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Optimization of emergency supplies paths based on dynamic real-time split delivery

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C H R O N I C L E

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A B S T R A C T

A multi-objective dynamic demand split delivery emergency material distribution model is developed to enhance the efficiency of emergency material distribution and facilitate the smooth progress of safety rescue operations during unconventional emergencies. This model incorporates the psychological view of those affected by disasters. The issue of dynamic demand may be transformed into a static demand problem by dividing the distribution time window into time domains of equal length. The optimization process is thereafter executed in real-time with the timed batch methodology. A refined ant colony method has been developed to address the model by integrating the attributes of the mathematical model, followed by doing an arithmetic case analysis. The findings indicate that the algorithm and mathematical model suggested in this study are efficacious in addressing the emergency material distribution issue, offering valuable decision-making advice and reference.

1. Introduction

Due to the frequent recurrence of several natural disasters and public health occurrences in recent times, a substantial number of catastrophes have ensued, leading to huge human casualties, extensive property destruction on a global scale, and profound psychological harm experienced by the affected individuals. In 2010, Yushu City, located in the Yushu Tibetan Autonomous Prefecture of Qinghai Province, had a seismic event with a magnitude of 7.1. This earthquake potentially impacted a significant population of over 200,000 people and tragically resulted in the loss of 2,698 lives (Ni et al., 2023). In 2013, the occurrence of the super typhoon Haiyan in China, the Philippines, and Vietnam resulted in a significant loss of human lives, with a recorded death toll of 36,185 individuals. Additionally, the economic impact of this event amounted to $3.69 billion in damages (Barmania, 2014). The COVID-19 pandemic, a distinct outbreak of the coronavirus, affected nearly 10% of the global population during the first six months of 2020, resulting in an estimated one million fatalities (Mason & Friese, 2020). Catastrophic occurrences, regardless of their origin in either a public health crisis or a natural catastrophe, can have a profound impact on a country or society, impairing its capacity to operate effectively. This leads to extensive harm to the environment, economy, and infrastructure, beyond the affected region's ability to independently address and mitigate the damage. The vulnerable living zones are a consequence of several circumstances, such as the fast rise of the population, the excessive concentration of people in certain areas, the development of infrastructure, the excessive consumption of resources, and the degradation of the environment (Djimesah et al., 2018; Ni et al., 2018).

The adaptability of emergency material management in a dynamic environment surpasses that of normal material management, owing to the inherent unpredictability of emergencies. Following emergencies, the conditions of disaster-stricken areas, including the environment, population distribution, and other factors, exhibit variations. Moreover, the availability of emergency resources and the promptness of response are limited, thereby posing challenges to the distribution of emergency materials due to resource constraints and time window limitations. Additionally, the pressing needs of affected individuals further accentuate the urgency of emergency material distribution (Wang & Sun, 2023; Wan et al., 2023). The consideration

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of cost-effectiveness and promptness in material transportation should be taken into consideration when devising route solutions for material transport vehicles. This will enable the development of a systematic and precise set of emergency material distribution routes that can effectively cater to the evolving requirements of disaster-affected areas. The objective is to ensure that each point receives the necessary materials within its specified demand window to the maximum extent possible. Historically, governmental initiatives in disaster relief have prioritized the efficient and timely delivery of commodities to affected individuals, with a particular emphasis on reducing distribution losses. When organizing the distribution of relief items, it is imperative that the government and social institutions consider the constraints imposed by limited financial resources. In this regard, particular emphasis is placed on the time cost and rate of material loss during the distribution process. The objective is to ensure that a maximum number of materials reach the disaster-stricken area without incurring any damage, thereby enabling affected individuals to benefit from as many resources as possible (Zhang et al., 2023). Nevertheless, in the process of coordinating the allocation of first disaster assistance, it is essential for the government and social organizations account for the constraints imposed by restricted resources. In situations when government emergency finances and social donor funds are constrained, enhancing the efficiency of emergency vehicle distribution routes may lead to improved overall outcomes by optimizing the scheme for vehicle distribution paths. This article examines the concept of distribution expenditures as a mean to reduce the financial burden of emergency response operations.

The Vehicle Routing Problem (VRP) exhibits a wide range of variations and has been widely used within the domain of emergency logistics (Ren et al., 2023; Peng et al., 2022; Liu et al., 2022). As per the established definition of humanitarian logistics, the process of transporting and storing goods, materials, and relevant information from the production site to the impacted region is executed, organized, and regulated with the objective of minimizing expenses while addressing the urgent requirements and mitigating the distress of the affected populace (Sentia et al., 2023). It is important to take into consideration the psychological aspect of emergency material distribution in order to mitigate psychological distress among the population and facilitate their prompt response to the exigencies of the disaster site throughout the course of emergency supply distribution. Wang et al. (2013) utilized prospect theory to measure independently the perceived temporal risk of the efficacy of material distribution and the perceived peril of time for populations with varying degrees of damage. They accomplished this by comparing the outcomes of their analysis to those of prior studies. Useche et al. (2017) examined the impact of stress-related working conditions and hazardous driving behavior on BRT drivers by collecting pertinent data through a survey and developing a structured equation model. Yu et al. (2018) suggested using cost loss to represent the psychology of pain in disaster victims in order to increase the efficiency and fairness of emergency relief allocation. They also suggested developing a multi-period emergency relief allocation model that considers people's pain in order to reduce rescue, derivation, and delayed punishment costs. Zhong (2021) applied prospect theory and inequity theory to analyze the risk perceptions of disaster victims regarding the arrival time of relief supplies and to develop a model for disaster victims' utmost satisfaction. Lu et al. (2022) adapted a collaborative truck and UAV distribution model to humanitarian logistics and pro-posed a UAV humanitarian pick-up and drop-off vehicle path problem with multiple objectives. Luo et al. (2023) proposed the allocation optimization model for discussion and algorithmic review and analysis, with the satisfaction of disaster victims as the research objective and the shortest allocation time, the minimum unmet demand, and the principle of maximum fairness as the indicators affecting this objective. The quantity of emergency supplies distributed and the timing of their arrival will have a direct impact on the victims' perception of their psychological torment and an indirect impact on the execution of relief efforts. In order to strengthen the post-disaster emergency supplies, alleviate the psychological trauma of the victims, and improve the efficacy of the current and subsequent phases of relief work, accurate measurement of the victims' psychological suffering and timely and equitable distribution of emergency supplies are crucial (Wang et al., 2023).

The initial proposition of the split delivery vehicle routing problem (SDVRP) can be attributed to Dror and Trudeau (1989). They further established that a distribution center that engages in delivering a product to a customer point, where the demand can be divided for distribution, outperforms the scenario where the customer demand can only be met by a single vehicle. This superiority is measured in terms of the distance covered by the vehicle and the number of vehicles employed. The topic of the SDVRP has received significant attention from scholars since its establishment. Academics have further explored this subject by including different study directions, assumptions, limitations, and other related aspects. The SDVRP problem has been influenced by various related problems such as the split delivery vehicle routing problem with time windows (SDVRPTW) (Bianchessi & Irnich, 2019), the split delivery vehicle routing problem with pick-up and deliveries (SVRPPD) (Gribkovskaia et al., 2007), and a multi-depot VRP with time windows, split pickup and split delivery (MDVRP-TW-SP-SD) (Dubey & Tanksale, 2023). These extended problems have considered different combinations of factors, thereby contributing to the development of the SDVRP problem.

The study conducted by Eydi et al. (2019) examined the fuel consumption aspect of the reverse logistics split delivery truck routing issue, with the objective of minimizing gasoline costs. To address this problem, the researchers devised a simulated annealing algorithm as a solution method. The split delivery vehicle route issue with a minimum number of transports was investigated by Han et al. (2016). They addressed this problem by establishing a preset splitting threshold, which imposed a minimum quantity of service per vehicle to each client. To tackle this problem, the researchers developed an adaptive variable neighborhood descent heuristic method. The study conducted by Haddad et al. (2018) examines the issue of split delivery truck routing, specifically focusing on the simultaneous distribution and collection of items. The use of random generating techniques for determining distribution and collecting sites presents a potential solution to the route issue. The topic of split delivery truck pathways with a time window was examined by McNabb et al. (2015). In their study, the authors focused on path planning, which included determining the optimal routes based on the geographical distances between consumers. To address this problem, they developed an ant colony algorithm as a solution strategy. In their study, Ren et al. (2023) formulated a mathematical model for the vehicle routing problem with split pickup and delivery and multi-category goods (VRPSPD-MCG). Additionally, they proposed an enhanced ant colony optimization approach to effectively address this issue. SDVRP application scenarios have expanded in addition to the actual application difficulties of network distribution of resources (food, fashion retail, etc.) (Cheikh et al., 2023; Ji et al., 2021; Bianchessi et al., 2019). Dinh et al. (2023) focused on the optimization of the inventory path issue via the use of split deliveries. Bortfeldt and Yi (2020) expanded the scope of research on the Stochastic Dynamic Vehicle Routing issue (SDVRP) by introducing the 3L-SDVRP issue. This novel problem formulated incorporates vehicle pathways, three-dimensional loading, and supplementary packing restrictions. Emergency supplies scheduling is a typical split delivery vehicle path problem, and the study demonstrates that the split delivery strategy can maximize vehicle transport flexibility, enhance vehicle capacity utilization, reduce vehicle resources and the number of emergency logistic paths, enhance transport cost and safety, and prevent hoarding and waste caused by simultaneous delivery of an excessive amount of supplies. Less research has been conducted on the SDVRP problem resolving the emergency material distribution problem, so this paper offers a solution to the emergency disaster relief problem.

The subsequent parts of this work are structured in the following manner. The second section of the paper elucidates the concept of linked issues and mathematical modelling. Section 3 elucidates the enhanced algorithm for ant colonies. Section 4 focuses on the analysis of simulation experiments conducted on the above issues. Section 5 encompasses a concise overview of the key findings and implications of the work, followed by a discussion on potential avenues for further investigation.

2. Model establishment

2.1. Problem description

Fig.1 illustrates a schematic representation of an emergency material distribution plan that takes into consideration the fluctuating demand and psychological effects, while using the principles of split delivery. The system may be described as consisting of many distribution centers and a fleet of distribution trucks. These trucks are filled to full capacity at the distribution center before departing, and upon completion of their distribution tasks, they return to the center from a nearby site. The distribution task for each demand point can be divided and allocated to multiple vehicles for the same demand point or allocated to a single vehicle for multiple demand points. For instance, if a vehicle's capacity is insufficient to fulfill the requirements of a distribution point, the vehicle may prioritize delivering the remaining materials to that specific demand point. Any unmet demand can then be addressed by another distribution vehicle, or the vehicle can be used to fulfill the subdivided demand. The primary aims of this study are to reduce the total expenses associated with distribution, mitigate the psychological distress experienced by those involved, and minimize the psychological burden placed on drivers.

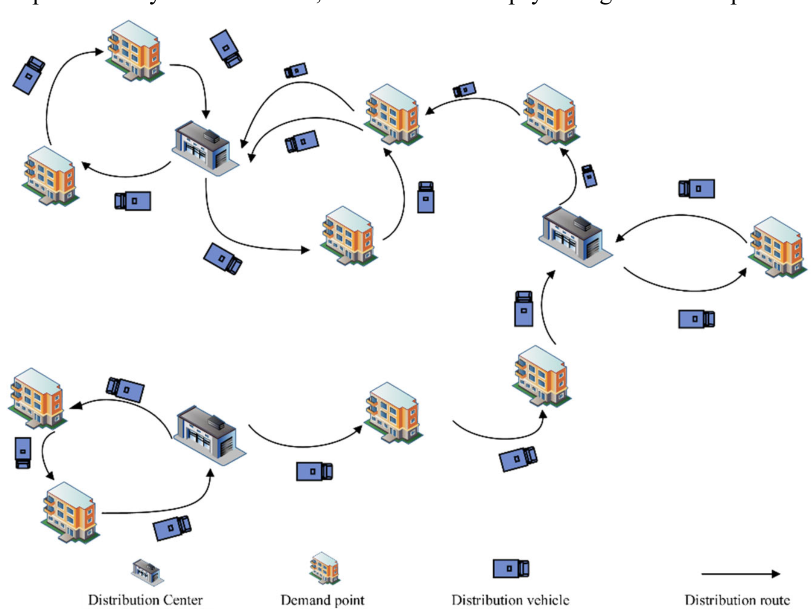

Fig. 1. The distribution diagram of emergency supplies in case of split delivery

Considering the characteristics of emergency supplies and the needs of the model, it is given the following assumptions:

Assumption 1. Distribution in the shortest possible time and with limited funds.
Assumption 2. Distribution vehicle maximum load capacity and speed are known.
Assumption 3. Distribution centers, demand points, and their locations are known, and each has various distribution vehicles of different sorts.
Assumption 4. Demand point timing is known.

Assumption 5. Full-load distribution vehicle leave the distribution center and can distribute at different demand sites.
Assumption 6. Demand for each demand point is unsplit delivery, and each demand point can only be met by a single vehicle.
Assumption 7. The distribution center meets demand at every demand point without considering material redeployment.
Assumption 8. Either delivery vehicle travels at a steady pace regardless of weather or traffic.
Assumption 9. Distribution vehicles depart from a distribution center and choose a nearby distribution center to return to.
Assumption 10. Distribution vehicles have no sequential requirements for distribution tasks at the point of demand.

2.2. Parameter setting

The parameters of the mathematical model are described in Table 1.

Table 1
Parameter description in mathematical model.

Symbol	Description
N	Collection of disaster sites.
K	Vehicle collection.
M	Number of vehicles collection.
v	Distribution center collection.
g_i	Emergency material requirements at disaster sites i.
d_{ij}	Distance of the affected point i through the disaster site j.
t_0	The time threshold for driver psychological change.
t_i	Time of vehicle arrival at the affected site i.
s_i	Service hours of delivery vehicles at the disaster site i.
v_k	The speed of the vehicle transported by the vehicle type k.
c_{k1}	Fixed cost of use of vehicles of type k.
c_{k2}	Transport costs per km for vehicles of type k.
c_{k3}	Cost per unit of carbon emissions for the $k-th$ model vehicle.
c_{k4}	Carbon dioxide factor for fuel emissions of the $k-th$ model vehicle.
e_c	Fuel consumption per unit distance.
e	The unit cost of the psychosensory counterpart of the distribution process.
e_r	The driver's coefficient of mental induction from point i to point j
$[e_0, l_0]$	Time window to receive dynamic demand
$[e_i, l_i]$	Service time window for demand point i
p_1	The unit penalty cost of overloading a distribution vehicle in its path.
p_2	The unit penalty cost of a distribution vehicle violating the latest time window restriction at the point of disaster.
Q_k	Maximum load capacity of distribution vehicles.
k	Number of models in distribution centers.
T_0	End time of the entire rescue operation.
P_i	Quantity of emergency supplies distributed at the affected point i.
P_h	Psychological compensation factors for driver pay.
h_0	Fixed pay before the point of psychological change in drivers.
h_1	Compensatory pay for each minute of driving beyond the driver's psychological change point.
E_r	Psychological costs of the driver's distribution process from point i to point j.
X_{ijhkm}	Represent vehicle m of model k in car park v is 1 when it travels between affected point i and affected point j , otherwise it is 0
w_{ijkm}	Represents the actual transportation volume of vehicle m

2.3. Split delivery real-time stage modelling

2.3.1. Dynamic real-time optimization stage analysis

An emergency makes demand unclear, and additional needs will develop throughout distribution. Distributing dynamic demand as many static issues via immediate or batch processing is the solution. As new demand points appear more frequently, the distribution path followed by frequent changes can meet their needs quickly, but if multiple demand points are changed frequently, this processing will increase the number of calculations, and the cost of the number of changes will increase as the number of changes increases. So, it has more practical restrictions. Hence, this article uses timed batch processing to collect dynamic demand each time and process accordingly. The dynamic vehicle distribution issue becomes a static route problem for each time. The workload is reduced by this processing procedure.

The distribution center has the capability to oversee the activities of distribution vehicles and establish communication channels with distribution personnel throughout the distribution process. Distribution centers play a crucial role in facilitating strategic decision-making processes aimed at effectively managing and responding to heightened levels of demand. The strategic positioning of distribution vehicles is determined by the location of the "virtual distribution center" and the remaining demand sites. The problem of static route planning in this case necessitates meticulous planning and optimization. The driver and the newly established route demonstrate effective coordination to optimize distribution efficiency. Fig. 2 illustrates the response of the distribution center to the demand observed at the impact areas throughout the two-stage distribution process.

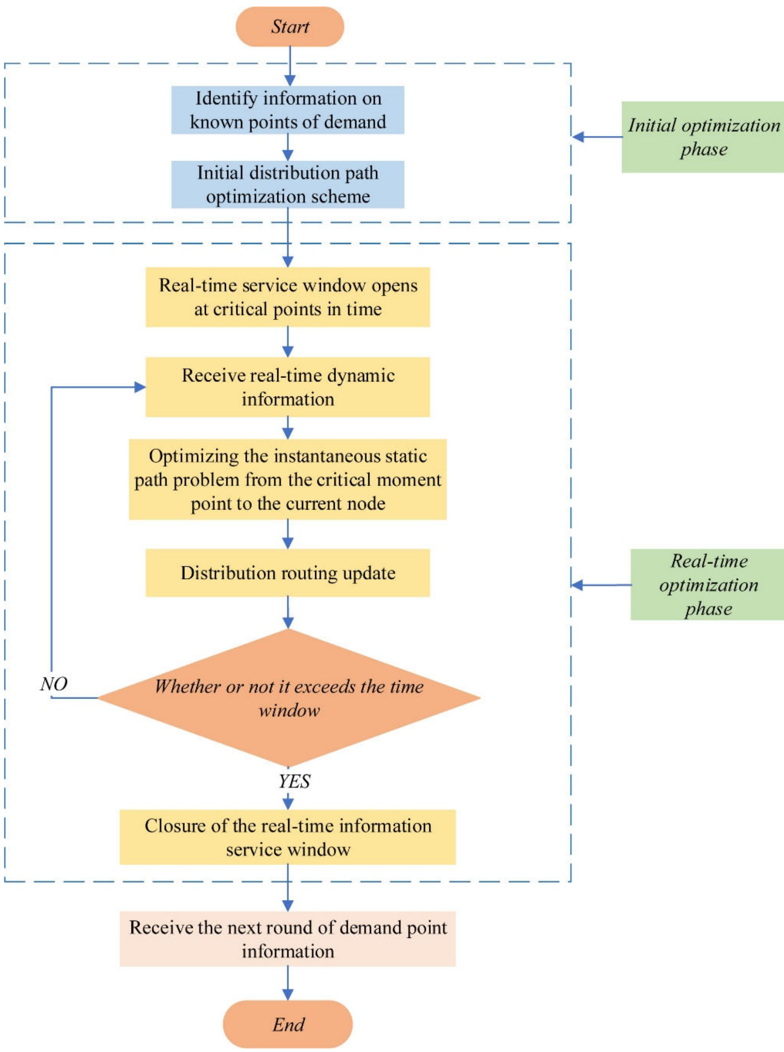

Fig. 2. The dynamic demand optimization process

Local optimization for increased demand saves time and improves accuracy. After distribution starts, the distribution centre gets additional duties. Next time slot is utilized to filter through fresh requests from the previous time slot and either optimize existing distribution vehicles or add new ones. The assumption that the number of vehicles used in the initial phase is M_h, in the real-time optimization phase has been completed for some of the affected points of the distribution task, this time, the distribution of vehicles on board the amount of $Q_{hm}, h = 1,2 \cdots, H, m = 1,2, \cdots, M$, M_h for the number of virtual distribution centres, number $v + V + 1, v + V + 2, \cdots, v + V + M_h$, the original distribution center is $v + 1, v + 2, \cdots, v + V$, the new departure of the distribution of vehicles for M_t.

2.3.2. Cost analyses

Fixed cost

The number of vehicles launched determines the amount of fixed costs, which include depreciation and maintenance. Thus, total fixed expenses are:

$$Z_1 = C_{k1} \sum_{j=1}^{N+H} \sum_{v=1}^{V+M_h} \sum_{k=1}^{K} \sum_{m=1}^{M+M_t} x_{0j}^{vkm} \tag{1}$$

Transport cost

Transport costs are variable costs incurred during the logistics and distribution process and are influenced by the distance travel by the distribution vehicle. Therefore, it can be stated as:

$$Z_2 = C_{k2} \sum_{i=1}^{N+H} \sum_{j=1}^{N+H} \sum_{v=1}^{V+M_h} \sum_{k=1}^{K} \sum_{m=1}^{M} d_{ij} x_{ij}^{vkm} + C_{k2} \sum_{i=1}^{N+H} \sum_{j=1}^{N+H} \sum_{v=1}^{V+M_h} \sum_{k=1}^{K} \sum_{m=1}^{M+M_t} d_{ij} x_{ij}^{vkm} \tag{2}$$

Carbon emission cost

The most significant carbon emission during distribution is carbon dioxide from motor fuels; this article examines the price of carbon emissions. Currently, estimates of carbon emissions are made using carbon levies and trade. Using the carbon tax measurement and the actual scenario, this paper's model calculates carbon emissions. The carbon emissions price is:

$$Z_3 = eC_{k3}C_{k4} \sum_{j=1}^{N+H} \sum_{v=1}^{V+M_h} \sum_{k=1}^{K} \sum_{m=1}^{M} d_{ij} x_{0j}^{vkm} + eC_{k3}C_{k4} \sum_{j=1}^{N+H} \sum_{v=1}^{V+M_h} \sum_{k=1}^{K} \sum_{m=1}^{M+M_t} d_{ij} x_{0j}^{vkm} \tag{3}$$

Time window violation penalty cost

The bulk of penalty costs are spent during the flexible and mixed time window limits since emergency supply distribution is time-sensitive and the longer the wait, the more lives would be lost. The cost of penalties is examined in this research. The precise time frame penalty cost is often ignored. The impacted point has an allowable time range between $[e_i, l_i]$ and anything outside of which results in a late arrival penalty. Arriving after the scheduled time will result in the following consequences:

$$Z_4 = P_2 \sum_{i=1}^{N+H} max\{t_i - l_i, 0\} \tag{4}$$

2.3.3. Psychological effect analyses

Waiting effect function

Holguín-Veras suggests incorporating logistical and scarcity costs into the objective function of post-disaster humanitarian assistance (Holguín-Veras et al., 2013). As the population grows, scarcity cost assesses the economic cost of experiencing a lack of commodities. Pay close attention to the emergency supply arrival waiting effect function to avoid secondary complications. A power function quantifies the psychological impact, so the delay effect function presented in this paper is:

$$M_1 = \sum_{i=1}^{N+H} \sum_{v=1}^{V+M_h} \sum_{k=1}^{K} \sum_{m=1}^{M+M_t} p_i^{vkm} \alpha (t_i - l_i)^u \tag{5}$$

Shortage effect function

Following a public health emergency, masks, disinfecting water, and protective clothing will be in short supply. This could cause pandemonium and threaten the stability of society. The psychological impact of the scarcity effect on people's performance is quantified using the same power function:

$$M_2 = \sum_{i=1}^{N+H} \sum_{v=1}^{V+M_h} \sum_{k=1}^{K} \sum_{m=1}^{M+M_t} \left(g_i - p_i^{vkm}\right) \alpha T_0^u \tag{6}$$

Climbing effect function

Prior to distribution, emergency supplies are required at a higher rate than at peak demand. It is subjective whether emergency supplies are distributed equitably. Some believe the arrangement is just, while others believe it is discriminatory. The following emergency supply maximal guarantee rate addresses this issue:

$$\varphi = \sum_{i=1}^{N+H} \sum_{v=1}^{V+M_h} max\left\{\frac{G_v}{g_i}\right\} \tag{7}$$

where φ is the maximum emergency material security rate at the point of demand and G_v is the supply of emergency material at the point of supply v.

On this basis, people's climbing effect function can be expressed as:

$$M_3 = \sum_{i=1}^{N+H} \sum_{v=1}^{V+M_h} \frac{G_v}{g_i} - \varphi \tag{8}$$

2.3.4. Driver psychological cost analysis

Driver psych-cost is influenced by salary, psychological cost, and leisure time per impacted point. This article examines how compensation affects the psychological costs of drivers before and after the critical attitude changes. Therefore, driver psychological costs are:

$$F_3 = P_h \sum_{k=1}^{K} \sum_{m=1}^{M} \sum_{v=1}^{V+M_h} \left(max\left(\sum_{i=1}^{N+H} (t_i - t_0)h_1, 0 \right) + h_0 \right) + P_h \sum_{k=1}^{K} \sum_{m=1}^{M+M_t} \sum_{v=1}^{V+M_h} \left(max\left(\sum_{i=1}^{N+H} (t_i - t_0)h_1, 0 \right) + h_0 \right) \tag{9}$$

2.3.5. Real-time dynamic stage model

The real-time optimization phase model is shown below:

$$minF_1 = Z_1 + Z_2 + Z_3 + Z_4 \tag{10}$$

$$minF_2 = M_1 + M_2 + M_3 \tag{11}$$

$$minF_3 = P_h \sum_{k=1}^{K} \sum_{m=1}^{M} \sum_{v=1}^{V+M_h} \left(max\left(\sum_{i=1}^{N+H} (t_i - t_0)h_1, 0 \right) + h_0 \right) + P_h \sum_{k=1}^{K} \sum_{m=1}^{M+M_t} \sum_{v=1}^{V+M_h} \left(max\left(\sum_{i=1}^{N+H} (t_i - t_0)h_1, 0 \right) + h_0 \right) \tag{12}$$

subject to

$$\sum_{i=1}^{N+H} \sum_{m=1}^{M+M_t} \sum_{k=1}^{K} g_i y_i^{vkm} \leq Q_k \tag{13}$$

$$\sum_{i=1}^{N+H} \sum_{v=1}^{V+M_h} \sum_{k=1}^{K} \sum_{m=1}^{M+M_t} y_i^{vkm} = 1 \tag{14}$$

$$\sum_{i=1}^{N+H} \sum_{v=1}^{V+M_h} \sum_{k=1}^{K} \sum_{m=1}^{M+M_t} x_{ij}^{vkm} = \sum_{i=1}^{N+H} \sum_{v=1}^{V+M_h} \sum_{k=1}^{K} \sum_{m=1}^{M+M_t} x_{ji}^{vkm} \tag{15}$$

$$\sum_{j=0}^{N+H} \sum_{v=1}^{V+M_h} \sum_{k=1}^{K} \sum_{m=1}^{M+M_t} x_{i0}^{vkm} = y_i^{vkm} \tag{16}$$

$$\sum_{i=0}^{N+H} \sum_{v=1}^{V+M_h} \sum_{k=1}^{K} \sum_{m=1}^{M+M_t} x_{0j}^{vkm} = y_i^{vkm} \tag{17}$$

$$t_j^{vmk} = t_i^{vmk} + s_i + \frac{d_{ij}}{v_k}, \forall i,j \in N+H, \forall k \in K, \forall m \in M+M_t, \forall v \in V+M_h \tag{18}$$

$$w_{0j}^{vmk} = x_{0j}^{vmk} Q_k, \forall i, j \in N + H, \forall k \in K, \forall m \in M + M_t, \forall v \in V + M_h \tag{19}$$

$$p_i^{vmk} = G_v - g_i, \forall i \in N + H, \forall k \in K, \forall m \in M + M_t, \forall v \in V + M_h \tag{20}$$

$$x_i^{vmk} \leq G_v, \forall i \in N + H, \forall k \in K, \forall m \in M + M_t, \forall v \in V + M_h \tag{21}$$

$$\sum_{i=1}^{S} \sum_{j=1}^{S} x_{ij}^{vmk} \leq |S| - 1, \forall S \in N + H, \forall k \in K, \forall m \in M + M_t, \forall v \in V + M_h \tag{22}$$

$$\sum_{i=1}^{N+H} \sum_{j=1}^{N+H} \sum_{m=1}^{M+M_t} x_{ij}^{vkm} \leq |M|, \forall k \in K, \forall v \in V + M_h \tag{23}$$

$$x_{ij}^{vmk} = \{0,1\}, y_i^{vkm} = \{0,1\} \tag{24}$$

$$e_i \leq t_i^{vmk} \leq l_i, \forall i \in N + H, \forall k \in K, \forall m \in M + M_t, \forall v \in V + M_h \tag{25}$$

$$\sum_{i=1}^{N+H} \sum_{v=1}^{V+M_h} \sum_{k=1}^{K} \sum_{m=1}^{M+M_t} Y_{ij}^{vkm} = 1 \tag{26}$$

$$\sum_{j=1}^{N+H} \sum_{v=1}^{V+M_h} \sum_{k=1}^{K} \sum_{m=1}^{M+M_t} Y_{ij}^{vkm} = 1 \tag{27}$$

Eq. (10) represents the minimum total distribution cost in the real-time optimization phase of the distribution process. Eq. (11) indicates that people have the lowest psychological effects including waiting effect, shortage effect and comparison effect. Eq. (12) indicates that the psychological cost to the driver is minimized. Eq. (13) represents the limit on the amount of emergency supplies that can be transported per vehicle. Eq. (14) indicates that the task of distributing emergency supplies at each disaster site i can be performed by one or more vehicles. Eq. (15) indicates that the vehicle returns to any of the nearest distribution centers after completing the distribution task. Eq. (16) and Eq. (17) represent the balance of the number of distribution vehicles entering and leaving each affected site. Eq. (18) denotes the time for vehicle m of model k to arrive at the disaster point j from the disaster i. Eq. (19) indicates that the vehicle is fully loaded when it departs from the distribution center. Eq. (20) represents the amount of material unsatisfied at the affected point i. Eq. (21) indicates that the supply of emergency supplies cannot exceed the reserve of the distribution center. Eq. (22) represent the elimination of subloop constraints and S is the set of affected points on a particular distribution route. Eq. (23) represents the vehicle usage constraint. Eq. (24) represents the range of values of the decision variable. Eq. (25) represent the time window constraint for the affected point i. Eq. (26) indicates that there is only one immediately preceding distribution disaster point in the vehicle distribution process. Eq. (27) indicates that there is only one immediate post-distribution disaster point in the vehicle distribution process.

3. Algorithm design

3.1. Ant colony algorithm fundamentals

The concept of the Ant Colony Algorithm (ACO), a bionic algorithm that emulates the foraging habits of ants in selecting shorter routes, was proposed by the Italian researcher M. Dorigo (Dorigo and Gambardella, 1997). Ants use pheromones as a means of marking the routes they traverse during foraging activities, afterwards selecting their subsequent course based on the concentration of these chemical signals. Initially, ants exhibit equal preference for each route since the pheromone concentration on all routes is the same. The concentration of pheromones exhibits fluctuations as an increasing number of ants discover food, so enhancing the preference of ants and causing subsequent ants that settle later to be more motivated to follow paths with higher concentrations. A reciprocal relationship exists between the ant population and the quantity of pheromones, resulting in positive feedback. Based on the above data, the colony will choose the optimal technique for foraging sustenance.

The basic flow of the ant colony algorithm:

Step 1: Initialize all the parameters.

The number of cycles, the number of populations, the number of stopping iterations, the pheromone concentration, and the factors including the heuristic factor, the expectation factor, and the volatility factor are set initially.

Step 2: Calculate the state transfer probability to select the next visited node.

The m ants are randomly placed on k different starting points, and the ants choose to go from node i to node j based on the pheromone concentrate and the heuristic of each path. where the transfer probability p of ant m can be expressed as:

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{\tau_{ij}^{\alpha}(t)\left(\frac{1}{d_{ij}}\right)^{\beta}(t)}{\sum_{j\in N_i^k}\tau_{ij}^{\alpha}(t)\left(\frac{1}{d_{ij}}\right)^{\beta}(t)}, j\in N_i^k\\ 0, j\notin N_i^k\end{cases} \tag{28}$$

where τ_{ij} is the pheromone concentration between nodes i, j at moment t.

Step 3: Update the table of taboos.

The forbidden table stores every node the ants travelled through, preventing repeated visits to the same node until all the ants have finished their visits.

Step 4: Record the optimal route obtained from the current visit.

Step 5: Update pheromone concentration.

With time, the pheromone left by the previously passed ants will become less and less, while the newly passed ants will release new pheromone, so the pheromone is injected while volatilized, thus updating the pheromone concentration in each pathway. The pheromone updating concentration formula as:

$$\tau_{ij}(t+n)=(1-\rho)\tau_{ij}(t)\times\Delta\tau_{ij} \tag{29}$$

$$\Delta\tau_{ij}=\sum_{m=1}^{M}\Delta\tau_{ij}^{k} \tag{30}$$

$$\Delta\tau_{ij}^{k}=\begin{cases}\frac{Z}{L_k}, Ant\ k\ passes\ through\ paths\ (i,j)\\ 0, else\end{cases} \tag{31}$$

where, ρ is the pheromone volatility factor, $0<\rho\le 1$. Z is the pheromone constant. L_k is the total length between the nodes visited by the ants, for this cycle. $\Delta\tau_{ij}$ is the incremental pheromone concentration on paths (i,j) for this iteration.

Step 6: Determine the number of iterations.

If the number of iterations is less than the maximum value, return to step 2, the number of ants $m=m+1$, and continue to enter the loop; if it is greater than the maximum value, output the optimal route, jump out of the loop, and end the process.

The flowchart of the ACO algorithm, as shown in Fig. 3.

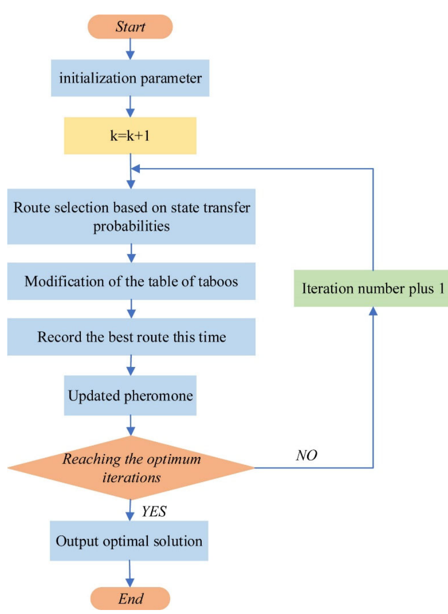

Fig. 3. Basic ant colony algorithm flow chart

3.2. Initial population dynamic chaos algorithm

Chaos seems irregular yet follows a rule that combines regular and irregular movement and merges need and chance (Ren et al., 2022). Chaos provides random variations without random factors (Yu et al., 2018). Ant colony algorithm generates random ants. Traversal and unpredictability of chaotic mapping seed the population. Chaotic mapping produces a more diverse population and more evenly distributed search space than randomization. This prevents the algorithm from prematurely evolving and reaching local maxima, boosting convergence speed and accuracy.

The fundamental principle of chaotic optimization is navigating through chaotic systems, with the Logistic chaotic (Han et al., 2022) perturbation equation being the prevailing choice for perturbation in contemporary use. Logistic sequences possess the potential for stochasticity and exhibit sensitivity to the starting value. Moreover, these sequences tend to have a more uniform distribution across the central area of the search space, while displaying a heightened likelihood of converging towards the boundary. The expression for the logistic mapping as:

$$x_{i+1} = \mu_i(1 - x_i), x_i \in [0,1] \tag{32}$$

When $\mu = 4$ the system is in a completely chaotic state. After many iterations, a small chaotic perturbation of the initial value x can cause completely different results.

Upon the incorporation of the Logistic chaotic system into the algorithm, the equation denoted as the Eq. (32) will undergo a modification resulting in its subsequent representation as the formula (33).

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} + \delta x_{ij}, x_i \in [0,1] \tag{33}$$

where x_{ij} is a chaotic variable, which can be obtained iteratively from Eq. (32). δ is the adjustment coefficient.

3.3. Building paths with the savings matrix

The saving matrix is introduced to guide the ants to choose a more economical route because the pheromone plays an increasing role in the later stages of the algorithm, weakening the influence of and on the search of the algorithm (Ma et al., 2023). The conservation matrix plans the best distribution routes with the correct quantity of conveyances by considering the distances between distribution centers and distribution sites. In this example, the distribution vehicle from the distribution center O must be distributed to two demand points, D_a and D_b, respectively. Distribution vehicles can meet both demand locations at once. If the distribution is done individually, the vehicle travels $D = 2(D_a + D_b)$. If it is done concurrently, it travels $D = D_a + D_b + D_{ab}$. The difference between the two distribution techniques is $D_a + D_b - D_{ab}$, as illustrated in Fig. 4. If this distribution path has multiple distribution points, the more demand points there are on this distribution path, the longer the distance that can be saved, within the loading range of the vehicle. The saved path as:

$$U_{ij} = D_{0i} + D_{0j} - D_{ij} \tag{34}$$

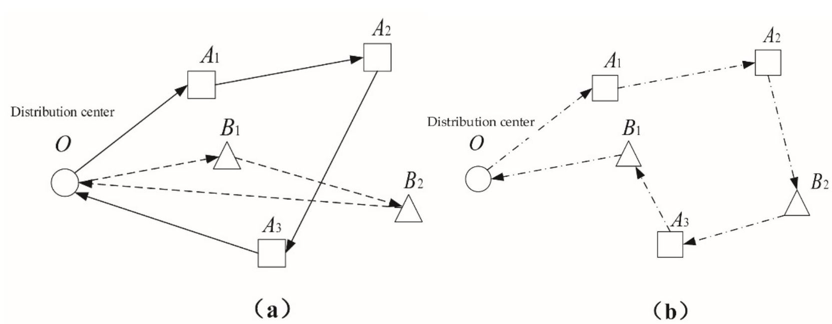

Fig. 4. (a) Individual distribution roadmap and (b) Roving distribution roadmap.

To avoid ants choosing with a probability of 0 and not being able to choose the next location, the probability formula is improved as:

$$p_{ij}^k(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t)\left(\frac{1}{d_{ij}}\right)^{\beta}(t)U_{ij}^{\theta}+1}{\sum_{j\in J_k}\left(\tau_{ij}^{\alpha}(t)\left(\frac{1}{d_{ij}}\right)^{\beta}(t)U_{ij}^{\theta}+1\right)}, j \in J_k \\ 0, j \notin J_k \end{cases} \tag{35}$$

where θ adapted value parameter.

3.4. Pheromone volatilization factor updating strategies

In the fundamental ACO algorithm, the pheromone update is exclusively applied to the pheromone on the more optimal path. However, it is worth noting that the sub-paths of the optimal path are not necessarily the shortest paths. Additionally, there may exist longer paths that can mislead the ants into selecting an incorrect path from the outset, consequently causing them to overlook the optimal path. To rectify this limitation, the literature introduces the concept of path contribution degree, as referenced in (Wu et al., 2013) and represented by Eq. (38). In the context of the optimum route, it is necessary to identify a sub-path that makes a significant contribution to the overall path, above the predetermined threshold for path contribution. Once this sub-path has been identified, the pheromone levels on this sub-path are updated twice using Eq. (39) and Eq. (40).

$$CDSP_{ij} = \frac{P(i,j)}{L_i} \tag{36}$$

$$\Delta\tau'_{ij} = \begin{cases} \dfrac{Q}{P(i,j)}, CDSP_{ij} > t_0 \\ 0, otherwise \end{cases} \tag{37}$$

$$\Delta\tau_{ijnew} = \begin{cases} \Delta\tau'_{ij} + \Delta\tau_{ij}, CDSP_{ij} > t_0 \\ \Delta\tau_{ij}, otherwise \end{cases} \tag{38}$$

The volatilization factor of pheromones in the basic ant colony algorithm remains constant. The amount of residual pheromone affects the speed at which the algorithm can identify the optimal solution. So, it is advisable to decrease the rate of pheromone evaporation on the more beneficial path, while increasing the rate of pheromone evaporation on the less positive path. This is because the inferior solution obtained during each iteration does not contribute to the improvement of the result. Hence, following the secondary update of the pheromone as described in literature (Wu et al., 2013), the algorithm's shortcomings in effectively identifying the optimal solution in the later stages have been partially addressed by increasing the number of iterations. Consequently, this leads to a decrease in the volatilization factor and a corresponding slowdown in the pheromone volatilization rate along the algorithm's path during the later stages. As a result, the ants' perception of pheromone increases accordingly. The enhancement of the secondary volatilization factor is as follows:

$$\rho^* = \begin{cases} \dfrac{1}{{NC_{max}}^2}, CDSP_{ij} > t_0 \\ C, otherwise \end{cases} \tag{39}$$

where C is a constant; NC_{max} denotes the number of iterations of the algorithm; $CDSP_{ij}$ is the path contribution degree; t_0 is the path contribution threshold (taken as a constant). The pheromone is updated according to Eq. (40).

$$\tau_{ij}(t+n) = (1-\rho)\tau_{ij}(t+n) + \rho^*\Delta\tau_{ijnew} \tag{40}$$

3.5. 3-opt local search strategy

The 3-opt operation is classified as a specific instance of the more general k-opt operation. The technique presented here offers a straightforward approach to address the local search aspect of the Travelling Salesman Problem (TSP). Based on the principle of 3-opt (Comert & Yazgan, 2023), it can be inferred that incorporating 3-opt into the local search procedure can enhance the accuracy of the algorithm's solutions. However, this improvement comes at the cost of increased computational time. To mitigate this, a sorting process is performed on the paths obtained after each iteration. Subsequently, the first $M/2$ paths from the sorted list are selected for the application of the 3-opt technique in the local search phase. Therefore, the enhancement of the algorithm's solution correctness leads to an acceleration in the convergence speed of the method, as seen in Fig. 5.

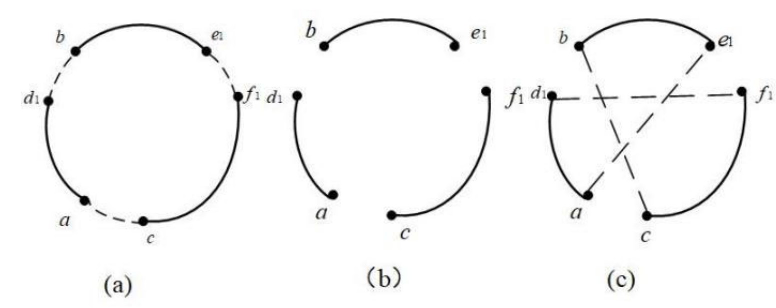

Fig. 5. (a) The initial connection state, (b) The state after the connection is disconnected and (c) Compose the connection state of the new route.

In Fig. 5, (a) is the initial connected state, (b) is the state after the connection is broken, disconnecting edges (a, c), (b, d_1), and (e_1, f_1) and replacing the previous route if the newly combined route is better, then keeping it. After linking (a, e_1), (c, b), and (d_1, f_1), update the best solution if $d(a, e_1) + d(c, b) + d(d_1, f_1) < d(a, c) + d(b, d_1) + d(e_1, f_1)$.

3.6. Improvement of ant colony algorithm flow

The flow chart of the improved ant colony algorithm is shown in Fig. 6.

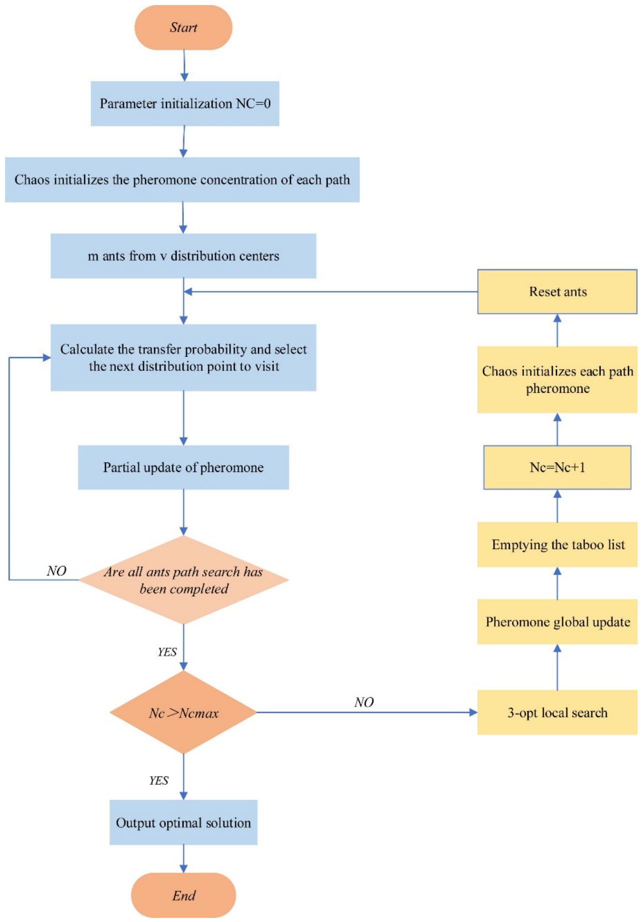

Fig. 6. Improved ant colony algorithm flow chart

Step 1: Initialize each parameter.

Step 2: Chaos initializes the pheromone concentration of each path.

Step 3: Create a taboo table and create heuristic factors.

Step 4: According to equation (28) the transfer probability of each ant can be derived and the next arriving distribution point can be selected.

Step 5: Determine whether the ant arrives at the designated distribution point, if it does, go to step 6, otherwise return to step 4.

Step 6: The number of ants $M = m + 1$, determine whether all the ants have completed the search of the path, if yes, proceed to step 7, otherwise go back to step 4.

Step 7: According to the global update rule, the pheromone is updated for the first time according to equations (29), (30), (31).

Step 8: Calculate the path contribution according to equation (36) and calculate the new pheromone change according to equations (37) and (38).

Step 9: Derive the secondary volatilization factor ρ^* according to equation (39) and update the pheromone twice according to equation (40) based on the global update rule.

Step 10: Sort all routes in ascending order, choose the first $M/2$ for local search, and update the distance of the optimum route achieved this time, L_{nc}, and the best route presently kept, L_{best}.

Step 11: Global pheromone concentration update.

Step 12: Determine whether this point coincides with the set termination conditions, if so, then it will continue to the next step. Otherwise, go back to the second step and repeat the next cycle.

Step 13: Terminate the loop and output the optimal path when the number of iterations reaches the maximum set value.

3.7. Algorithm performance test analysis

3.7.1. Experimental design

The dataset R101 from Solomon (1989) was used to simulate the augmented ant colony approach described in this work, with the purpose of testing and evaluating the effectiveness of the strategy. Table 2 presents the key attributes of the distribution vehicle, which is designed to operate at a consistent velocity. As seen in Table 3, the parameters of the algorithm have been determined.

Table 2
Basic parameter setting

Parameter	Definition	Value
Q_k	Vehicle load (kg)	500
v_k	Vehicle distribution speed (km/h)	30
e	Unit fuel consumption (yuan/km)	0.15
c_{k1}	Vehicle fixed cost (yuan)	200
c_{k2}	Vehicle transportation cost (yuan/km)	5
c_{k3}	Cost per unit of carbon emissions (yuan/kg)	0.25
c_{k4}	Carbon dioxide emission factor for fuel	2.68

Table 3
Algorithm parameter setting

Parameter	IACO	ACO
α	1	1
β	3	3
ant_{num}	20	20
NC_{max}	200	200
Q	20	20
ρ	0.1	0.1
t_0	0.4	-

3.7.2. Analysis of result

The solution methodology was implemented and computed using MATLAB R2020b on a 64-bit host system equipped with a 2.70GHz Intel(R) Core (TM) i5-11400H CPU and running Windows 11. The distribution scheme using the fundamental ACO method and the distribution scheme employing the enhanced ACO algorithm in this research article are developed. The dispersion roadmap of the ant colony method is seen in Fig. 7. The distribution roadmap of the enhanced ACO algorithm is shown in Fig. 8.

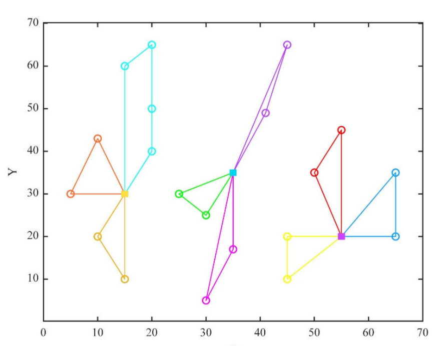

Fig. 7. Basic ant colony algorithm distribution roadmap

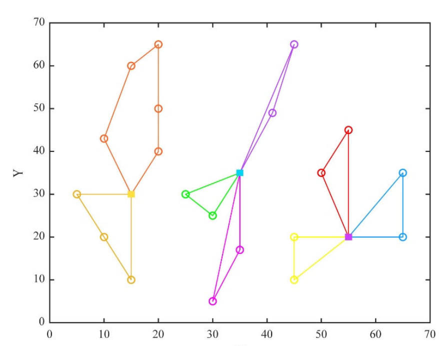

Fig. 8. Improved ant colony algorithm distribution roadmap

To assess the efficacy of the enhanced ACO algorithm, this study compares the computational outcomes of the improved ACO algorithm proposed in this paper with those of the basic ACO algorithm. The comparison is conducted under identical parameter settings and operating conditions. Multiple experiments are performed using both the ACO algorithm and the improved ACO algorithm, and the average results of these experiments are presented in Table 4. The algorithm's convergence diagram is shown in Fig. 9.

Table 4
Experimental results with two algorithms

Algorithm	Vehicles	Distribution cost (yuan)	Iteration number
ACO	9	3894.11	200
IACO	7	3383.99	200

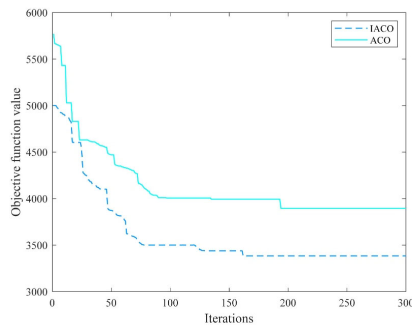

Fig. 9. Algorithm convergence chart

Based on the comparative analysis, the basic ant colony algorithm utilizes a total of 9 cars, but the improved ant colony algorithm necessitates the usage of 7 vehicles. The enhanced ant colony algorithm yields a decrease of 22.2% in the number of cars needed. The distribution cost of the basic ACO algorithm amounts to $3894.11, while the enhanced ACO algorithm incurs a distribution cost of $3383.99. Consequently, the relative cost of distribution between the two algorithms indicates a 15.4% reduction in expenses for the better ACO method. The convergence diagram reveals that the fundamental ant colony algorithm demonstrates rapid convergence during its first stages. However, it is prone to being trapped in local optima, resulting in the production of subpar solutions. This study presents an enhancement to the ant colony method, resulting in better convergence speed and solution quality. The efficacy of the enhanced ACO method is validated.

4. Example simulation

4.1. Illustrative example

An optimal allocation of emergency resources during the response phase would enhance the efficiency of resource distribution, therefore mitigating potential dangers to public health, ensuring the safety of individuals, and fostering economic growth. Hence, this study utilizes data pertaining to the allocation of emergency resources in Hubei Province amidst the prevalence of public health incidents. The data used in this study is sourced from the Wuhan Health Commission, the National Health Commission, and relevant literature (Chen et al., 2020), with appropriate adjustments made to align with the research aims of this publication.

Table 5
Distribution center and vehicle information

Distribution center	X/km	Y/km	Vehicle loading volume（box）	Vehicle fixed cost（yuan）	Vehicle transport costs (yuan /km)	Unit fuel consumption (yuan/km)	Vehicle distribution speed (km/h)
A	24.7	51.1	500	200	5	0.15	30
			800	300	8	0.17	
B	34.8	60.9	500	200	5	0.15	30
			800	300	8	0.17	
C	28.0	62.0	500	200	5	0.15	30
			800	300	8	0.17	
D	37.4	52.7	500	200	5	0.15	30
			800	300	8	0.17	
E	23.0	58.9	500	200	5	0.15	30
			800	300	8	0.17	

In this research, the distribution centers selected for their abundance of resources in epidemic prevention throughout the specified period include certain hospitals and the Wuhan Red Cross warehouse (Hidayat et al., 2022). These centers are denoted by the letter N. Each distribution center is equipped with a limited number of distribution vehicles, categorized into two distinct types. These vehicles are interconnected to facilitate the transfer of goods between various distribution centers. Table 5 displays the relevant data pertaining to the distribution centers. To assess the suitability of each data point for efficient processing, the specific data information was analyzed using a sample of 17 designated hospitals, which served as the first distribution demand point, as shown in Table 6.

Table 6
The information on each demand point

Demand point	X/km	Y/km	e_i	l_i	Dwell time/min	q_i/(box)
H_1	29.2	67.3	10:00	10:30	17	186
H_2	26.0	58.8	8:40	9:00	17	196
H_3	30.7	63.1	10:20	11:00	15	144
H_4	27.8	55.4	11:05	11:30	16	152
H_5	33.8	54.8	11:25	12:00	17	181
H_6	38.6	63.0	11:50	12:30	16	159
H_7	27.3	57.2	12:30	13:30	16	161
H_8	38.6	62.2	9:10	10:00	17	194
H_9	27.2	63.4	8:40	9:30	14	100
H_{10}	41.8	50.5	10:10	10:30	15	115
H_{11}	18.1	49.9	12:00	12:50	20	140
H_{12}	44.7	44.7	9:45	10:10	17	198
H_{13}	28.0	61.4	9:50	10:10	16	285
H_{14}	33.4	58.7	8:55	9:40	16	167
H_{15}	29.7	60.6	9:40	10:10	14	165
H_{16}	30.4	59.4	10:15	10:50	16	138
H_{17}	33.3	53.0	11:45	12:10	15	169

The distribution center formulates distribution routes for the delivery of emergency supplies based on the initial demand data collected. The distribution center incorporates dynamic demand throughout the material distribution process by integrating the demand within a pre-established timeframe. Additionally, it engages in dynamic route updating to promptly fulfill the material requirements of the demand point. The distribution center commences its distribution operations and initiates the real-time service window at 8:00 a.m. This window is used to organize the freshly acquired demand points for the purpose of real-time optimization. The supplementary demand locations are designated by the letter H and are assigned a numerical value. The dynamic information of the demand points is shown in Table 7.

Table 7
The information of add new demand point

Demand point	X/km	Y/km	e_i	l_i	Dwell time/min	q_i/(box)
H_{18}	31.3	60.9	10:00	10:30	16	129
H_{19}	27.9	57.6	8:40	9:00	15	139
H_{20}	19.9	59.9	10:20	11:00	16	141

Table 8 displays the parameters associated with the model and algorithm. According to the literature (Song et al., 2021), it is recommended to set α_1=0.846 and μ_1=1.761 for the psychological distress impact. The solution technique was implemented and computed using MATLAB R2020b on a 64-bit host system equipped with a 2.70GHz Intel(R) Core (TM) i5-11400H CPU and running Windows 11.

Table 8
Setting table of parameters

Parameter	Definition	Value
P_2	Penalty cost of violating time window constraints (yuan/min)	10
t_0	Driver psychological change threshold (min)	100
h_0	Fixed pay before driver mindset change (yuan)	3000
h_1	Compensatory pay per minute over the driving time threshold (yuan)	10
P_h	Psychological compensation factor for drivers' salary	0.001
C_{k3}	Unit cost of carbon emissions (yuan/kg)	0.25
C_{k4}	Carbon dioxide emission factor for fuel	2.68
α	Pheromone importance factor	1
β	Heuristic function importance factor	3
ρ	Pheromone volatilization factor	0.1
t_0	Path contribution threshold	0.4
ant_{num}	Ant population	20
NC_{max}	Maximum number of iterations	200

4.2. Optimization result analysis

4.2.1. Initial distribution results for split delivery

The allocation of emergency supplies in the event of split delivery is addressed via the use of the modified ACO technique, which was derived from the first phase of the optimization model. The model shown in Fig.10 incorporates considerations for dynamic demand and psychological consequences. The solutions to this problem are displayed in Fig.10. The exact routes of distribution are included in Table 9, along with a summary of the findings associated with each route.

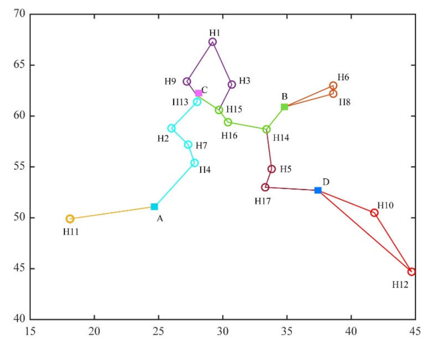

Fig. 10. Improved ant colony algorithm distribution roadmap (Initial stage)

Table 9
Distribution routes and distribution results (Initial stage)

Distribution center	Vehicle route	F_1	F_2	F_3
A	Type 1: A-H11-A Type 2: A-H4-H7- H2-H13-C	674.82	712768.71	6.00
B	Type 1: B-H8-H6-B	247.15	49968.60	3.00
C	Type 1: C-H15-H16-H14-B Type 2: C-H9-H1-H3-H15-C	535.39	338371.08	6.00
D	Type 1: D-H10-H12-D Type 2: D -H17-H5-H14 -B	577.22	295007.45	6.00

The optimization of the distribution channel led to a total of seven vehicles being necessary to accomplish the distribution process. The distribution fleet consisted of four type 1 vehicles and three type 2 vehicles, resulting in a distribution cost of 2034.58 yuan. Additionally, the psychological effects, encompassing the waiting effect, climbing effect, and shortage effect, amounted to a total of 1396119.71 yuan. Furthermore, the psychological cost incurred by the driver was 21 yuan.

4.2.2. Split delivery distribution results after adding demand

Fig. 11 displays the distribution plan derived from the optimization model of emergency material distribution, using the modified ACO approach. The use of this model in examining the first phase of direct delivery for fresh demand included an assessment of both the psychological impacts on recipients and the dynamic nature of demand. Table 10 displays the specific distribution routes and the corresponding consequences of the implemented solutions.

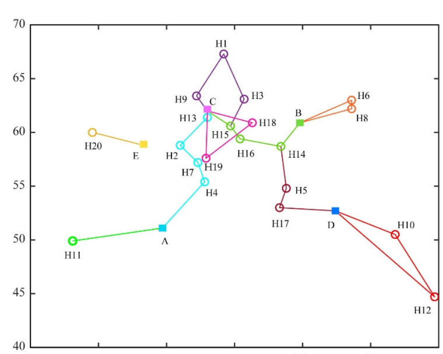

Fig. 11. Improved ant colony algorithm distribution roadmap (Demand add)

Table 10
Distribution routes and distribution results (Demand add)

Distribution center	Vehicle route	F_1	F_2	F_3
A	Type 1: A-H11-A Type 2: A-H4-H7- H2-H13-C	674.82	712768.71	6.00
B	Type 1: B-H8-H6-B	247.15	49968.60	3.00
C	Type 1: C-H15-H16-H14-B Type 1: C-H18-H19-C Type 2: C-H9-H1-H3-H15-C	799.76	395593.42	9.00
D	Type 1: D-H10-H12-D Type 2: D -H17-H5-H14 -B	577.22	295007.45	6.00
E	Type 1: E-H20-E	233.23	3230.80	3.00

After optimizing the distribution route, a total of nine cars were needed for the distribution assignment. The fleet comprised nine vehicles, specifically six type 1 distribution vehicles and three type 2 distribution vehicles. The overall distribution cost amounted to 2532.18 yuan. Additionally, the psychological effects, encompassing the waiting effect, climbing effect, and shortage effect, reached a total of 1456568.98 yuan. Furthermore, the psychological cost incurred by the driver was 27 yuan.

4.2.3. Real-time demand split delivery optimization phase distribution results

Fig. 12 illustrates the roadmap for the optimization model of emergency material distribution. This model accounts for dynamic demand and the psychological effects of split delivery. This issue was addressed by using an enhanced iteration of the ACO technique. The distribution routes and their corresponding solutions are shown in Table 11.

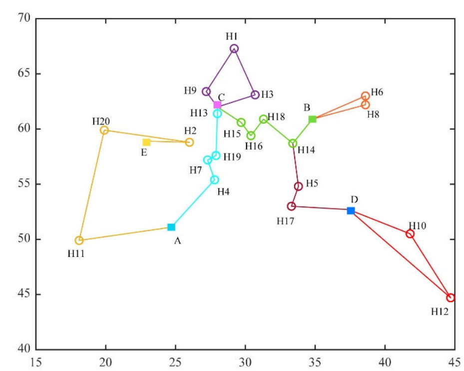

Fig. 12. Improved ant colony algorithm distribution roadmap (Dynamic real-time phase)

Table 11
Distribution routes and distribution results (Dynamic real-time phase)

Distribution center	Vehicle route	F_1	F_2	F_3
A	Type 1: A-H11-H20-H2-E Type 2: A-H4-H7-H19-H13-C	732.69	865144.36	6.00
B	Type 1: B-H8-H6-B	247.15	49968.60	3.00
C	Type 1: C-H9-H1-H3-C Type 2: C-H15-H16-H18-H14-B	534.02	255825.89	6.00
D	Type 1: D-H10-H12-D Type 2: D -H17-H5-H14 -B	577.22	295007.45	6.00

The distribution task necessitates the utilization of a combined fleet of seven vehicles, comprising four type 1 distribution vehicles and three type 2 distribution vehicles. The overall cost associated with the distribution process amounts to 2091.08 yuan. Additionally, the psychological impacts, encompassing the waiting effect, comparison effect, and shortage effect, collectively contribute to a total of 1465946.3. Furthermore, the psychological cost incurred by the driver is estimated at 21 yuan. The distribution route was optimized in such a way that the job of distributing needed a total of seven cars to be successfully executed.

4.3. Comparative analyses of results

This study employs a real-time optimization methodology to fulfil the distribution requirements for newly emerged needs. The proposed strategy is contrasted with the conventional practice of dispatching more trucks from the distribution centre to cater to the new demands, as per the first phase.

Table 12 presents a comparison of various factors, namely the quantity of delivery vehicles, the overall cost of delivery, the psychological impact on individuals, and the psychological burden on drivers. This comparison is made between two modes of direct delivery for new demand: the initial stage and the real-time optimization stage in the context of split delivery.

Table 12
Comparison of the two models

Mode	Number of delivery vehicles	Carbon emission cost	Total cost of delivery	Peoples climbing effect	Psychological cost to drivers
New demand direct delivery	9	11.53	2532.18	83.07	27
Real-time optimised model distribution	7	11.08	2091.08	37.71	21

The analysis reveals that the implementation of the new demand direct delivery mode necessitates the utilization of nine vehicles to successfully accomplish the delivery task. The carbon emission cost associated with the delivery process amounts to 11.53 yuan. Furthermore, the total delivery cost is calculated to be 2,532.18 yuan. Additionally, the psychological cost incurred by the driver is estimated at 27 yuan, while the perceived comparison effect among individuals stands at 83.07. The real-time optimization mode necessitates the use of seven vehicles in order to successfully accomplish the delivery work. The carbon emission cost associated with the delivery process amounts to 11.08 yuan. The whole delivery cost totals 2,091.08 yuan, which includes the psychological cost incurred by the driver amounting to 21 yuan. Additionally, the people's comparison effect is measured at 37.71. The whole expenditure associated with distribution amounts to $2091.08. Additionally, the psychological cost incurred by drivers is valued at 21 yuan, while the impact of the mounting effect on individuals amounts to 37.71. The real-time optimized distribution model has notable advantages in several aspects, including the reduction in the number of distribution trucks, the overall cost of distribution, the impact on human behaviour, and the psychological burden on drivers. The real-time optimized distribution model exhibits a reduction in the number of cars used, specifically two less vehicles compared to the new demand direct distribution model. Additionally, this model achieves a decrease in carbon cost by 3.8%, a reduction in the overall cost of distribution by 17.4%, and a decrease in the psychological cost experienced by drivers by 22.2%.

In brief, the use of the real-time optimized distribution model yielded an enhanced distribution solution in the context of an optimization model for the allocation of emergency supplies. This model considers the dynamic demand and psychological factors involved in split delivery. The outcomes of implementing the real-time optimized distribution model demonstrate a reduction in multiple aspects, including the cost of carbon emissions, the overall distribution cost, and the number of vehicles required for distribution. Additionally, this model offers certain benefits in terms of mitigating the psychological impact on individuals and the psychological burden on drivers. These advantages are observed when comparing it to the direct distribution model, which involves incorporating new demand during the initial phase of distribution. Hence, it can be argued that the real-time optimized distribution model possesses the potential to minimize the number of vehicles required for distribution tasks, thereby reducing carbon emissions and distribution costs. Moreover, this model has shown some improvement in mitigating the physical strain and resource scarcity experienced by individuals involved in the distribution process. Consequently, it effectively alleviates the psychological burden on drivers during distribution operations.

5. Conclusions

This study investigates the emergency distribution optimisation problem, considering dynamic demand and psychological effects. The objective is to ensure efficient distribution while working within limited funds. To address the unique characteristics of emergency material distribution, two optimization models are developed: an initial stage distribution optimization model and a real-time optimization stage distribution model. These models consider factors such as fixed costs, transportation costs, carbon emission costs, penalty costs for exceeding time window limitations, psychological effects on individuals, and psychological costs for drivers. Through simulation using an arithmetic example, the advantages of the real-time optimization mode for emergency material distribution, considering dynamic demand and psychological effects, are demonstrated.

This paper discusses four aspects of our research:

- The fundamental components of the recent demand for a certain time frame, thereafter divided into several equal time intervals to facilitate batch processing for real-time optimization, serve as the foundation for the dynamic demand. To optimize the efficiency of the rescue operation, the dynamic vehicle distribution problem is transformed into a static vehicle distribution route for each time interval.
- The aim is to minimize the overall distribution cost, which encompasses carbon emission cost, fixed cost, trans-shipment cost, and penalty cost for time window violations. This objective is pursued while ensuring distribution efficiency and working within limited capital. To achieve this, a real-time optimization model for the split delivery is developed, accounting for dynamic demand and psychological effects.
- This paper presents an optimization model for emergency material distribution, which is solved using an ant colony

algorithm. The algorithm incorporates dynamic demand and psychological effects into the optimization process. To ensure randomness in the initial solution, a chaotic initialization technique is employed. Additionally, a conservation matrix is introduced, and the pheromone is volatilized twice based on a volatilization factor to enhance the accuracy and convergence ability of the algorithm. Furthermore, the ants are guided to select a more cost-effective path through the application of the 3-opt local search strategy, and a local search is performed to obtain a more optimal solution or solution set.

- This article examines the optimization model proposed for the distribution of emergency supplies, taking into consideration dynamic demand and psychological effects. The model is further explored through illustrative examples. The models of the first stage with divided delivery, the initial stage with direct distribution of extra demand, and the initial stage with real-time optimization are thoroughly solved and studied. The scenario of split delivery serves as a compelling illustration of the advantages associated with the use of real-time optimization techniques for effectively managing dynamic demand. The proposed method offers a feasible approach to optimizing the distribution of paths in response to the dynamic need for emergency supplies. Additionally, it provides a decision framework and innovative concepts that may assist rescue organizers in efficiently organizing quick response and vehicle distribution.

The research conducted in this paper facilitates the optimization of vehicle utilization for distribution tasks, resulting in reduced carbon emissions, lower distribution costs, improved efficiency in handling inclines and shortages, and decreased psychological burden on drivers during the distribution process. This research offers rescue organizers a foundation for decision-making and novel concepts for expeditious response and strategic allocation of vehicles. It enables the development of an effective vehicle routing strategy for the distribution of emergency supplies, with the aim of minimizing losses caused by disasters. The inclusion of psychological factors of individuals affected by disasters in the optimization of emergency material distribution contributes to enhancing the effectiveness of emergency management mechanisms, enriching the theoretical foundations of emergency management, emphasizing the importance of a people-centered approach, and broadening the scope of application for emergency management theory. As a result, it is imperative for rescue organizers and decision-makers to prioritize the psychological well-being of those affected and improve the distribution system. This will enable them to effectively meet the evolving needs of the distribution process in a timely and efficient manner, while also ensuring its overall effectiveness.

This paper focuses solely on the dynamic demand and psychological effects of the emergency supplies distribution path optimization problem; therefore, the following areas require additional study:

- This work only focuses on the optimization issue of emergency material distribution paths, specifically in the context of a single material distribution scenario. However, in practical scenarios there is sometimes a need to distribute a wide range of items or to distribute products that are combined. This requires more investigation into the issue of distributing emergency resources across many categories.
- The current distribution approach lacks consideration for many elements such as traffic, weather, and vehicle failure. It only focuses on optimizing the distribution issue assuming a constant speed. To address the impact of different factors on vehicle speed, it is necessary to study the distribution problem in a more comprehensive manner.

Conflicts of interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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Data availability statement

All data generated or analyzed during this study are included in this paper.

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