared and non-shared vehicle scenarios

Scenario	Delivery time (h)	Waiting time (h)	Transportation cost ($)	Penalty cost ($)	Rental cost ($)	Total cost ($)	Total time (h)	Number of vehicles
Shared vehicles	3.7	0.6	3425.2	320	400	4145.2	4.3	2 (2*)
Non-shared vehicles	4.2	1.0	3824.2	1120	600	5544.2	5.2	3 (0*)

*: The number of shared vehicles.

In Table. 6, adopting a vehicle-sharing mode between different satellites in the same enclosed area can evidently reduce the total cost (i.e., $4,145.2) and simultaneously improve the emergency response speed with less total time (i.e., 4.3 h). From the composition of the total cost, the vehicle-sharing-based delivery mode can reduce the number of used vehicles (i.e., two shared vehicles), thereby reducing vehicle rental costs. The transportation and penalty costs under the vehicle-sharing mode are lower than those in the non-shared mode because of the reduced waiting time. Therefore, the shared use of vehicles has a remarkable cost-saving advantage on the basis of the collaborative mode.

5.5. Results of profit allocation

For each collaboration participant, the reasonableness of the profit allocation is a key factor that determines whether he/she is willing to participate in the collaborative alliance. Therefore, for this part of the cost savings, i.e., additional profit, we compare four profit/cost allocation methods, namely, Shapley value method (SVM), nucleus method (NM), cost gap allocation method (CGAM), and equal profit method (EPM) (Shapley, 1964; Tijs and Driessen, 1986; Kumoi and Matsubayashi, 2014). On the basis of "Snowball" theory (Lozano et al., 2013), we select the Shapley value method as the profit allocation method based on the core distance between the core center and the result of each method.

Table 7 Core distance comparison in accordance with SVM, NM, CGAM, EPM, and Core center

Facility	SVM	NM	CGAM	EPM	Core center
DC1	3211.4	2902.7	3189.4	3400.8	2944.4
DC2	2992.4	3232.7	3301.6	2332.0	3150.2
DC3	2938.4	3142.7	2948.2	2623.4	2996.8
DC4	2944.1	3157.7	3202.4	2574.9	2925.6
DC5	3209.2	2737.7	2792.3	3935.2	3180.1
DC6	2825.7	2947.7	2687.3	3255.0	2924.0
Distance	**332.4**	529.2	607.0	1349.0	-

In accordance with the results shown in Table 7, the SVM is selected as the fair allocation strategy for the additional profit of the smallest core distance (i.e., 332.4) between this method and the core center (2944.4, 3150.2, 2996.8, 2925.6, 3180.1, 2924.0). Therefore, the SVM can be considered to be beneficial to the stable maintenance of the collaborative alliance. SVM is widely used in cost/profit allocation based on the marginal contribution value of each member to the alliance. The specific profit allocation results are shown in Table 8.

Table 8 Profit allocation based on Shapley value method under the 63 possible collaborative alliances

Alliance	DC1	DC2	DC3	DC4	DC5	DC6
{DC1}	1050.0	-	-	-	-	-
{DC2}	-	720.0	-	-	-	-
{DC3}	-	-	810.0	-	-	-
{DC4}	-	-	-	795.0	-	-
{DC5}	-	-	-	-	1215.0	-
{DC6}	-	-	-	-	-	1005.0
{DC1,DC2}	1209.2	879.2	-	-	-	-
{DC1,DC3}	1035.2	-	795.2	-	-	-
{DC1,DC4}	1156.7	-	-	901.7	-	-
{DC1,DC5}	1179.9	-	-	-	1344.9	-
{DC1,DC6}	1041.9	-	-	-	-	996.9
{DC2,DC3}	-	868.3	958.3	-	-	-
{DC2,DC4}	-	853.5	-	928.5	-	-
{DC2,DC5}	-	711.9	-	-	1206.9	-
{DC2,DC6}	-	768.6	-	-	-	1053.6
{DC3,DC4}	-	-	958.3	943.3	-	-
{DC3,DC5}	-	-	801.9	-	1206.9	-
{DC3,DC6}	-	-	818.1	-	-	1013.1
{DC4,DC5}	-	-	-	786.9	1206.9	-
{DC4,DC6}	-	-	-	803.1	-	1013.1
{DC5,DC6}	-	-	-	-	1223.1	1013.1
{DC1,DC2,DC3}	1327.2	1160.4	1076.3	-	-	-
{DC1,DC2,DC4}	1376.0	1072.8	-	1095.3	-	-
{DC1,DC2,DC5}	1329.6	861.6	-	-	1327.3	-
{DC1,DC2,DC6}	1372.1	1098.8	-	-	-	1142.5
{DC1,DC3,DC4}	1269.4	-	1071.0	1177.5	-	-
{DC1,DC3,DC5}	1261.9	-	883.8	-	1433.6	-
{DC1,DC3,DC6}	1216.4	-	992.7	-	-	1194.4
{DC1,DC4,DC5}	1233.2	-	-	840.2	1283.4	-
{DC1,DC4,DC6}	1276.3	-	-	1037.6	-	1132.8
{DC1,DC5,DC6}	1120.8	-	-	-	1302.1	954.0
{DC2,DC3,DC4}	-	1067.7	1172.6	1142.7	-	-
{DC2,DC3,DC5}	-	1050.5	1140.5	-	1389.1	-

{DC2,DC3,DC6}	-	1076.8	1126.4	-	-	1221.6
{DC2,DC4,DC5}	-	1073.7	-	1148.7	1427.1	-
{DC2,DC4,DC6}	-	1081.5	-	1116.1	-	1241.1
{DC2,DC5,DC6}	-	939.8	-	-	1394.3	1241.0
{DC3,DC4,DC5}	-	-	1123.7	1108.7	1372.2	-
{DC3,DC4,DC6}	-	-	1161.9	1146.9	-	1216.7
{DC3,DC5,DC6}	-	-	1020.8	-	1425.8	1232.0
{DC4,DC5,DC6}	-	-	-	951.6	1371.6	1177.8
{DC1,DC2,DC3,DC4}	1929.3	1727.6	1725.8	1744.8	-	-
{DC1,DC2,DC3,DC5}	1768.0	1556.6	1578.8	-	1829.8	-
{DC1,DC2,DC3,DC6}	1767.1	1627.5	1521.4	-	-	1636.9
{DC1,DC2,DC4,DC5}	1751.9	1592.4	-	1571.0	1803.0	-
{DC1,DC2,DC4,DC6}	1918.3	1723.4	-	1662.2	-	1758.8
{DC1,DC2,DC5,DC6}	1829.8	1648.7	-	-	1876.6	1741.2
{DC1,DC3,DC4,DC5}	1837.4	-	1727.9	1684.2	1940.3	-
{DC1,DC3,DC4,DC6}	1750.7	-	1636.3	1681.2	-	1698.1
{DC1,DC3,DC5,DC6}	1734.7	-	1634.6	-	1944.0	1704.8
{DC1,DC4,DC5,DC6}	1825.2	-	-	1655.9	1920.4	1769.8
{DC2,DC3,DC4,DC5}	-	1558.4	1608.4	1616.6	1862.9	-
{DC2,DC3,DC4,DC6}	-	1626.7	1707.2	1696.8	-	1775.7
{DC2,DC3,DC5,DC6}	-	1561.2	1642.2	-	1910.1	1742.7
{DC2,DC4,DC5,DC6}	-	1662.2	-	1674.0	1952.3	1766.3
{DC3,DC4,DC5,DC6}	-	-	1684.2	1615.0	1893.8	1738.3
{DC1,DC2,DC3,DC4,DC5}	2460.5	2181.5	2317.0	2309.1	2394.1	-
{DC1,DC2,DC3,DC4,DC6}	2333.5	2209.6	2122.4	2263.3	-	2167.7
{DC1,DC2,DC3,DC5,DC6}	2377.9	2204.5	2190.4	-	2533.3	2352.7
{DC1,DC2,DC4,DC5,DC6}	2351.9	2188.9	-	2196.1	2398.2	2366.3
{DC1,DC3,DC4,DC5,DC6}	2275.9	-	2134.9	2156.2	2419.0	2176.8
{DC2,DC3,DC4,DC5,DC6}	-	2218.9	2240.9	2272.7	2486.0	2398.8
{DC1,DC2,DC3,DC4,DC5,DC6}	3211.4	2992.4	2938.4	2944.1	3209.2	2825.7

Table 8 shows the profit allocation results of 63 possible collaborative alliances. DC1, DC2, DC3, DC4, DC5, and DC6 receive profits of 3211.4, 2992.4, 2938.4, 2944.1, 3209.2, and 2825.7, respectively, when all logistics center facilities form a shared delivery alliance. To explore the incentives of the allocated profits for each member, we use Eq. (32) to calculate the percentage of cost reduction for each member in each collaborative alliance. Taking DC1 as the first participant of the collaborative alliance as an example, we obtain collaborative alliance routes that satisfy the SMP, as shown in Fig. 15.

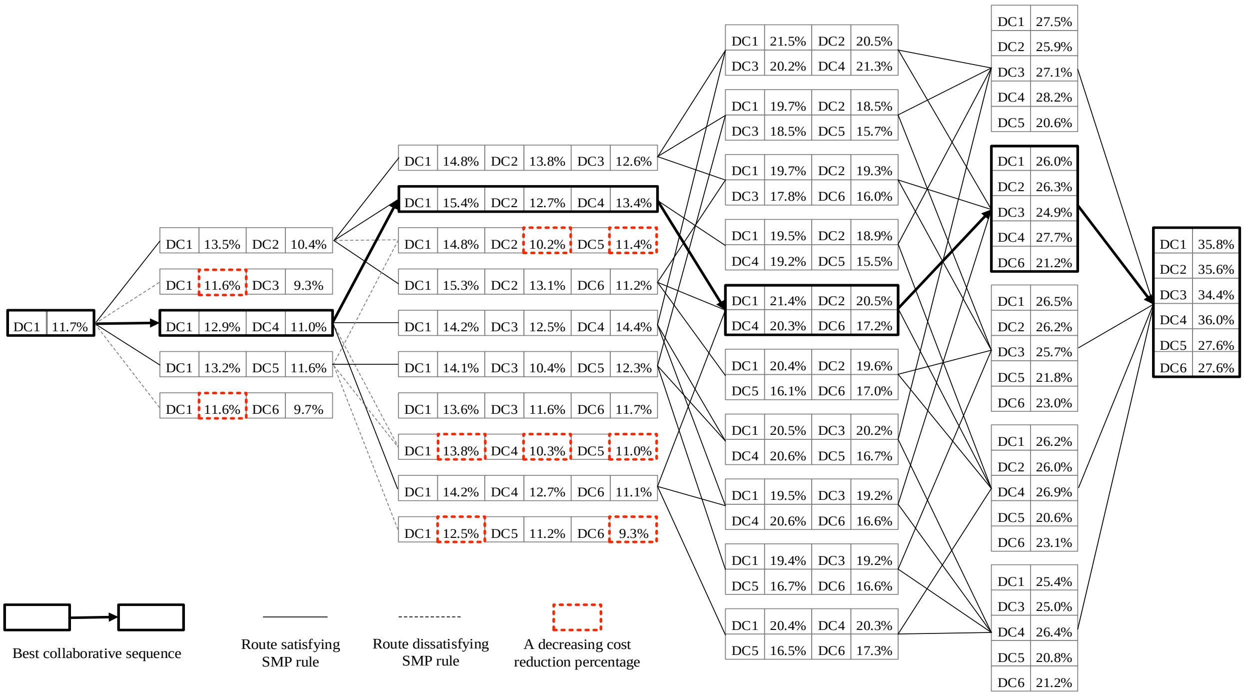

Fig. 15 Collaborative alliance routes that satisfy the SMP

As shown in Fig. 15, an incremental cost reduction percentage is obtained that can satisfy the SMP when a new member takes part in the collaborative alliance, including the members in the original collaborative alliance and the newly joined member (Cruijssen et al., 2010). Conversely, a collaborative sequence that violates the SMP is considered an unreasonable collaborative sequence, which is highlighted with a red dotted box and needs to be eliminated because the addition of new members damages the interests of the original alliance members. Fig. 15 shows the gradual deepening of the collaborative alliance from left to right. The collaborative sequence is terminated when the dotted line connection appears in the collaborative sequence, that is, SMP is unsatisfied. Among the many feasible collaboration sequences, we determine the optimal collaborative strategy through a strategy called maximizing the minimum cost reduction percentage. On the basis of this strategy, each member can save the largest cost percentage when participating in the collaborative alliance, that is, DC1 first, followed by DC4, DC2, DC6, DC3, and DC5. During the formation of the best collaborative sequence, the percentage change in the cost reduction of each member is shown in Fig. 16.

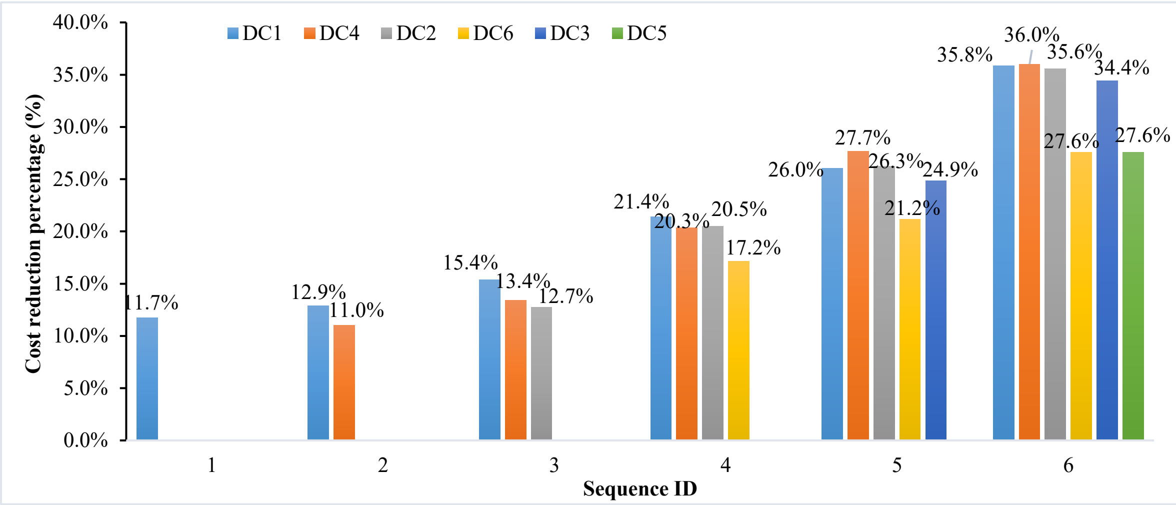

Fig. 16 Cost reduction percentages for the best collaborative sequence

In Fig. 16, DC1 first joins the collaborative alliance and receives 11.7% of the cost reduction, and DC4 joins the collaborative alliance. The cost reduction percentage of DC1 increases from 11.7% to 12.9%, and DC4 receives 11.0% of the cost reduction. DC2, DC4, DC6, DC3, and DC5 enter the collaborative alliance until all the members join. In the grand collaborative alliance of {DC1, DC4, DC2, DC6, DC3, DC5}, the members in grand collaborative alliance obtain the largest cost savings of 35.8%, 36.0%, 35.6%, 27.6%, 34.4%, and 27.6%, respectively.

5.6. Managerial implications

Ensuring the continuous supply of living materials is an important measure to maintain social stability when natural disasters or emergencies occur. In particular, a connectable emergency logistics network and an effective emergency logistics strategy are the prerequisites for achieving this goal. On the basis of the background of the COVID-19 outbreak in 2020, this study proposes an emergency logistics network under a collaborative delivery mode and the conditions of cross-regional roadblocks and limited resources by using the existing road transportation network. This study can provide theoretical and practical references for the formulation of government emergency response policies and the design of logistics enterprise delivery models.

From the perspective of decision-makers and business operation managers, this study has the two following implications. On the one hand, government administrators can impose cross-regional transportation and quarantine policies by promoting the collaboration of multiple enterprises and facilities and forming alternative services in enclosed areas to ensure the normal supply of residents' living materials and reduce the risk of virus transmission due to cross-regional transportation. On the other hand, logistics companies under the collaborative delivery mode can reduce the quarantine cost and waiting time caused by cross-regional transportation and utilize tight transportation resources through customer service sharing and vehicle sharing. Therefore, this study has promotion significance in the emergency logistics design, especially in emergency logistics network design where roads are undamaged and man-made traffic restrictions, such as epidemic situations, are found in terms of transportation cost, emergency response speed, and full use of transportation resources.

6. Conclusions

This study focuses on the optimal design of emergency logistics network in the face of a natural disaster or some unexpected events considering the multi-facility collaboration and multiple objectives. To address the problem, we first establish a state–space–time network-based mixed-integer programming model to characterize the basic operating mode and optimal design of a two-echelon emergency logistics network. Due to government macro-control and financial subsidies, cross-regional transportation is reduced in emergencies and the service area should be divided into multiple sub-regions based on customer geographic location and time windows. Therefore, we develop a 3D *k*-means clustering algorithm considering the time window and geographic coordinate indices to decompose the complex network into multiple subnetworks with enclosed areas. In multiple subregions, we consider multiple objectives in terms of the delivery cost, the delivery time, and the number of vehicles in order to obtain good-quality solutions that meet the customer demands with low costs and high emergency response speed in the case of limited transportation resources. As such, we combine the improved CW saving method and the improved NSGA-II algorithm with elite retention mechanism to search for Pareto frontiers in the multi-objective NP-hard problem. A case study in Chongqing, China has demonstrated that the proposed two-stage hybrid heuristic algorithm is stable and excellent in terms of calculation and optimization performance. Taking cost as the main indicator, we also discuss the additional profits that logistics companies gain from participating in collaborative alliances and the optimal collaborative sequence to maintain the stability of the alliance. It shows that the proposed collaborative strategy has a clear positive effect on the optimization of emergency logistics networks.

This study is conducted based on the assumption that the government can guarantee the stability of demand through purchase restriction or quantitative supply. In the future, the emergency logistics network optimization under demand uncertainty should be considered for more practical applications of the proposed model and methods. In addition, cost savings are considered as the sole incentives for logistics companies to form the collaborative alliances in the current study. Other factors for the formation and maintenance of collaboration such as the government regulation and the special industry standards in case of an emergency can be further explored. Last but not the least, the emergency scenarios considered by this study are concerned with general natural disasters or accidents. It would be very interesting to focus on one particular scenario and incorporate its special characteristics in the model. For example, for the outbreak of COVID-19 pandemic, we can introduce a virus transmission model and evaluate the advantages and disadvantages of the collaborative strategy based on the breadth of virus transmission.

Acknowledgments

This research is supported by National Natural Science Foundation of China (Project No. 71871035), Humanity and Social Science Youth Foundation of Ministry of Education of China (No. 18YJC630189), Key Science and Technology Research Project of Chongqing Municipal Education Commission (No. KJZD-K202000702), Social Science Planning Foundation of Chongqing of China (No. 2019YBGL054), and Key Project of Human Social Science of Chongqing Municipal Education Commission (No. 20SKGH079), This research is supported by 2018 Chongqing Liuchuang Plan Innovation Project (No. cx2018111).

References

Akbari, V., Salman, F. S., 2017. Multi-vehicle synchronized arc routing problem to restore post-disaster network connectivity. European Journal of Operational Research, 257(2): 625-640.

Alikar, N., Mousavi, S. M., Ghazilla, R. A. R., Tavana, M., Olugu, E. U., 2017. Application of the NSGA-II algorithm to a multi-period inventory-redundancy allocation problem in a series-parallel system. Reliability Engineering & System Safety, 160: 1-10.

Balcik, B., 2017. Site selection and vehicle routing for post-disaster rapid needs assessment. Transportation Research Part E: Logistics and Transportation Review, 101: 30-58.

Balcik, B., Beamon, B. M., 2008. Facility location in humanitarian relief. International Journal of Logistics-Research and Applications, 11(2): 10-121.

Baruah, P., Chinnam, R. B., Korostelev, A., Dalkiran, E., 2016. Optimal soft-order revisions under demand and supply uncertainty and upstream information. International Journal of Production Economics, 182: 14-25.

Bayram, V., Yaman, H., 2015. A stochastic programming approach for shelter location and evacuation planning. RAIRO-Operations Research, 52(3): 779-805.

Berktas, N., Kara, B.Y., Karasan, O. E., 2016. Solution methodologies for debris removal in disaster response. EURO Journal on Computational Optimization, 4: 403-445.

Camacho-Vallejo, J. F., Gonzalez-Rodriguez, E., Almaguer, F. J., Gonzalez-Ramirez, R. G., 2015. A bi-level optimization model for aid distribution after the occurrence of a disaster. Journal of Cleaner Production, 105: 134-145.

Campbell, A. M., Vandenbussche, D., Hermann, W., 2008. Routing for relief efforts. Transportation Science, 42(2): 127-145.

Celik, M., Ergun, O., Johnson, B., Keskinocak, P., Lorca, A., Pekgun, P., Swann, J., 2012. Humanitarian logistics. In: INFORMS Tutorials in Operations Research: New Directions in Informatics, Optimization, Logistics, and Production. INFORMS, USA, 18-49.

Chen, X., Gao, X. Y., Hu, Z. Y., Wang, Q., 2019. Population monotonicity in newsvendor game. Management Science, 65(5): 2142-2160.

Clarke, G., Wright, J. W., 1964. Scheduling of vehicles from a central depot to a number of delivery points. Operations Research, 12: 568-581.

Cleophas, C., Cottrill, C., Ehmke, J. F., Tierney, K., 2019. Collaborative urban transportation: Recent advances in theory and practice. European Journal of Operational Research, 273(3): 801-816.

Cruijssen, F., Borm, P., Fleuren, H., Hamers, H., 2010. Supplier-initiated outsourcing: a methodology to exploit synergy in transportation. European Journal of Operational Research, 207(2): 763-774.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multi-objective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 6: 182-197.

Duque, P. M., Dolinskaya, I. S., Sörensen, K., 2016. Network repair crew scheduling and routing for emergency relief

distribution problem. European Journal of Operational Research, 248(1): 272-285.
Duque, P. M., Sörensen, K., 2011. A GRASP metaheuristic to improve accessibility after a disaster. OR Spectrum, 33(3), 525-542.
Galindo, G., Batta, R., 2013. Review of recent developments in OR/MS research in disaster operations management. European Journal of Operational Research, 230(2): 201-211.
Gansterer, M., Hartl, R. F., 2020. Shared resources in collaborative vehicle routing. TOP, 28(1): 1-20.
Govindan, K., Jafarian, A., Khodaverdi, R., Devika, K., 2014. Two-echelon multiple vehicle location-routing problem with time windows for optimization of sustainable supply chain network of perishable food. International Journal of Production Economics, 152: 9-28.
Hamacher, H. W., Tjandra, S.A., 2001. Mathematical Modelling of Evacuation Problems: A state of Art. Fraunhofer-Institut fur Techno-und Wirtschaftsmathematik, Fraunhofer (ITWM), Kaiserslautern.
Holguín-Veras, J., Jaller, M., Van Wassenhove, L. N., Pérez, N., Wachtendorf, T., 2012. On the unique features of post-disaster humanitarian logistics. Journal of Operations Management, 30(7–8): 494-506.
Huang, M., Ren, L., Lee, L. H., Wang, X. W., 2015. 4PL routing optimization under emergency conditions, Knowledge-Based Systems, 89: 126-133.
Huang, M., Smilowitz, K., Balcik, B., 2013. A continuous approximation approach for assessment routing in disaster relief. Transportation Research Part B: Methodological, 50: 20-41.
Karlaftis, M. G., Kepaptsoglou, K. L., Lambropoulos, S., 2007. Fund allocation for transportation network recovery following natural disasters. Journal of Urban Planning and Development, 133(1): 82-89.
Kumoi, Y., Matsubayashi, N., 2014. Vertical integration with endogenous contract leadership: Stability and fair profit allocation. European Journal of Operational Research, 238: 221-232.
Lozano, S., Moreno, P., Adenso-Díaz, B., Algaba, E., 2013. Cooperative game theory approach to allocating benefits of horizontal cooperation. European Journal of Operational Research, 229: 444-452.
Mahmoudi, M., Zhou, X. S., 2016. Finding optimal solutions for vehicle routing problem with pickup and delivery services with time windows: a dynamic programming approach based on state–space–time network representations. Transportation Research Part B: Methodological, 89: 19-42.
Oruc, B. E., Kara, B. Y., 2018. Post-disaster assessment routing problem. Transportation Research Part B: Methodological, 116: 76-102.
Osman, M. S., Ram, B., 2017. Routing and scheduling on evacuation path networks using centralized hybrid approach. Computers & Operations Research, 88: 332-339.
Ozguven, E. E., Ozbay, K., 2012. Case Study-Based Evaluation of Stochastic Multicommodity Emergency Inventory Management Model. Transportation Research Record, 2283: 12-24.
Ozkapici, D. B., Ertem, M. A., Aygunes, H., 2016. Intermodal humanitarian logistics model based on maritime transportation in Istanbul. Natural Hazards, 83(1): 345-364.
Rancourt, M. È., Cordeau, J. F., Laporte, G., Watkins, B., 2015. Tactical network planning for food aid distribution in Kenya. Computers & Operations Research, 56: 68-83.
Rath, S., Gutjahr, W. J., 2014. A math-heuristic for the warehouse location–routing problem in disaster relief. Computers & Operations Research, 42: 25-39.
Sahin, H., Kara, B. Y., Karasan, O. E., 2016. Debris removal during disaster response: a case for turkey. SOCIO-Economic Planning Sciences, 53: 49-59.
Santos, M. J., Amorim, P., Marques, A., Carvalho, A., Povoa, A., 2020. The vehicle routing problem with backhauls towards a sustainability perspective: a review. TOP, 28(2): 358-401.
Shapley, L. S., 1953. A value for n-person games. Annals of Mathematics Study, 28: 307-317.
Sheu, J. B., 2007. An emergency logistics distribution approach for quick response to urgent relief demand in disasters.

Transportation Research Part E: Logistics and Transportation Review, 43(6): 687-709.
Shin, Y., Kim, S., Moon, I., 2019. Integrated optimal scheduling of repair crew and relief vehicle after disaster. Computers & Operations Research, 105: 237-247.
Solomon, M., 1987. Algorithms for the vehicle routing and scheduling problems with time window constraints. Operations Research, 35(2): 254-265.
Tijs, S. N., Driessen, T. S. H., 1986. Game theory and cost allocation problems. Management Science, 32: 1015-1028.
Wang, Y., Yuan, Y. Y., Guan, X. Y., Xu, M. Z., Wang, L., Wang, H. Z., Liu, Y., 2020. Collaborative two-echelon multicenter vehicle routing optimization based on state-space-time network representation. Journal of Cleaner Production, 258: 120590.
Wang, Y., Zhang, J., Assogba, K., Liu, Y., Xu, M. Z., Wang, Y. H., 2018. Collaboration and transportation resource sharing in multiple centers vehicle routing optimization with delivery and pickup. Knowledge-Based Systems, 160: 296-310.
Yan, S., Shih, Y. L., 2009. Optimal scheduling of emergency roadway repair and subsequent relief distribution. Computers & Operations Research, 36(6): 2049-2065.
Zhang, M. X., Yan, H. F., Wu, J. Y., Zheng, Y. J., 2020. Quarantine Vehicle Scheduling for Transferring High-Risk Individuals in Epidemic Areas. International Journal of Environmental Research and Public Health, 17(7): 2275.
Zhang, S. W., Guo, H. X., Zhu, K. J., Yu, S. W., Li, J. L., 2017. Multistage assignment optimization for emergency rescue teams in the disaster chain. Knowledge-Based Systems, 137: 123-137.
Zhou, X. Y., Shi, Y. Q. Y., Deng, X. Y., Deng, Y., 2017. D-DEMATEL: a new method to identify critical success factors in emergency management. Safety Science, 91: 93-104.

Appendix

Some symbol definitions and explanations are utilized to construct the time-discrete two-echelon emergency logistics network optimization model and can be listed below.

Set

ϕ_k : Set of state–space–time arcs in truck k's pickup and delivery network, $k \in K$.

ϕ_v : Set of state–space–time arcs in vehicle v's pickup and delivery network, $v \in V$.

Input parameters

m_k : Maintenance cost for each truck.

m_l : Maintenance cost of facility l, $l \in L$.

m_v : Maintenance cost for each vehicle.

m_s : Maintenance cost of logistics satellite s, $s \in S$.

$\left[Et_j, Lt_j\right]$: Service time windows for the logistics facility or satellite $j, j \in L \cup S$.

$\left[Et_q, Lt_q\right]$: Service time windows for the logistics satellite or customer $q, q \in L \cup D$.

Tt_{ijk} : Travel time of truck k traveling from node i to node j.

Tt_{pqv} : Travel time of vehicle v traveling from node p to node q.

Q_j^k : Delivery demand of logistics facility j served by truck k.

Q_q^v : Delivery demand of customer q served by vehicle v.

α_1 : Cost coefficient when the first-echelon logistics center facilities form a collaborative alliance.

α_2 : Cost coefficient when the second-echelon logistics satellites form a collaborative alliance.

β_1: Subsidy coefficient when the first-echelon facilities form a collaborative alliance.

β_2: Subsidy coefficient when the second-echelon satellites form a collaborative alliance.

Decision variables

$x_{(i,j,t,t',\omega,\omega',k)}$: Decision variables. If truck *k* travels from node *i* at time *t* in state ω and arrives at node *j* at time *t'* in state ω', $x_{(i,j,t,t',\omega,\omega',k)}=1$; otherwise $x_{(i,j,t,t',\omega,\omega',k)}=0$.

$y_{(p,q,\tau,\tau',w,w',v)}$: Decision variables. If vehicle *v* travels from node *p* at time *t* in state *w* and arrives at node *q* at time *t'* in state w', $y_{(p,q,\tau,\tau',w,w',v)}=1$; otherwise $y_{(p,q,\tau,\tau',w,w',v)}=0$.

θ_l: Decision variables. If delivery center *l* joins in the collaborative alliance, $\theta_l=1$; otherwise $\theta_l=0$.

Other variables

c_l: Collaborative cost when delivery center *l* joins in the collaborative alliance.

λ_l: Financial subsidy from the government that depends on delivery center *l*'s service demand.

Dt_i^k: Departure time of truck *k* from logistics delivery center *i*.

At_j^k: Arrival time of truck *k* at the logistics center or satellite j.

Wt_j^k: Waiting time of truck *k* at the logistics center or satellite *j*.

Dt_p^v: Departure time of vehicle *v* from logistics satellite *p*.

At_q^v: Arrival time of vehicle *v* at the logistics satellite or customer *q*.

Wt_q^v: Waiting time of the vehicle *v* at the logistics satellite or customer *q*.

N_l^k: Number of trucks used by logistics facility *l*, $l \in L$.

N_s^v: Number of vehicles used by logistics satellite *s*, $s \in S$.

$Q_{ll'}$: Shared delivery demands from facilities l' to l in the first echelon.

$Q_{ss'}$: Shared customers' demands from satellites s' to s in the second echelon.