



Research article

Optimization of regional emergency supplies distribution vehicle route with dynamic real-time demand

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Abstract: Given the particular characteristics of a sudden outbreak of an epidemic on a regional scale and considering the possible existence of a latent period process, this paper takes the distribution of regional emergency supplies as the research object. Form the proposes a dynamic vehicle path problem from the perspective of real-time demand changes. First, when there is a sudden outbreak of a small-scale epidemic, there is uncertainty about demand in the epidemic area. The objective functions of minimizing the vehicle travel route cost of emergency vehicles, the late arrival penalty cost of emergency vehicles, and the fixed cost of emergency vehicles, as well as the objective function of minimizing the total distance traveled by vehicles, are established. Second, a mathematical model of the dynamic real-time demand vehicle route problem is built using the actual vehicle routing problem as a basis. The model is then solved using the SFSSA method. Finally, the computational results demonstrate that the SFSSA algorithm can effectively reduce transportation cost and distance when solving the constructed mathematical model problem, providing a solution to the problem of optimizing the route of emergency material distribution vehicles for a regional scale.

Keywords: epidemic emergency; material distribution; route optimization; SFSSA algorithm

1. Introduction

In recent years, the earth's ecological environment has deteriorated, resulting in many natural catastrophes and public health crises that are hazardous to people's lives and have a considerable negative impact on the economy [1]. The most recent case was the Corona Virus Disease 2019

(COVID-19) in late 2019, which swept the world and caused huge losses not only economically but also socially, with people at risk of losing their jobs, the virus spreading in food and supply chains disrupted [2]. In public health emergencies, there are many uncertainties in dispatching emergency logistics vehicles within regional prevention and control, and subjective decisions will limit emergency rescue efficiency. Therefore, an objective analysis of the actual problem and developing a reasonable dispatching plan is the key to improving emergency rescue efficiency [3]. Following the COVID-19 outbreak, the epidemic has not been completely eradicated, with fewer large outbreaks but frequent regional ones. Given the potential for the sudden emergence of new points of need in the epidemic area and the continuing spread of the epidemic, the rational and practical delivery of relief supplies to the various points of need in the epidemic area is an appropriate countermeasure required to address the problem.

The distribution of emergency supplies is addressed in this study by means of the vehicle routing problem with dynamic real-time demand (VRPDRTD). Emergency logistics must take into account not only the cost of transport but also the efficiency and effectiveness of the distribution of emergency supplies. Firstly, to ensure the timeliness of rescue, the emergency supplies need to be transported to the disaster point at the earliest possible time. Considering the delay in emergency vehicle material distribution, this paper sets up the time window constraint for emergency material distribution. Secondly, to ensure the effectiveness of emergency distribution vehicles in the delivery of materials and make the model more in line with actual needs, the load of emergency materials of the delivery vehicles is constrained during the modeling process of this paper. Thirdly, given the dynamics of the outbreak and its evolution, the needs of the endemic areas are also dynamic. Therefore, the emergency distribution plan in this document will be adapted and updated to dynamic real-time needs. Finally, the model considers minimizing vehicle travel distances to ensure a reasonable distribution route for supplies.

The study of regional emergency material distribution considers this research problem's specificity. This research creates a mathematical model of the regional emergency material distribution vehicle route optimization issue based on four factors: distribution time window, vehicle loading, dynamic real-time demand, and distance traveled. On this basis, the sine cosine and firefly perturbed sparrow search algorithm (SFSSA) is applied to enhance the algorithm search mechanism by introducing chaotic tent mapping, initializing the population to improve the algorithm search mechanism, using the improved sine cosine optimization algorithm with random weights at the discoverer position to improve the local search ability of the algorithm, and introducing the firefly algorithm at the end of the algorithm to perturb the sparrow search algorithm [4]. Finally, the problem is solved by simulation experiments. The results of the simulations show that the algorithm used is better than the SSA and GA algorithms at solving the problem of figuring out the best route for emergency supplies to be delivered across a region.

The remaining work of this paper is organized as follows. Section II reviews the literature related to the vehicle routing problem, dynamic vehicle routing problem, and emergency material distribution problem. Section III defines the related issues as well as mathematical modeling. Section IV describes the SFSSA algorithm. Section V performs the verification analysis of the above problems.

2. Literature review

The vehicle routing problem (VRP) has been studied for more than 60 years and was first

proposed by Dantzig and Ramser in 1959 [5]. VRP is also a classic NP-Hard problem as a classic optimization combination problem in operations research [6]. The VRP problem has been widely involved in the joint transport of drones and trucks [7], electric vehicles' routes [8], and the optimization of green vehicles' routes [9]. Currently, most objective functions for solving vehicle route problems focus on solving cost-minimization problems. For example, Minh Anh Nguyen et al. consider combined drone and truck transport as a solution to the "last mile" delivery problem to minimize transport costs [10]. Hornstra et al. developed cost models, including cost fitness functions such as route and cargo picking costs [11]. Xia et al. consider the problem of the inability to split customer requirements and thus discrete split delivery according to orders and solve the model by designing a new forbidden search algorithm [12]. The literature still has cost minimization as a research objective. Faced with a shortage of transport resources during a public health emergency, the above literature problem does not apply to solving the problem of vehicle routing for the distribution of emergency supplies [13].

The dynamic vehicle route problem has received more attention from academics as they confront vehicle route optimization issues. The research field and application scope of the dynamic vehicle route problem is extensive, which promotes the new direction and progress of the study of DVRP [14]. For example, Sabar et al. examine dynamic vehicle routing with previous customer uncertainty. The goal of the study is to include new customers in the program. Minimize cost problems for all customers without violating problem constraints. The problem is solved using the adaptive method combined with the evolutionary operator and local search method. Help decision-makers design the best solution [15]. Li et al. study the periodic dynamic vehicle route problem based on delayed service according to the continuous updating problem of customer demand and design a hybrid variable neighborhood artificial bee colony algorithm with a multi-stage solution, which can better balance the route update and vehicle real-time information matching problem for new and old customers [16]. Xiang Xiaoshu et al. proposed an ACO-CD algorithm based on coverage diversity based on the dynamic vehicle route problem with unknown customer demand. They verified the effectiveness of the algorithm by testing it [17]. Resmi Ramachandran Pillai and Michael Arock proposed capacitated DVRP with time windows (CDVRPTW), which was used to solve the CDVRPTW problem by combining the improved firefly algorithm with spike nerve P [18]. Jiang et al. proposed deep reinforcement learning algorithms to solve the problem of dispatching emergency supplies with dynamic demand changes [19].

When optimizing the route of emergency distribution vehicles, it is necessary to consider the special aspects of emergency logistics, improve the efficiency of rescue time, make reasonable arrangements for the distribution of emergency supplies, and other issues for which emergency logistics is an essential part of the solution [20]. For example, Du et al. introduced a UAV vehicle route optimization problem with time window constraints to improve the efficiency of medical supplies delivery. They formulated a mixed integer programming model considering contactless delivery, total transit time, and customer service time windows [21]. Espejo-Díaz and Guerrero consider that the affected population's psychological affordability affects emergency supplies' distribution. Therefore construct mathematical models to balance the cost of rescue routes [22]. Suzuki examines how the choice of material convergence (MC) method affects emergency supplies "last mile" distribution. The paper refers to two analytical methods. One is the P method (transport of primary emergency supplies to the affected area first). The other is the M method (including emergency and non-emergency supplies for shipments to affected areas). Finally, it is proved that the M method practice is more

effective than the P method [23]. Mishra et al. present a dynamic planning model with a sliding time window based on disaster scenario dynamics to analyze catastrophe indicators and distribute emergency supplies effectively, which helps deal with the distribution of emergency supplies in regional outbreaks [24].

In addition, the problem of emergency material distribution vehicle routes is a complex multi-objective optimization problem. In solving such problems, precise algorithms have certain limitations in dealing with such practical issues. More heuristic algorithms, such as the genetic algorithm [25], ant colony optimization algorithm [26], and particle swarm optimization algorithm [27], are used to solve this problem. This paper uses the group intelligence algorithm of recent years to solve the algorithm. It is feasible to solve practical problems by improving the algorithm.

In summary, due to the sudden epidemic outbreak, the government has adopted regional prevention and control measures that require the timely supply of daily supplies to the population. Moreover, in the relevant research on the problem of emergency material distribution vehicles, most of the objective functions constructed by the appropriate models of existing problems are considered with the goal of cost minimization, which is impractical in evaluating the actual epidemic problem. Therefore, this paper studies the problematic situation of optimizing the route of emergency material distribution vehicles in the background of epidemic prevention and control in the region. The research ideas in this paper are as follows.

1) The uncertainty factors due to the outbreak of regional epidemics are considered to build a mathematical model of the emergency material distribution vehicle route optimization issue from four aspects: time window limitation, vehicle loading, dynamic real-time demand, and driving distance.

2) In this paper, considering the increase of material demand points and demand in the epidemic prevention and control region, the dynamic real-time demand in the prevention and control region is more in line with the actual situation of emergency material demand in the event of an epidemic, to cope with the negative impact on society after the sudden outbreak of the epidemic.

3) The SFSSA algorithm is used to solve the model. The experiment proves that the SFSSA algorithm is superior to the SSA and GA algorithms.

3. Model establishment

3.1. Problem description

Following the COVID-19 outbreak, the epidemic has not been completely eradicated and the government will usually resort to city closures or area-wide closure and control measures in the face of a continuous and uninterrupted outbreak. To prevent the spread of the epidemic, people must stay at home under a quarantine policy until the epidemic disappears. But, this would prevent individuals from going out and purchasing the necessities for their everyday lives, such as daily medications for their families. The commodities that inhabitants need daily would need to be distributed by the government at each demand point. Therefore, a practical solution is needed for the issue of efficiently and timely distributing aid to the numerous locations of need in the epidemic regions.

This paper's problem is optimizing regional emergency material distribution vehicle routes under dynamic real-time demand: One emergency material distribution center and N demand points in a range-determined prevention and control area. The geographical location of each node is known, and the distribution process is a closed loop. The starting point of all distribution vehicles is the emergency

material distribution center. Demand point requirements, maximum vehicle load capacity, and demand point delivery windows are known. Demand point requirements combined do not exceed the vehicle load sum, allowing for mixing emergency supplies at different demand points and fixed service times at demand points.

The following fundamental model assumptions are established in this research to comprehend the study and model better.

- 1) At the beginning of the rescue, the emergency material delivery vehicle departs from the distribution center, and upon completion of the delivery, all vehicles return to the distribution center.
- 2) Sets the location of the distribution center unchanged, and no out-of-stock status exists.
- 3) Consideration is given only to the distribution of emergency supplies, i.e., the flow of emergency supplies is unidirectional.
- 4) Emergency material delivery vehicles travel uniformly during the delivery process.
- 5) The demand point has requirements for the service time window, and the delivery vehicle can arrive at the delivery demand point earlier but not later.
- 6) During the period, it is required that all demand points must be visited, each demand point can only be served by one vehicle for delivery, and each demand point can only be called once.
- 7) All distribution vehicles have the exact vehicle parameters, i.e., the same model, each vehicle has the same emergency supplies, and the maximum load capacity of each vehicle is known.
- 8) The material requirements at the point of demand do not exceed the vehicle's maximum capacity.
- 9) No consideration is given to other external factors during the travel of emergency material distribution vehicles.

3.2. Parameter setting

The meanings of the mathematical symbols in the model are shown in Table 1 below.

Table 1. Parameter setting.

Symbol	Description
N	The collection of demand points, $N = \{1, 2, \dots, n\}$
K	The collection of available automobiles, $K = \{1, 2, \dots, k\}$
Q	Maximum load per vehicle and approved load
L	The farthest distance the car can go is $L > 0$
δ	The maximum number of vehicles that can be used to transport emergency supplies
q_{ij}	loading a vehicle from demand point i to j
p_i^r	The number of materials allocated at the demand point
d_{ij}	Vehicles may travel a non-negative distance between demand points i and j if $(0 \leq i \neq j \leq N)$ exists.
t_{ij}	The amount of time it takes a car to get from demand point i to point j $(0 \leq i \neq j \leq N)$
td_i	The moment when dynamic demand first appeared
$[E_0, L_0]$	The time window for receiving dynamic demand points by emergency material distribution centers
N_u	The new demand point specifications, $N_u = \{n + 1, n + 2, \dots, n + m\}$
s_i	The service time at the demand point i where $k = \{1, 2, \dots, k\}$ and $i = \{1, 2, \dots, n\}$
t_{ki}	Vehicle k travel time to demand point i
t_{k0}	Vehicle k timing of departure from the distribution point for emergency supplies
l_{ki}	Vehicle k should depart after it has served demand point i , $l_{ki} = a_{ki} + s_i$
$[E_i, L_i]$	The window of service for demand point i
α	L_i unit penalty cost factor for being beyond the time frame
C	Cost of unit distance
F_k	Use of a vehicle for a fixed cost, $F_k > 0$

The meanings of the decision variables in the model are shown in Table 2 below.

Table 2. Decision variable settings.

Symbol	Description
x_{kij}	Vehicle k performs a distribution duty between demand points i and j , x_{kij} is 1; otherwise, x_{kij} is 0
y_{ki}	Vehicle k service demand point i , y_{ki} is 1, otherwise y_{ki} is 0

3.3. Model construction

As this research exclusively addresses regional epidemics that take place on a regional scale, there is no problem with a widespread epidemic state or the distribution of supplies across provinces and cities. As a result, the government takes precautions to keep residents quarantined within their homes. Because of this, the primary concern that we focus on is how to reduce the cost of distribution, which takes into account both the cost of the vehicle's route and the cost of the vehicle's stationary use. Another vehicle delay penalty cost is taken into consideration given that the emergency circumstance is taken into account. In this paper, we consider the costs incurred in the process of emergency material distribution as vehicle route cost, vehicle delayed arrival penalty cost, and vehicle fixed use cost, respectively, and each cost is specified as follows.

1) Vehicle route cost:

$$\min Z_1 = \sum_{i \in N \cup N_u} \sum_{j \in N \cup N_u} \sum_{k=1}^K d_{ij} \cdot x_{kij} \cdot C \quad (1)$$

2) Vehicle delayed arrival penalty cost:

$$\min Z_2 = \sum_{i \in N \cup N_u} \sum_{k=1}^K \alpha \cdot \max\{t_{ki} - L_i, 0\} \quad (2)$$

3) Vehicle fixed cost:

$$\min Z_3 = \left[\sum_{i \in N \cup N_u} \sum_{j \in N \cup N_u} \sum_{k=1}^K x_{kij} \right] * F_k \quad (3)$$

In addition to this point of interest, given that we are located in a control area for the regional distribution of materials, we have set as one of our priorities the reduction of the total distance that needs to be traveled by vehicles in the event of an emergency. Thus, the objective function that minimizes the total cost of vehicle route cost, vehicle delayed arrival penalty cost, vehicle fixed cost, and the objective function that minimizes the total distance traveled by the vehicle is constructed, and the optimization model of the regional emergency material distribution vehicle route problem under real-time dynamic demand is as follows.

$$\min Z_1 = (z_1, z_2, z_3) \quad (4)$$

$$\min Z_2 = \sum_{i \in N \cup N_u} \sum_{j \in N \cup N_u} \sum_{k=1}^K d_{ij} \cdot x_{kij} \quad (5)$$

s.t.

$$\sum_{j \in N \cup N_u} \sum_{k=1}^K x_{kij} = 1, \quad \forall i \in N \cup N_u \quad (6)$$

$$\sum_{i \in N \cup N_u} \sum_{k=1}^K x_{kij} = 1, \quad \forall j \in N \cup N_u \quad (7)$$

$$\sum_{i \in N \cup N_u} q_i y_{ik} \leq Q, \quad \forall k \in K \quad (8)$$

$$q_{1j} = x_{1j} Q, \quad \forall j \in N \cup N_u, \forall k \in K \quad (9)$$

$$\sum_{i \in N \cup N_u} x_{kih} = \sum_{i \in N \cup N_u} x_{khj}, \quad \forall h \in N \cup N_u, \forall k \in K \quad (10)$$

$$\sum_{i \in N \cup N_u} p_i^r \leq Q * \delta, \quad (11)$$

$$\sum_{j \in N \cup N_u} x_{k1j} = \sum_{i \in N \cup N_u} x_{ki1}, \quad \forall k \in K \quad (12)$$

$$\sum_{i \in N} x_{kij} = y_{ki}, \quad \forall j \in N \quad (13)$$

$$\sum_{i \in N_u} x_{kij} = y_{ki}, \quad \forall j \in N_u \quad (14)$$

$$\sum_{i \in N \cup N_u} \sum_{j \in N \cup N_u} d_{ij} \cdot x_{kij}, \quad \forall k \in K \quad (15)$$

$$\sum_{i \in N} \sum_{j \in N} x_{kij} = \sum_{i \in N} \sum_{h \in N} x_{kjh}, \quad i \neq j \neq h, \forall k \in K \quad (16)$$

$$\sum_{i \in N_u} \sum_{j \in N_u} x_{kij} = \sum_{i \in N_u} \sum_{p \in N_u} x_{kjp}, \quad i \neq j \neq p, \forall k \in K \quad (17)$$

$$E_i \leq a_{ki} \leq L_i, \quad \forall k \in K, i \in N \cup N_u \quad (18)$$

$$a_{ki} + s_i + t_{ij} = a_{kj}, \quad \forall k \in K, i \in N \cup N_u \quad (19)$$

$$td_i \in [E_0, L_0], \quad i \in N \cup N_u \quad (20)$$

$$Q > 0, p_i^r > 0, q_i > 0 \quad (21)$$

Equation (4) is the objective function of minimizing the cost of the mathematical model. The first term is the vehicle route cost, the second is the vehicle delayed arrival penalty cost, and the third is the vehicle fixed cost. Equation (5) is the objective function of minimizing the total distance traveled by the vehicle for the mathematical model.

Equations (6) and (7) for each demand point to accept only one emergency vehicle once the distribution of emergency supplies services, dynamic real-time demand, including the initial demand point and new demand points. Equation (8) represents the vehicle capacity constraint, i.e., the vehicle does not exceed the maximum vehicle capacity when departing from the distribution center. Equation (9) indicates that all vehicles exiting from emergency material distribution centers are fully loaded. Equation (10) suggests that a vehicle visiting this demand point must leave from this demand point. Equation (11) indicates that the total demand for supplies at the demand point cannot exceed the service capacity of the emergency supplies distribution center. Equation (12) shows ensuring that each vehicle departs from the distribution center and returns to the distribution center. Equations (13) and (14) are

expressed as the exact vehicle access demand point constraint and additional demand point constraint. Equation (15) is described as a vehicle travel distance constraint; that is, the total distance traveled by any vehicle k must not exceed its maximum travel distance. Equations (16) and (17) are expressed as demand point location and additional demand point location access constraints; for any vehicle k , the flow to access demand point j is conserved, i.e., the flow to and from demand point j is the same. Equation (18) represents the time window constraint for demand point i . Equation (19) is the time to calculate the vehicle's arrival at the demand point j . Equation (20) indicates the time to limit the emergence of dynamic demand within a defined period. Equation (21) is expressed as a non-negative variable constraint.

3.4. Dynamic real-time demand information processing strategy

Because COVID-19 is highly infectious and has an incubation period, it is not possible to determine whether the patients carrying the virus have themselves become mobile. Furthermore, because it is not certain that mobility has occurred, it is also uncertain as to whether or not other areas are already infected with the virus. Based on information from the center for disease control and prevention (CDC), the government will determine whether there are any suspected cases in the area (e.g., residents who have been in contact with patients with COVID-19 or who have traveled to medium- to high-risk areas). The site will be closed-off management and its residents isolated. In the process of emergency material distribution, the location of the demand point in the epidemic area is not static, and the location of the demand point also changes dynamically, which requires the dispatching system to respond quickly to meet the demand for emergency materials at the demand point, as shown in Figure 1. This study considers the dynamic real-time demand problem, which is based on the government through the CDC to get the existence of the situation described above will be closed to manage the area designated as a material demand point. The government will be all residents of the area nucleic acid testing. Based on the samples taken, the CDC will determine the presence of positive patients, according to the test results, to determine whether a new demand point has been added. Therefore, in this paper, considering the particular characteristics of the post-epidemic outbreak situation, dynamic real-time demand includes both the increase and the increase or decrease of demand of initial demand points.

As shown in Figure 2, the emergency distribution center receives real-time demand information one after another in the time window $[E_0, L_0]$. When the interval between this moment and the last optimized processing time reaches T , the moment is taken as a time separation point $u(t)$, called the batched processing moment, as shown in Figure 2. According to the established optimization criterion, it is possible to divide the receiving time window $[E_0, L_0]$ into, e.g., stemmed time intervals $[u(t-1), u(t)]$, which in turn transforms the dynamic vehicle route problem into multiple instantaneous static vehicle route problems.

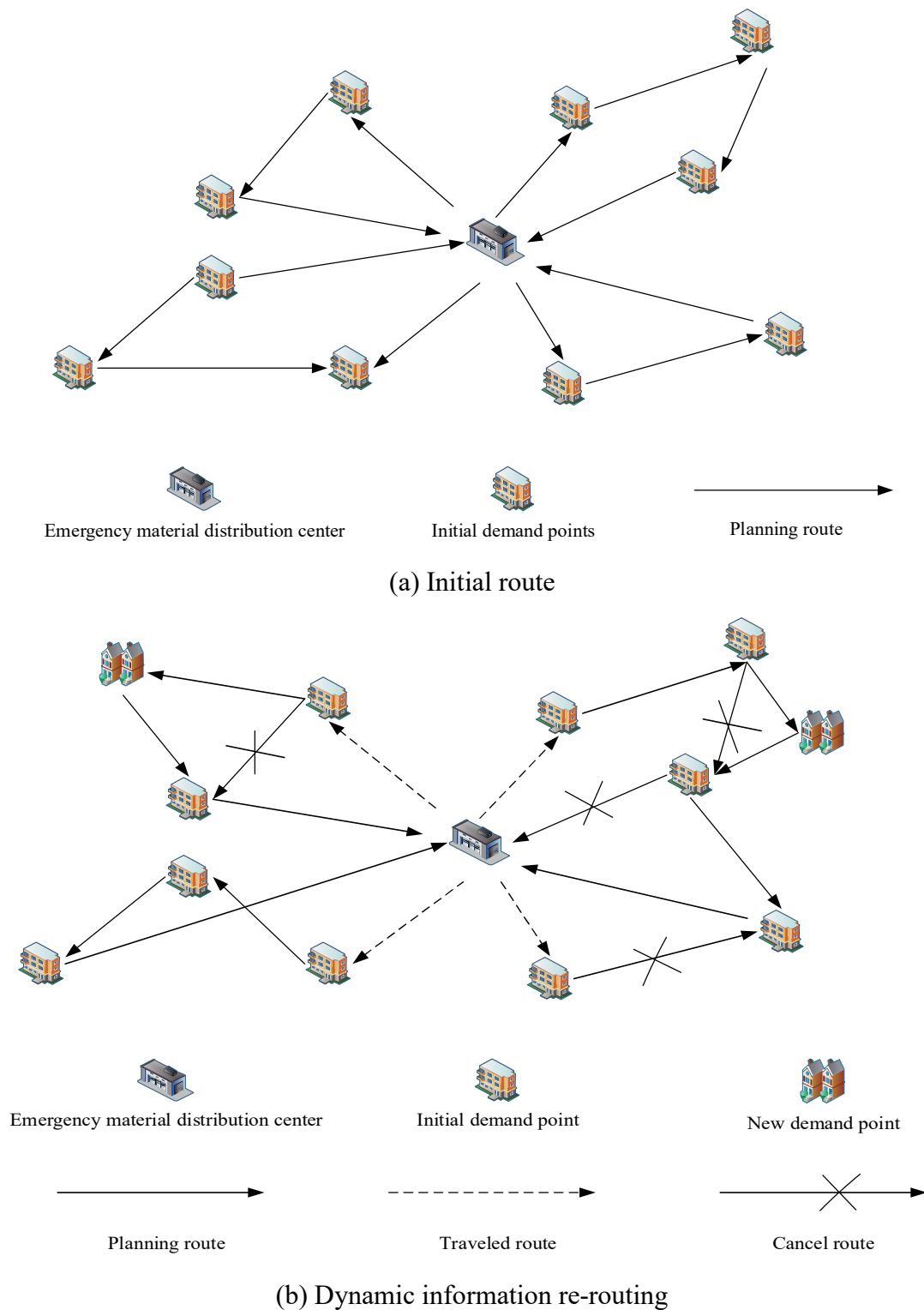


Figure 1. Dynamic vehicle route optimization schematic.

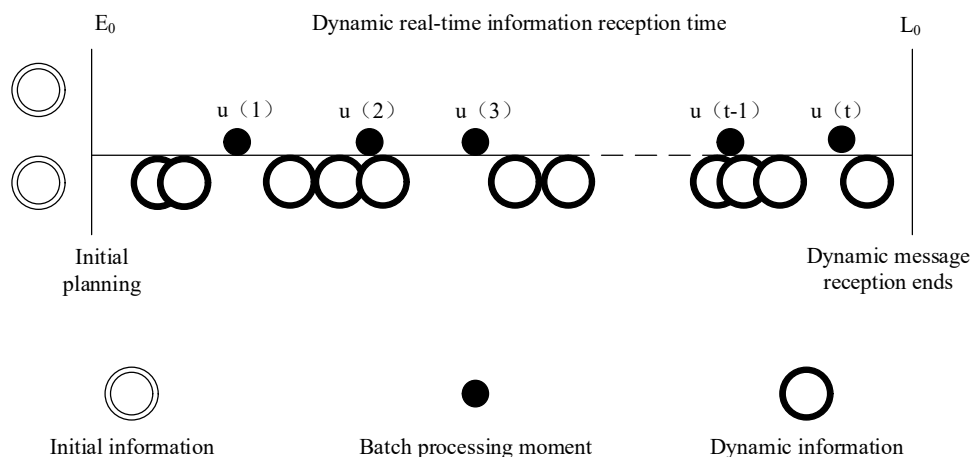


Figure 2. Dynamic batching optimization strategy.

Due to the increase in demand at the initial demand point in the dynamic real-time demand problem considered in this paper, there may be an urgent need for this material at the demand point. Let a demand point m issue a dynamic demand request at the moment $td (td > u(t))$, t_{km} denotes the start time of vehicle k service demand point m in the original plan distribution scheme, the service time window of the new demand point m will be $[e_i, l_i]$, if $l_i \leq u(t) + T$, then the demand is an urgent demand problem. To quickly respond to this type of urgent demand problem, the urgent dynamic demand moment td of this type is chosen as the next batch processing moment $u(t + 1)$, and the demand point of the urgent demand is inserted into the original route to form a new route planning. This research examines the emergency material distribution route optimization issue to get a viable distribution route. This paper considers the emergency material distribution route optimization problem focusing on bringing a reasonable distribution route. The strategy considers the urgent needs of demand points that can be processed promptly to improve the efficiency of emergency supplies distribution, which can effectively avoid the penalty costs arising from delays. According to the analysis above, the initial planning and dynamic demand stages may address the emergency material distribution route optimization issue while considering the dynamic real-time demand. The two-stage solution procedure is described below and may be seen in Figure 3.

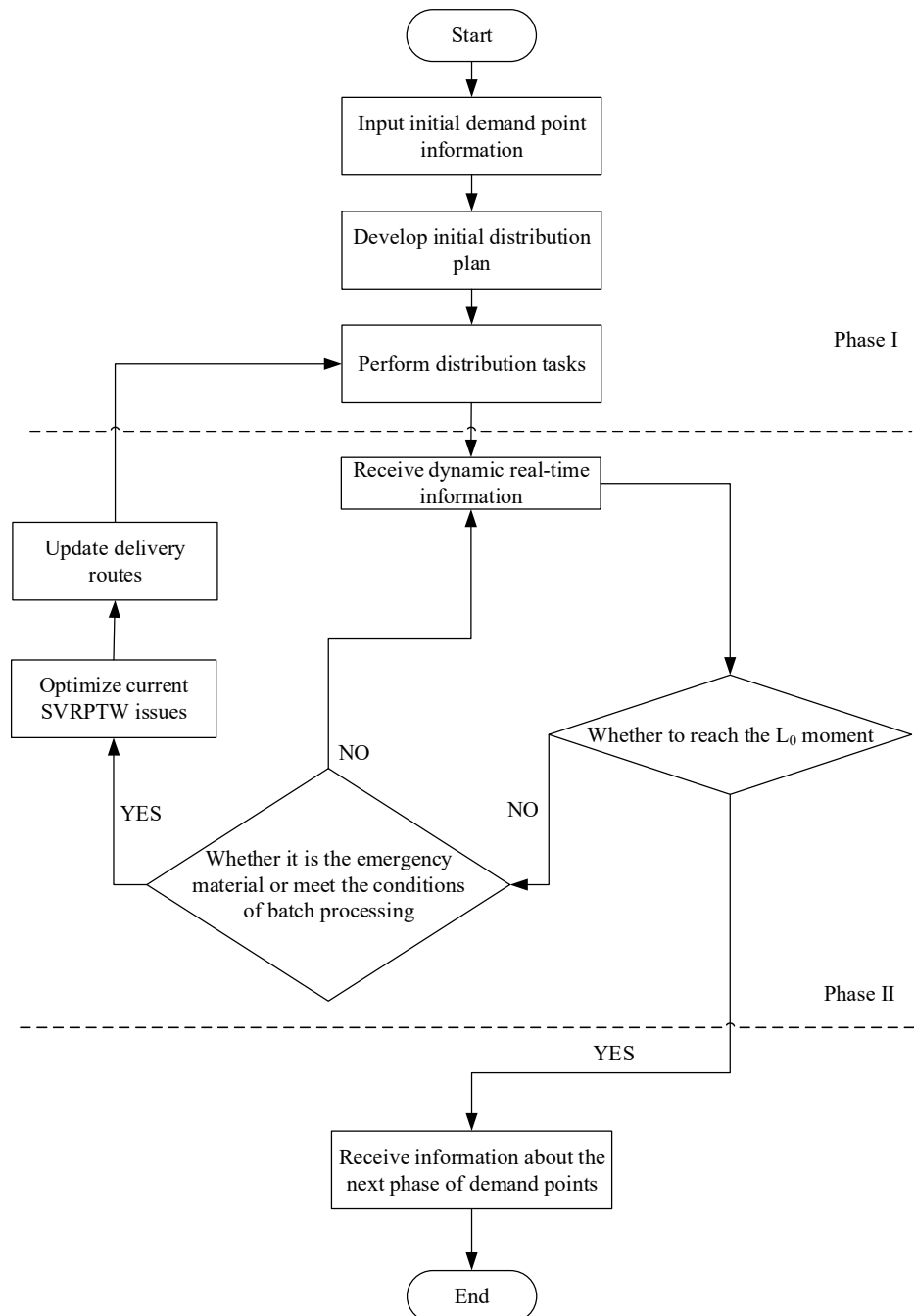


Figure 3. Two-phase flow diagram with real-time dynamic demand.

4. Model solution

4.1. The basic sparrow search algorithm

The sparrow search algorithm (SSA) is a swarm intelligence optimization algorithm proposed by Xue and Shen in 2020, which mainly simulates the predatory and anti-feeding behavior of sparrow groups [28]. Individual sparrows are usually classified as explorers, followers, and scouts. In their natural state, individuals watch each other, and followers in a sparrow group typically compete for the

food resources of their high-feeding peers to improve their predation rate. While foraging, all individuals remain alert to their surroundings to prevent the arrival of natural predators [29].

In the sparrow search algorithm, the best individual within the group is given priority in the search process to obtain food. As an explorer, it has access to a more extensive foraging search range than its followers. During each iteration, the explorer's position is updated in the following manner.

$$X_{id}^{t+1} = \begin{cases} X_{id}^t \cdot \exp\left(-\frac{i}{\alpha \cdot iter_{max}}\right) & , R_2 < ST \\ X_{id}^t + Q \cdot L & , R_2 \geq ST \end{cases} \quad (22)$$

where X_{id} denotes the position of a single sparrow, i marks the current iteration, $iter_{max}$ denotes the maximum iteration, α is a random number between $[0, 1]$, R_2 ($R_2 \in [0, 1]$) and ST ($ST \in [0.5, 1]$) denoting the warning value and safety value, respectively, Q denotes a random number adhering to the normal distribution, L is a $1 \times d$ matrix, meaning that each of its elements is 1.

The location of followers is updated in the following manner.

$$X_{id}^{t+1} = \begin{cases} Q \cdot \exp\left(\frac{X_{worst}^t - X_{id}^t}{i^2}\right) & , i > \frac{n}{2} \\ X_{best}^{t+1} + |X_{id}^t - X_{best}^{t+1}| \cdot A^+ \cdot L & , i \leq \frac{n}{2} \end{cases} \quad (23)$$

where X_{best} represents the location of the best explorer, X_{worst} is the current global worst position, and n represents the size of the population. A^+ is $A^+ = A^T(AA^T)^{-1}$, where A is a $1 \times d$ matrix with each element randomly assigned to 1 or -1.

The location of the scout is updated in the following manner.

$$X_{id}^{t+1} = \begin{cases} X_{best}^t + \beta \cdot |X_{id}^t - X_{best}^t| & , f_i > f_g \\ X_{i,j}^t + K \cdot \left(\frac{|X_{id}^t - X_{worst}^t|}{(f_i - f_w) + \varepsilon}\right) & , f_i = f_g \end{cases} \quad (24)$$

where X_{best} denotes the current global optimal position, β is the step control parameter, K denotes a random number within the range $[-1, 1]$, f denotes the fitness value, f_g and f_w denote the current optimal and worst fitness values, respectively, and ε is a constant to prevent the denominator from being 0.

The basic SSA algorithm flows as follows.

Step 1. Initialize the population and the number of iterations, and initialize the explorer and follower ratio.

Step 2. The fitness values are calculated and ranked.

Step 3. The explorer position is updated according to Eq (25). When $R_2 < ST$, the surrounding environment is safe, no natural enemies appear, and the explorer will conduct an extensive search. When $R_2 \geq ST$, it means that natural enemies appear, and a warning signal needs to be sent to the sparrows in the population, at which time all sparrows need to fly to other safe places to find food.

Step 4. The location of the follower is updated using Eq (26). When $i > \frac{n}{2}$, the i^{th} the follower is in a bad position and hence extremely hungry, and the follower must fly to other locations to get food. When $i \leq \frac{n}{2}$ is reached, the i^{th} the follower is looking for food in the ideal location.

Step 5. The scout position was updated using Eq (27). When $f_i > f_g$, the sparrow is on the periphery of the population and is highly vulnerable to predator attack. When $f_i = f_g$, the scout knows

the danger and should move closer to other sparrow positions to avoid being attacked.

Step 6. Calculate the fitness value and update the sparrow position.

Step 7. If the stop condition is satisfied, exit and output the result; otherwise, repeat the execution of Step 2.

4.2. Improving the sparrow search algorithm

The mathematical model constructed in this paper has a complex problem with many constraints, which makes the objective function very sensitive to personal changes. SSA algorithms that use global update policies tend to be less effective at solving such mathematical models. Tent chaotic mapping has good ergodicity and randomness characteristics [30]. Introducing it into the basic SSA algorithm in the initial static phase can significantly improve the population diversity and the ability to jump out of the local optimum of the SSA algorithm. In the sparrow search algorithm, the explorer's position is constantly updated during the food search. When the explorer finds the optimal place, many sparrows are attracted to concentrate together, increasing the probability of the population falling into a local solution. Therefore, during the dynamic demand change phase, the sine and cosine features in the sine and cosine algorithm are utilized at the explorer position to fluctuate toward the optimal solution position [31]. Furthermore, introducing random inertia weights can balance the global convergence ability and improve the algorithm's ability to find the optimal global solution [32]. Finally, the optimal route planning route is updated using the firefly perturbation strategy [33]. Make the algorithm more suitable for the mathematical model of this paper in solving this problem. The SFSSA algorithm flow chart is shown in Figure 4.

Before describing the algorithm, a symbolic description of the improved sparrow search algorithm is given in Table 3.

Table 3. Symbolic description of the SFSSA algorithm.

Symbols	Description
Z_i^d	The original chaotic sequence in the interval (0,1)
$X_{i,max}^d$	Maximum value for the X_i^d sequence
$X_{i,min}^d$	The minimum value for the X_i^d sequence
X_i^d	Sequences of the population after chaotic disturbances
r_0	The range $[0,2\pi]$ contains random numbers
r_1	The range $[0,2]$ contains random numbers
μ	The random inertia weighting factor
I_0	Source of firefly light intensity
β_0	Maximum firefly attraction strength
γ	Brightness absorption coefficient
$r_{i,j}^2$	The separation in space between fireflies i and j
x_i^d, x_j^d	The locations of i and j in the d-dimensional space of sparrows
α	Step factor in the $[0, 1]$ range
ϵ	Random figures between $[-0.5, 0.5]$

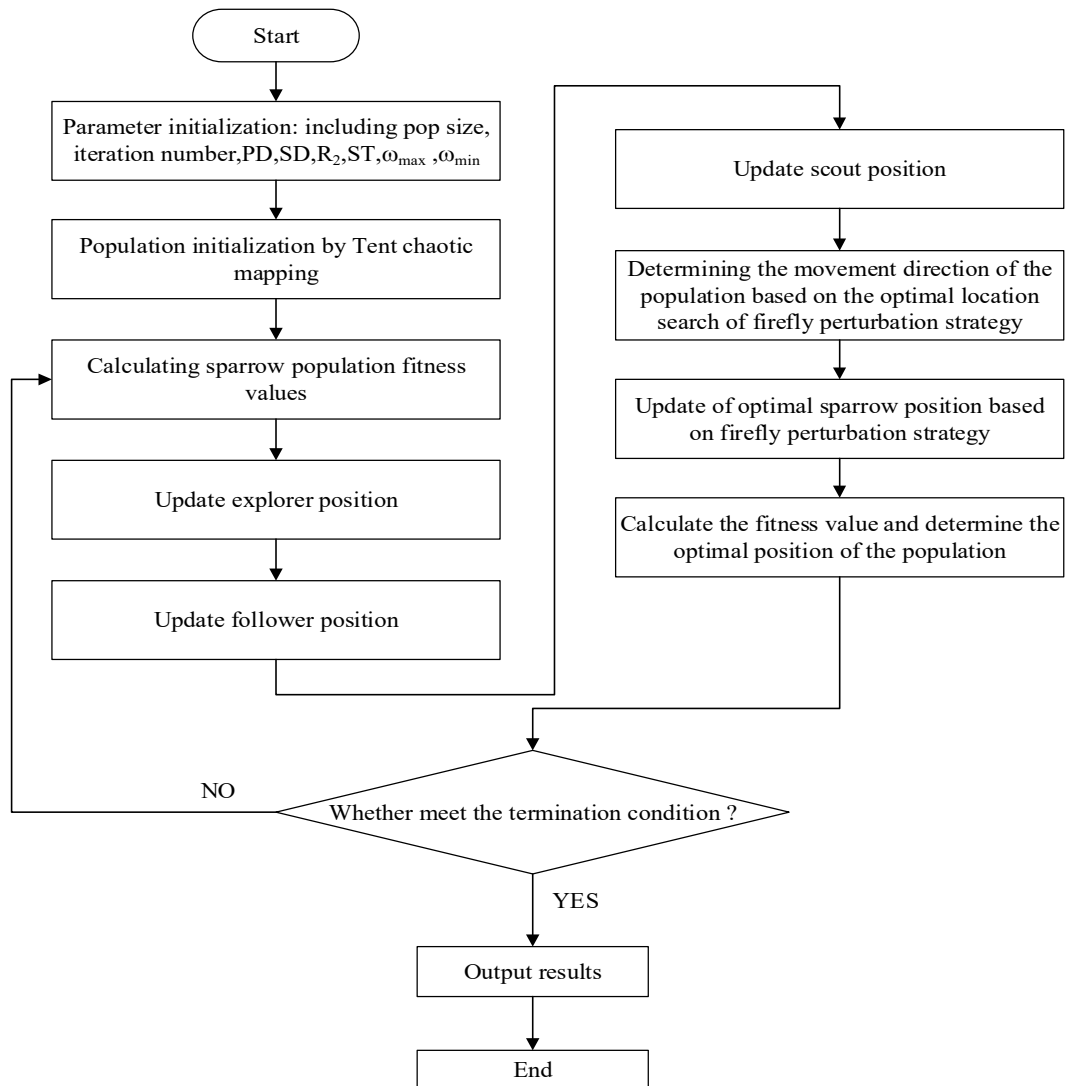


Figure 4. SFSSA algorithm flowchart.

Step 1. Initialize parameters.

Population size N , the maximum number of repetitions, explorer PD , scout SD , warning value R_2 , and safety value ST are among the parameter settings.

Step 2. Initialize the population based on tent chaos mapping.

The chaotic tent sequences are introduced in the initialization population stage to increase the population diversity and speed up the convergence speed of the SSA algorithm in the early stage by using the characteristics of chaotic sequences [34].

The chaotic tent mapping generating sequence initialization population improvement SSA algorithm is expressed in the manner shown below.

$$Z_i^d = \begin{cases} 2Z_i^d & , 0 \leq Z_i^d < 0.5 \\ 2(1 - Z_i^d) & , 0.5 \leq Z_i^d \leq 1 \end{cases} \quad (25)$$

To avoid the chaotic tent sequence from falling into small and unstable periodic points during the

iteration, a random variable $rand(0,1) \times \frac{1}{N_T}$ is introduced to the original chaotic tent map expression, and the improved chaotic tent map expression is as follows.

$$Z_i^d = \begin{cases} 2Z_i^d + rand(0,1) \times \frac{1}{N_T} & , 0 \leq Z_i^d < 0.5 \\ 2(1 - Z_i^d) + rand(0,1) \times \frac{1}{N_T} & , 0.5 \leq Z_i^d \leq 1 \end{cases} \quad (26)$$

Generating chaotic variables Z_i^d carrier substitution into the space to be solved by Eq (26) [35].

$$X_i^d = X_{i.min}^d + Z_i^d (X_{i.max}^d - X_{i.min}^d) \quad (27)$$

Step 3. Calculate population fitness values.

The fitness value f_i is calculated for each sparrow based on the objective function value (fitness function value). In this model, the current optimal fitness value f_g and the corresponding optimal position X_{best} are selected, and the current worst fitness value f_w and the corresponding worst position X_{worst} are selected.

Step 4. Update explorer location.

In the basic sparrow search algorithm, when $R_2 < ST$, the explorer gets smaller in each dimension of the individual sparrow as the number of iterations is updated, and the search space gradually decreases, increasing the probability of falling into the optimal local solution. Therefore, a random weight factor is introduced in the explorer position to improve the sine cosine optimization algorithm. The random weight factor ω is introduced to enhance the search ability in the early search period and balance the global exploration. The parameter r_0 helps the algorithm to search in $[0, 2\pi]$ to avoid falling into the local optimum in the late search period and improve the local pioneering ability. The equation of this process is shown as follows.

$$\omega = \omega_{min} + (\omega_{max} - \omega_{min}) \sin\left(\frac{t\pi}{iter_{max}}\right) \quad (28)$$

$$X_{id}^{t+1} = \begin{cases} (1 - \omega) \cdot X_{id}^t + \omega \cdot \sin r_0 \cdot |r_1 \cdot X_{best} - X_{id}^t| & , R_2 < ST \\ (1 - \omega) \cdot X_{id}^t + \omega \cdot \cos r_0 \cdot |r_1 \cdot X_{best} - X_{id}^t| & , R_2 \geq ST \end{cases} \quad (29)$$

Step 5. Update the location of followers.

Step 6. Update the scout location.

Step 7. Based on the optimal location search of the firefly perturbation strategy, determine the direction of population movement.

The equation for the degree of firefly luminescence is as follows.

$$I = I_0 \cdot e^{-\gamma r_{ij}^2} \quad (30)$$

The following is the equation for the attraction of fireflies.

$$\beta = \beta_0 \cdot e^{-\gamma r_{ij}^2} \quad (31)$$

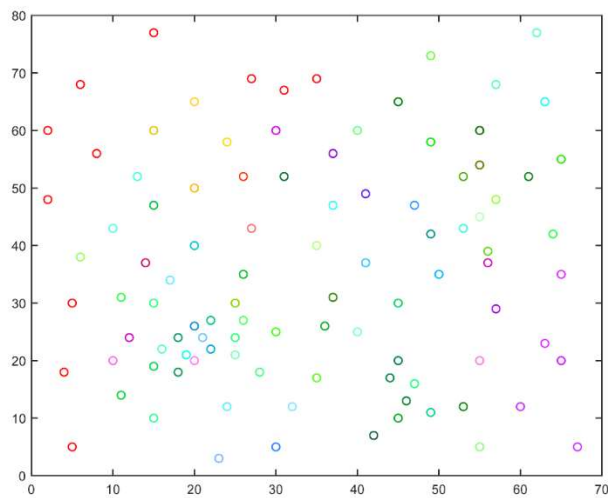
Step 8. The firefly perturbation approach is used to update the ideal location.

The firefly at x_i^d will move to x_j^d according to the equation below, if a firefly at $x_j^d = (x_1^d, x_2^d, x_3^d \dots, x_j^d)$ is brighter than a firefly at $x_i^d = (x_1^d, x_2^d, x_3^d \dots, x_i^d)$ [36].

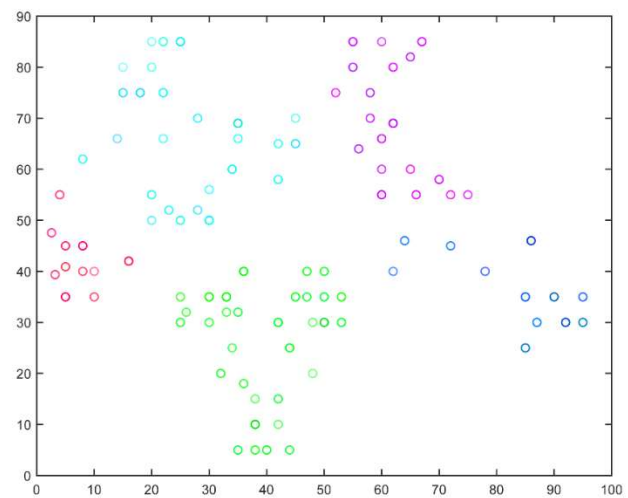
$$x_i^d = x_i^d + \beta_0 \cdot e^{-\gamma r_{ij}^2} \cdot (x_j^d - x_i^d) + \alpha \cdot \epsilon \quad (32)$$

Step 9. Calculate the fitness value and decide where the population should be placed.

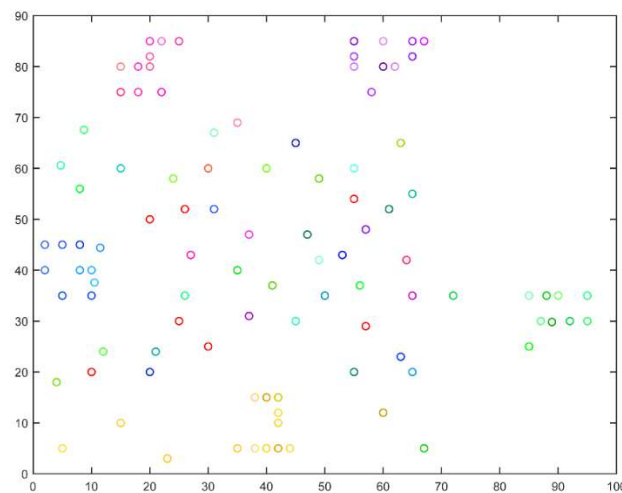
Step 10. If the stop condition is met, go on and output the outcome; otherwise, repeat step (3).



(a) R class demand point location distribution map



(b) C class demand point location distribution map



(c) RC class demand point location distribution map

Figure 5. Location map of each type of demand point.

4.3. Algorithm performance test analysis

4.3.1. Solomon benchmark test

The SFSSA algorithm is used for comparison tests with the SSA algorithm and the GA algorithm to verify the effectiveness and merit-seeking ability of the SFSSA algorithm, and the classical data sets (Solomon benchmark data sets R, C and RC) are selected for the experiments [37]. The Solomon benchmark test dataset contains five parameters: vehicle capacity, location, demand point demand, demand time window, and service time. The dataset categories are divided into six classes, R1, R2, C1, C2, RC1 and RC2, where the data of class R conforms to the characteristics of randomly dispersed geographic information data, the data of class C conforms to the features of accumulation, and the data of class RC serves to the parts of mixed random and agglomeration. Classes R1, C1 and RC1 have a narrower scheduling range, with fewer functional requirements per vehicle. More comprehensive scheduling ranges for classes R2, C2 and RC2 and more functional requirements per vehicle. The distribution of demand point locations for classes R, C and RC is shown in Figure 5.

4.3.2. Numerical experiments

The comparison results of class R, class C and class RC datasets are in Tables 4–6, respectively. The parameters of the GA algorithm are adjusted such that it has a crossover probability of 0.9, a variance probability of 0.09, several iterations of 100, and a population size of 1000. Similarly, this is done to evaluate the algorithm's performance for its fairness. The parameters of the SSA method are configured to have a population size of 1000, an SD of 0.1, an ST of 0.8, iterations equal to 100, and a PD value of 0.2. The experiments are programmed using MATLAB R2020b and run on a 64-bit host with Intel(R) Core(TM) i5-11400H @ 2.70GHz and Windows 11.

Table 4. R class data algorithm comparison.

Datasets	SFSSA			SSA			GA		
	Cost	Distance	Time	Cost	Distance	Time	Cost	Distance	Time
R101	24771	2287.1	28.95	25040	2324.0	28.30	27912	2571.2	36.67
R102	24797	2309.7	33.17	25621	2382.1	36.49	26313	2441.3	40.44
R103	24548	2284.8	31.93	25082	2318.2	36.85	27425	2572.5	40.82
R104	23640	2184.0	30.69	24571	2297.1	36.51	25830	2403.0	40.52
R105	24751	2295.1	30.52	24843	2324.3	36.68	26988	2518.8	41.21
R201	23747	2204.7	29.57	24048	2224.8	35.79	26462	2466.2	38.96
R202	24004	2230.4	28.93	25002	2340.2	36.59	26724	2492.4	40.52
R203	23746	2214.6	29.90	24115	2251.5	36.98	27608	2580.8	40.51
R204	24260	2236.0	29.11	24319	2271.9	35.92	25303	2350.3	35.97
R205	24143	2254.3	35.04	24381	2268.1	35.79	26151	2435.1	38.40

Comparison results in Tables 4–6 show that SFSSA outperforms SSA and GA in class R, C, and RC data sets jointly selected as R101-R105, C101-C105, and RC101-RC105 comparison results. The comparative analysis of the experimental results shows that the traditional GA is less effective in solving the vehicle route problem, especially when the number of demand points is significant. It is

difficult for the GA to find a more excellent solution; SSA runs better results in solving the vehicle route problem than GA; SFSSA can achieve better solutions in solving the vehicle route problem than SSA and GA. Therefore, SFSSA can effectively solve the vehicle route problem with good computational performance and better finding ability, which is suitable for studying vehicle route problems.

Table 5. C class data algorithm comparison.

Datasets	SFSSA			SSA			GA		
	Cost	Distance	Time	Cost	Distance	Time	Cost	Distance	Time
C101	23937	2163.7	31.02	25690	2339.0	27.89	30062	2756.2	44.05
C102	21548	1944.8	27.85	23659	2135.9	27.97	22352	2025.2	32.59
C103	21948	1984.8	30.25	23205	2100.5	26.98	23587	2148.7	36.13
C104	21144	1904.4	29.27	21165	1916.5	30.72	24912	2281.2	37.72
C105	22454	2015.4	27.43	23070	2067.0	27.00	28225	2582.5	37.40
C201	22337	2033.7	31.07	22359	2035.9	26.71	22877	2087.7	35.60
C202	21520	1952.0	27.10	22230	2023.0	26.59	23139	2113.9	31.25
C203	21748	1974.8	27.17	22256	2025.6	26.45	23207	2120.7	36.20
C204	21325	1932.5	33.54	21513	1951.3	30.89	23841	2184.1	35.51
C205	21658	1955.8	30.22	22147	2014.7	36.83	23345	2144.5	40.49

Table 6. RC class data algorithm comparison.

Datasets	SFSSA			SSA			GA		
	Cost	Distance	Time	Cost	Distance	Time	Cost	Distance	Time
RC101	26832	2483.2	34.69	29793	2779.3	31.48	3066.9	2836.9	33.42
RC102	26676	2477.6	33.61	27992	2609.2	29.09	29162	2706.2	34.68
RC103	27585	2568.5	27.49	27867	2596.7	27.70	30679	2877.9	34.26
RC104	26705	2470.5	27.91	27013	2501.3	27.54	30102	2810.2	38.41
RC105	27330	2533.0	32.04	27941	2594.1	27.86	31874	2987.4	31.58
RC201	26819	2491.9	27.86	27753	2575.3	30.75	30853	2875.3	33.27
RC202	26493	2439.3	27.69	26671	2477.1	27.13	29583	2758.3	34.64
RC203	26277	2427.7	27.83	28689	2678.9	31.69	30212	2791.2	31.77
RC204	26167	2416.7	27.67	27273	25373	27.07	29025	2692.5	36.65
RC205	26927	2492.7	28.35	27064	2516.4	27.57	29294	2729.4	32.72

5. Simulation experiment and analysis

5.1. Model data

In this paper, the city of Handan in northern China is selected for the study. Thirty identified closed management community points and one emergency supplies distribution center are simulated and chosen in a 70×70 km prevention and control area of Handan city. The information on the location coordinates of each demand point, the demand for emergency supplies, the time window information, and the service time is shown in Table 7. Since there is an incubation period for the novel coronavirus, the suspected patient location will be sealed and managed based on the presence of alleged patient cases. The government department requires the first large-scale nucleic acid testing to be conducted

on the same day, and the suspected patient will be sealed and managed at home. The community health care worker will conduct nucleic acid testing at home and upload the test results of all nucleic acids in the area through the CDC. The location is judged to be the initial demand point based on whether there are positive patients. Figure 6 shows the location distribution of the initial demand points.

Table 7. Initial demand point information table.

No.	X (km)	Y (km)	Demand (box)	Time Window(h)	Service Time(h)
1	35	35	0	1:00–23:00	22
2	41	49	10	5:00–6:30	0.25
3	35	17	7	5:30–7:00	0.24
4	55	45	13	5:40–6:40	0.48
5	10	43	9	5:50–6:50	0.2
6	55	60	26	6:00–7:00	0.63
7	30	60	6	6:00–7:20	0.35
8	20	65	12	6:10–7:10	0.23
9	50	35	9	6:20–7:20	0.33
10	30	25	13	6:30–8:00	0.5
11	15	10	20	6:40–7:50	0.37
12	30	5	8	6:30–8:10	0.4
13	10	20	19	6:50–9:20	0.45
14	5	30	2	7:00–9:00	0.6
15	20	40	12	7:00–8:30	0.55
16	15	60	27	7:10–9:40	0.7
17	45	65	9	7:30–9:50	0.65
18	45	20	11	7:40–10:00	0.8
19	45	10	18	7:50–10:20	0.75
20	55	5	29	8:10–9:30	0.41
21	65	35	3	8:30–10:30	1
22	65	20	6	8:50–10:20	0.66
23	45	30	17	8:50–9:40	0.85
24	35	40	16	8:40–10:00	0.9
25	41	37	16	9:00–10:40	0.88
26	64	42	19	9:00–10:10	0.54
27	40	60	21	9:20–11:00	0.63
28	31	52	27	9:30–10:50	0.64
29	35	69	13	9:40–10:30	0.75
30	53	52	11	10:00–11:50	0.87
31	65	55	14	10:10–11:50	0.96

The initial planning phase was classified based on the data from the first day's first nucleic acid test results. Due to the existence of the incubation period of the virus, which may lead to undetected results of the first round of nucleic acid testing, additional positive patients appear through the second round of nucleic acid testing, and the patient area needs to be quarantined. The new demand point information is based on the second round of nucleic acid test results conducted the day before and the

latest data statistics shown by the CDC, which is divided into new demand points according to the location of new positive patients. At 4:30, all the vehicles scheduled for distribution started their tasks from the emergency material distribution center with a full load. The dynamic information receiving window of the day was opened to receive two kinds of dynamic demand requests: the increase of demand points and the increase or decrease of demand quantity of the initial demand points that appeared in the emergency material distribution. The dynamic demand information is shown in Table 8.

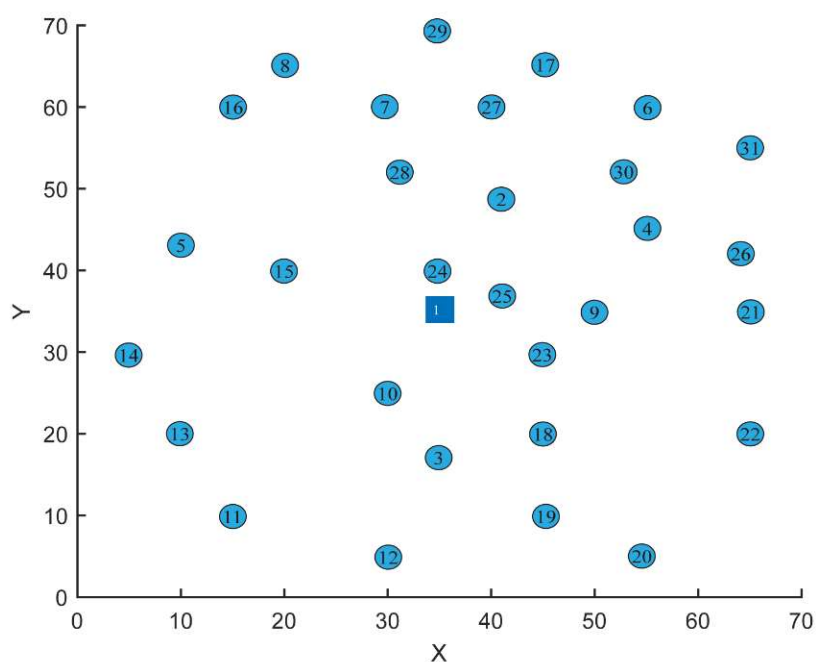


Figure 6. Initial demand point location distribution map.

Table 8. Dynamic demand information table.

Receiving time	NO.	Change type	X (km)	Y (km)	Demand (box)	Time Window (h)	Service Time (h)
4:38	32	New	63	65	3	7:10–9:00	0.89
4:50	12	Add	30	5	12	6:30–8:10	0.4
5:00	7	Add	30	60	10	6:00–7:20	0.35
5:36	14	Add	5	30	5	7:00–9:00	0.6
5:45	21	Add	65	35	4	8:30–10:30	1
5:58	33	New	52	27	5	9:30–11:30	0.94
6:13	18	Add	45	20	13	7:40–10:00	0.8
6:36	22	Add	65	20	11	8:50–10:20	0.66
6:57	17	Add	45	65	10	7:30–9:50	0.65
7:08	24	Add	35	40	26	8:40–10:00	0.9
7:23	27	Add	40	60	31	9:20–11:00	0.63

5.2. Model parameter

The parameters involved in the vehicle route optimization model under dynamic real-time demand established by the SFSSA algorithm are $PD = 0.2$, $SD = 0.1$, $ST = 0.8$, $\omega_{max} = 1$, $\omega_{min} = 0.4$, the number of iterations is 100, the population size is 5000, the start-up cost of each emergency vehicle is 100 RMB/vehicle; the maximum capacity of each emergency vehicle carrying goods is 100 boxes; the average vehicle driving speed is 60km/h; the unit route cost of emergency vehicles is 10 RMB/km; emergency distribution vehicles can arrive at the distribution demand point in advance, but not in delay, and the penalty cost of delayed arrival is 100 RMB/h. The solution to the algorithm is computed programmatically using MATLAB R2020b running on a 64-bit host with an Intel(R) Core(TM) i5-11400H @ 2.70 GHz and Windows 11.

5.3. Result analysis

5.3.1. Initial planning result

Based on the previous introduction of dynamic real-time demand information divided into an initial demand point distribution scheme and a dynamic demand distribution scheme, the SFSSA algorithm is adopted for solving. The results are compared and analyzed with the SSA algorithm and GA algorithm. The parameters of the comparison algorithm are set: PD of the SSA algorithm is 0.2, SD is 0.1, ST is 0.8, the number of iterations is 100, and the population size is 1000. The crossover probability of the algorithm is 0.9, the variance probability is 0.09, the number of iterations is 100, and the population size is 5000. The initial demand point information in Table 4 is imported into MATLAB and compared with both the SSA algorithm and GA algorithm in five aspects: vehicle total load rate, fixed cost, route cost, distance traveled, and penalty cost, respectively, and the comparison results are shown in Table 9. the SFSSA initial phase distribution scheme is shown in Table 10. the SSA initial phase distribution scheme is shown in Table 11. the GA initial distribution phase scheme is shown in Table 12.

Table 9. Initial phase algorithm effectiveness comparison results.

Algorithm	Total load rate					Fixed cost (yuan)	Route cost (yuan)	Distance (km)	Penalty cost (yuan)
SFSSA	100%	95%	86%	80%	62%	500	5176.249	517.6249	0
SSA	100%	98%	97%	80%	48%	500	5239.169	523.9169	0
GA	97%	90%	86%	76%	74%	500	5821.094	582.1094	0

According to the results shown in Tables 9–12, according to the planned distribution route scheme, the emergency distribution vehicles are fully loaded according to the algorithm for suitable matching vehicles, all of which transport the materials reasonably to the demand point. Since the initial phase delivery vehicles are five vehicles, the fixed cost of the vehicles is the same, both 500 yuan. In the distribution of materials to each demand point, the algorithm is different in the distribution scheme, so the planned distribution route is different, which causes the distance and distance of the driving route and the cost difference of the driving route. The SFSSA algorithm finally solves the vehicle travel distance of 517.6249 km, and the SSA algorithm finally solves the vehicle travel distance of 523.9169

km. The GA algorithm finally solves the vehicle travel distance of 582.1094 km. The SFSSA algorithm has advantages over the other two in planning the shortest distribution route problem. The SFSSA algorithm driving route cost is 5176.249 yuan, the SSA algorithm driving route cost is 5239.169 yuan, GA algorithm driving route cost is 5821.094 yuan, so the SFSSA algorithm driving route cost is also the least. The penalty costs are all 0 yuan. The optimal distribution roadmap in the initial phase of the SFSSA algorithm is shown in Figure 7. the optimal distribution roadmap in the initial phase of the SSA algorithm is shown in Figure 8. the optimal distribution roadmap in the initial phase of the GA algorithm is shown in Figure 9.

Table 10. SFSSA initial phase distribution program.

Vehicle	Distribution route	Vehicle effective distribution quantity (cases)	Vehicle payload rate
1	1→25→26→9→21→22→20→19→1	100	100%
2	1→10→13→11→12→3→18→23→1	95	95%
3	1→2→27→29→17→7→28→1	86	86%
4	1→24→4→31→6→30→1	80	80%
5	1→15→8→16→5→14→1	62	62%

Table 11. SSA initial phase distribution program.

Vehicle	Distribution route	Vehicle effective distribution quantity	Vehicle payload rate
1	1→25→9→26→21→22→20→19→1	100	100%
2	1→30→4→31→6→29→8→17→1	98	98%
3	1→15→16→5→14→13→11→12→1	97	97%
4	1→24→28→7→27→2→1	80	80%
5	1→23→18→10→3→1	48	48%

Table 12. GA initial phase distribution program.

Vehicle	Distribution route	Vehicle effective distribution quantity	Vehicle payload rate
1	1→15→16→5→14→11→13→12→1	97	97%
2	1→24→23→22→21→26→4→25→1	90	90%
3	1→28→29→27→31→30→1	86	86%
4	1→2→17→6→7→8→10→1	76	76%
5	1→9→18→20→19→3→1	74	74%

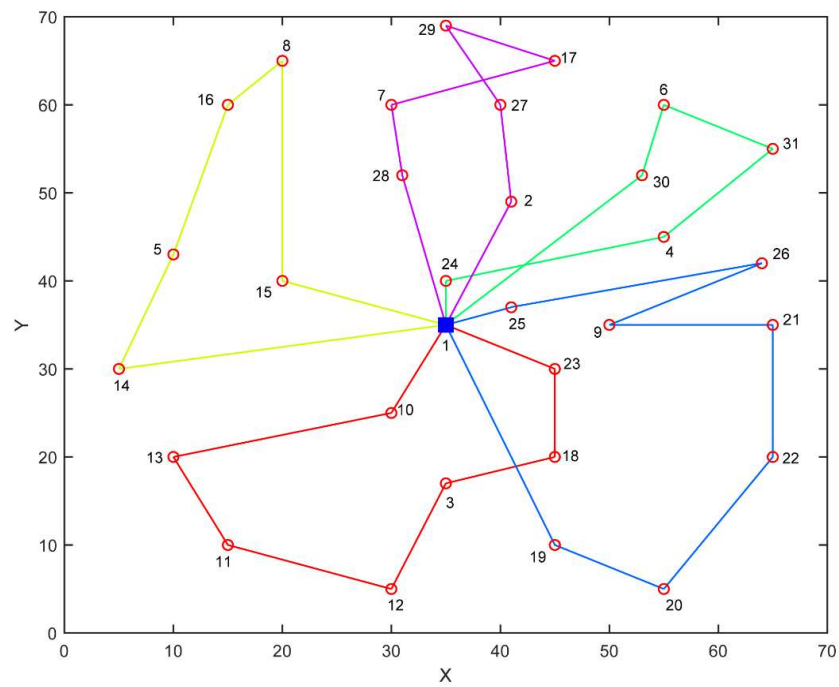


Figure 7. SFSSA algorithm initial phase optimal distribution route diagram.

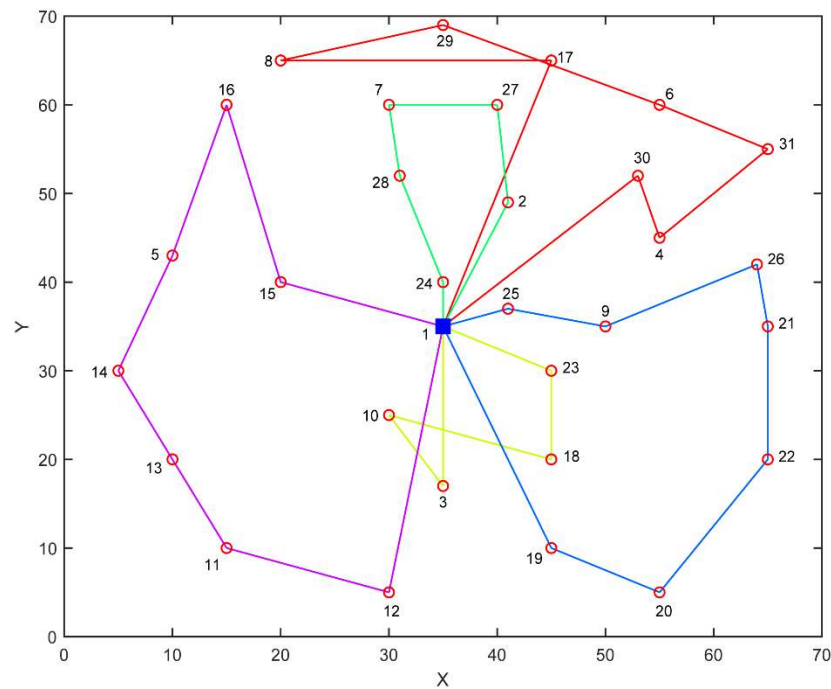


Figure 8. SSA algorithm initial phase optimal distribution route diagram.

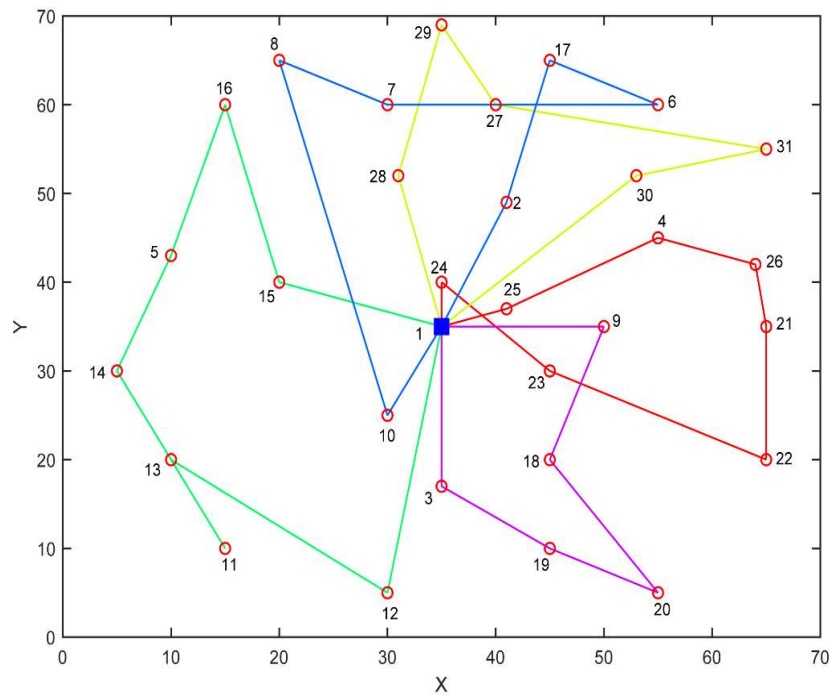


Figure 9. GA algorithm initial phase optimal distribution route diagram.

5.3.2. Dynamic planning result

During the dynamic adjustment phase, as shown in Table 8, various dynamic requirements information has emerged. According to dynamic information batch optimization criteria and emergency material re-optimization strategy for processing, when dynamic requirements information appears, determine whether it is a particular emergency. If so, re-align the distribution route immediately. Otherwise, Determine whether the batch time has been reached and if so, batch processing of all dynamic orders; Otherwise, continue to accept dynamic information. The SFSSA dynamic phase distribution scheme is shown in Table 14. The SSA dynamic phase delivery scheme is shown in Table 15. The GA dynamic distribution phase program is shown in Table 16.

Table 13. Dynamic phase algorithm effectiveness comparison results.

Algorithm	Total load rate					Fixed cost (yuan)	Route cost(yuan)	Distance (km)	Penalty cost (yuan)
SFSSA	100%	97%	95%	91%	88%	500	5615.772	561.5772	0
SSA	100%	98%	96%	93%	84%	500	5818.303	581.8303	0
GA	100%	99%	95%	95%	82%	500	6204.163	620.4163	0

Table 14. SFSSA dynamic phase distribution program.

Vehicle	Distribution route	Vehicle effective distribution quantity (cases)	Vehicle payload rate
1	1→24→23→33→4→30→26→9→1	100	100%
2	1→6→27→29→17→32→31→1	97	97%
3	1→2→28→7→8→16→5→1	95	95%
4	1→25→21→22→20→19→18→1	91	91%
5	1→10→12→11→13→14→15→3→1	88	88%

Table 15. SSA dynamic phase distribution program.

Vehicle	Distribution route	Vehicle effective distribution quantity (cases)	Vehicle payload rate
1	1→18→19→20→22→21→31→30→1	100	100%
2	1→23→9→25→4→26→33→3→12→1	98	98%
3	1→10→11→13→14→16→8→1	96	96%
4	1→2→6→32→17→27→29→1	93	93%
5	1→24→28→7→5→15→1	84	84%

Table 16. GA dynamic phase distribution program.

Vehicle	Distribution route	Vehicle effective distribution quantity (cases)	Vehicle payload rate
1	1→10→3→20→22→19→18→9→1	100	100%
2	1→28→29→27→32→31→30→1	99	99%
3	1→15→16→14→13→11→12→1	95	95%
4	1→5→8→7→6→17→2→4→33→1	95	95%
5	1→24→23→21→26→25→1	82	82%

Based on the results shown in Table 13, considering the new increase in demand point materials and demand point supplies volume increase, according to the dynamic real-time demand for optimal processing of the distribution route program, emergency distribution vehicles' total rate according to the algorithm for suitable matching vehicles, all the materials will be transported to the demand point reasonably. Since the locations of the two newly added demand points are still within the distribution range, and the increase in the number of materials at the demand points does not exceed the vehicle total load rate, the number of distribution vehicles in the dynamic optimization phase remains at five, so the fixed cost of vehicles remains unchanged. Compared with the initial stage of the vehicle total rate SFSSA, SSA, GA vehicle utilization rate have significantly improved, SFSSA algorithm vehicles 1, 2, 3, 4, 5 have reached more than 85%, so reflect the SFSSA algorithm in the dynamic adjustment of the optimal route can be in the premise of ensuring the accurate delivery of supplies, service to more demand points. As the results shown in Tables 14–16, the SFSSA algorithm finally solves the vehicle travel distance of 561.5772 km. The SSA algorithm finally solves the vehicle travel distance of 581.8303 km. The GA algorithm finally solves the vehicle travel distance of 620.4163 km. It can be seen that the SFSSA algorithm in planning the shortest distribution route problem compared to The SFSSA algorithm has certain advantages over the other two algorithms. The driving route cost of the

SFSSA algorithm is 5615.772 yuan, the driving route cost of the SSA algorithm is 5818.303 yuan, and the driving route cost of the GA algorithm is 6204.163 yuan. Figures 10–12 show the optimal distribution route diagram of the dynamic phase of the SFSSA algorithm, the optimal distribution route diagram of the dynamic phase of the SSA algorithm, and the optimal distribution route diagram of the GA algorithm, respectively.

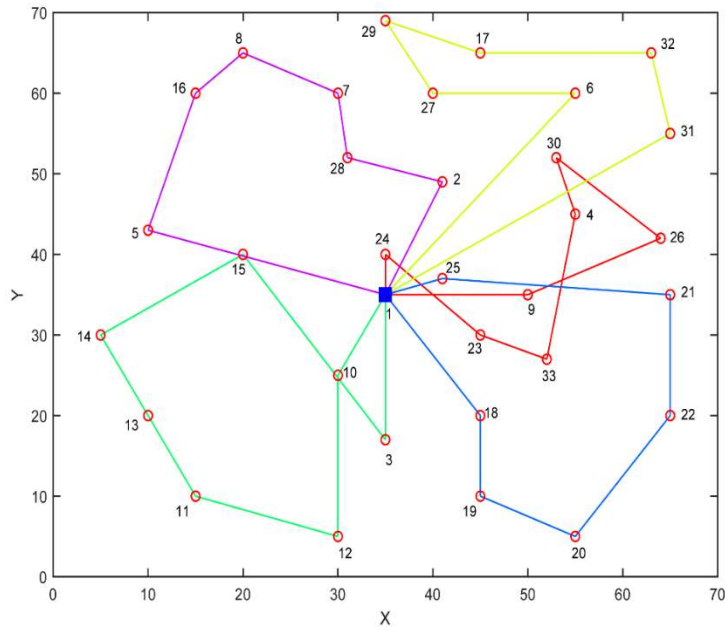


Figure 10. SFSSA algorithm dynamic phase optimal distribution route diagram.

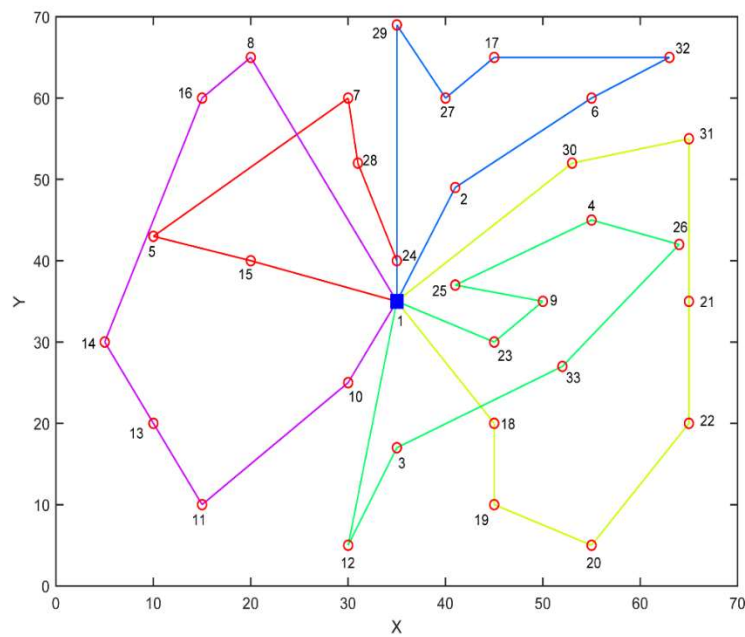


Figure 11. SSA algorithm dynamic phase optimal distribution route diagram.

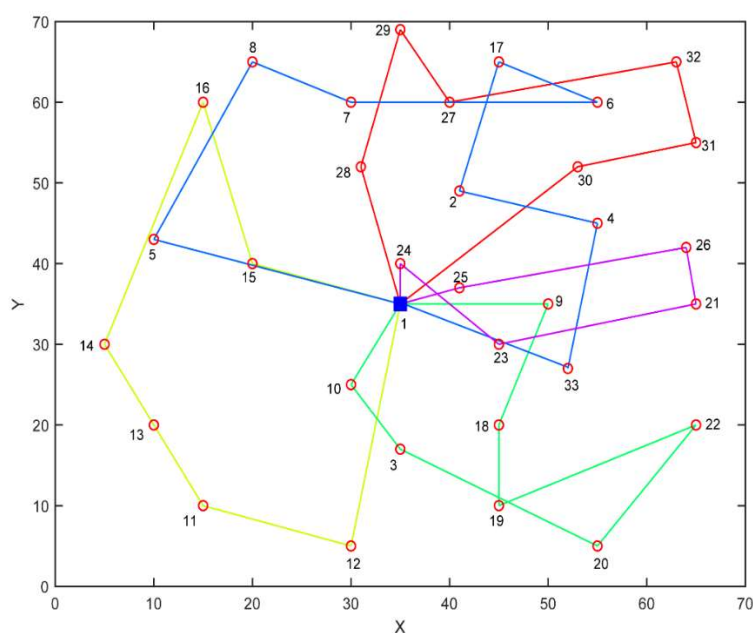


Figure 12. GA algorithm dynamic phase optimal distribution route diagram.

5.3.3. Comparative analysis of results

To validate the effectiveness of the proposed SFSSA algorithm in resolving the regional emergency material distribution problem, comparative experiments were chosen to examine the performance of the SSA algorithm and the GA algorithm in determining the issue during the initial and dynamic planning stages. In the initial phase, according to the analysis of the initial results above, the SFSSA algorithm has a shorter distance and lower cost than the SSA algorithm and GA algorithm in terms of distribution route distance and route cost. This paper considers the impact of an incubation period in the epidemic area, resulting in increased demand and new demand points in the epidemic area. According to the above, the SFSSA algorithm compares the results of the distribution scheme in the initial and dynamic planning phases. In terms of vehicle utilization, according to the rational arrangement of emergency supplies by emergency distribution centers, five emergency vehicles are also used for delivery due to the dynamic real-time requirements phase change. However, vehicle utilisation increased by 9.6% during the dynamic planning phase. In this way, a dynamically adjusted optimal route can serve more demand points, improve vehicle utilization and reduce unnecessary waste of resources.

At the same time, according to the results of the dynamic planning phase above, the vehicle load rate is equal, and the fixed vehicle cost is RMB 500 for vehicle use. The cost of the vehicle delay penalty was zero since there was no delay in distribution throughout the transportation procedure. Regarding route cost, the SFSSA algorithm is 202.531 Yuan and 588.391 Yuan less than the SSA and GA algorithms. Similarly, in terms of distance traveled, the SFSSA algorithm is 20.2531 km and 58.8391 km less than the SSA and GA algorithms. The SFSSA algorithm is 3.48% lower than the SSA algorithm. It is 9.48% lower than the GA algorithm. Therefore, according to the real-time changes in material demand points and demand in the affected areas, to respond to the needs of the epidemic

regions promptly, the service requirements arrangements for the initial and dynamic planning phases have been arranged more rationally. We have achieved the goal of effectively reducing delivery costs and increasing vehicle load rates. To a certain extent, government spending can be reduced for the government emergency management department in response to emergency material distribution links to provide specific reference opinions.

6. Conclusions, limitations, and future research

In this paper, we study the emergency material distribution route problem with dynamic real-time demand using the regional small-scale epidemic situation problem as an example. We develop a mathematical model for the emergency material distribution route optimization problem by considering some practical constraints such as the shortest driving route, fixed cost, delayed delivery penalty cost, minimization of route cost, time window restriction, and vehicle total load rate. Based on this, an SFSSA algorithm is used to optimize the distribution route of emergency supplies under dynamic real-time demand. Finally, the epidemic data of Handan city is selected to generate simulation experiments and compared with the SSA algorithm and GA algorithm. The experimental results demonstrate that, compared to other algorithms, the SFSSA algorithm has the lowest vehicle route and route cost, which increases the effectiveness of emergency supplies distribution and can significantly lower transportation costs, highlighting the SFSSA algorithm's advantages in solving dynamic vehicle route problems. The emergency relief distribution route plan, which takes into account the real-time dynamic demand, not only responds to the dynamic demand of the epidemic area in real-time but also improves the government's efficiency in emergency relief distribution, reduces the financial expenditure and provides decision support for the relevant enterprises in formulating the emergency relief distribution plan, which is of practical value.

Limitations at this stage of the paper:

It is important to take a more all-encompassing approach to the issue of the dynamic vehicle route. This paper only considers objective and specific quantitative factors such as the quantity and cost of supplies, and the starting point is in considering the government side as the central point, without considering the humanistic care-oriented factors, such as the psychological changes of the residents in the infected areas; and the occurrence of unexpected events, including the problem of emergency vehicle breakdown and whether the drivers can complete the distribution work; as well as the influence of external environmental conditions and other factors, lacking a careful consideration of more elements.

In terms of the solution algorithm, we try to apply the SFSSA algorithm to solve the problem. Since the vehicle route problem is an NP-hard problem, we try to solve it with the new intelligent algorithm. However, the superiority of the algorithm still needs further improvement. Many vehicle route problems are still handled in the previous literature by conventional intelligence algorithms such as the GA algorithm, ACO method, PSO algorithm, etc. In this study, we attempt to address the issue using the SFSSA algorithm, an upgraded intelligent algorithm; nonetheless, the method's improvement still has to be strengthened.

Future directions of this article:

Consider the problem of vehicle running speed when considering the dissatisfaction of residents in infected areas waiting for supplies, only a uniform rate is considered in this paper, and the vehicle speed change can be considered to improve the speed of supplies distribution.

Consideration is given to using a multiple of vehicles and warehouses to distribute products in order to increase distribution efficiency. Consider using the backup vehicle for distribution if the primary vehicle breaks down or the driver is unable to finish the distribution task.

To improve the efficiency of material distribution, we consider using multiple vehicles and warehouses to distribute materials. Vehicle breakdowns and drivers failing to complete the distribution work will affect the distribution efficiency, and we are considering enabling spare vehicles for distribution.

The SFSSA algorithm's solution performance may yet be improved by more development effort.

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The research data utilized to substantiate the conclusions of this study are included in Tables 7 and 8 in the publication.

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Conflict of interest

The authors declare there is no conflict of interest.

References

1. Q. Jia, Y. Guo, G. L. Wang, S. J. Barnes, Big data analytics in the fight against major public health incidents (Including COVID-19): a conceptual framework, *Int. J. Environ. Res. Public Health*, **17** (2020), 6161. <https://doi.org/10.3390/ijerph17176161>
2. Q. G. Zhu, Impact of the COVID-19 pandemic on major world economies and China's countermeasures, *J. Shanghai Jiaotong Univ.*, **28** (2020), 87–99. <https://doi.org/10.13806/j.cnki.issn1008-7095.2020.05.009>
3. J. C. Jiang, Q. Q. Li, L. X. Wu, W. Tu, Multi-objective emergency material vehicle dispatching and routing under dynamic constraints in an earthquake disaster environment, *ISPRS Int. J. Geo-Inf.*, **6** (2017), 142. <https://doi.org/10.3390/ijgi6050142>
4. X. Y. Ren, S. Chen, K. Y. Wang, J. Tan, Design and application of improved sparrow search algorithm based on sine cosine and firefly perturbation, *Math. Biosci. Eng.*, **19** (2022) 11422–11452. <https://doi.org/10.3934/mbe.2022533>
5. G. B. Dantzig, J. H. Ramser, The truck dispatching problem, *Manage. Sci.*, **6** (1959), 80–91. <https://doi.org/10.1287/mnsc.6.1.80>
6. M. Alweshah, M. Almiani, N. Almansour, S. A. Khalaileh, H. Aldabbas, W. Alomoush, et al., Vehicle routing problems based on harris hawks optimization, *J. Big Data*, **9** (2022). <https://doi.org/10.1186/s40537-022-00593-4>
7. X. N. Zhang, L. Jiang, C. Y. Liang, J. F. Dong, W. X. Lu, N. Mladenovic, Optimization approaches for the urban delivery problem with trucks and drones, *Swarm Evol. Comput.*, **75** (2022), 101147. <https://doi.org/10.1016/j.swevo.2022.101147>

8. I. Kucukoglu, R. Dewil, D. Cattrysse, The electric vehicle routing problem and its variations: A literature review, *Comput. Ind. Eng.*, **161** (2021), 107650. <https://doi.org/10.1016/j.cie.2021.107650>
9. R. Moghdani, K. Salimifard, E. Demir, A. Benyettou, The green vehicle routing problem: A systematic literature review, *J. Cleaner Prod.*, **279** (2020), 123691. <https://doi.org/10.1016/j.jclepro.2020.123691>
10. M. A. Nguyen, G. T. H. Dang, M. H. Hà, M. T. Pham, The min-cost parallel drone scheduling vehicle routing problem, *Eur. J. Oper. Res.*, **299** (2022), 910–930. <https://doi.org/10.1016/j.ejor.2021.07.008>
11. R. P. Hornstra, A. Silva, K. J. Roodbergen, L. C. Coelho, The vehicle routing problem with simultaneous pickup and delivery and handling costs, *Comput. Oper. Res.*, **115** (2020), 104858. <https://doi.org/10.1016/j.cor.2019.104858>
12. Y. K. Xia, Z. Fu, L. J. Pan, F. H. Duan, Tabu search algorithm for the distance-constrained vehicle routing problem with split deliveries by order, *PLOS ONE*, **13** (2018), e0195457. <https://doi.org/10.1371/journal.pone.0195457>
13. H. S. Liu, Y. X. Sun, N. Pan, Y. Li, Y. Q. An, D. L. Pan, Study on the optimization of urban emergency supplies distribution paths for epidemic outbreaks, *Comput. Oper. Res.*, **146** (2022), 105912. <https://doi.org/10.1016/j.cor.2022.105912>
14. B. H. O. Rios, E. C. Xavier, F. K. Miyazawa, P. Amorim, E. Curcio, M. J. Santos, Recent dynamic vehicle routing problems: A survey, *Comput. Ind. Eng.*, **160** (2021), 107604. <https://doi.org/10.1016/j.cie.2021.107604>
15. N. R. Sabar, S. L. Goh, A. Turkey, G. Kendall, Population-based iterated local search approach for dynamic vehicle routing problems, *IEEE Trans. Autom. Sci. Eng.*, **30** (2021). <https://doi.org/10.1109/tase.2021.3097778>
16. Y. Li, H. M. Fan, X. N. Zhang, A periodic optimization model and solution for capacitated vehicle routing problems with dynamic requests, *Chin. J. Manage. Sci.*, **30** (2022), 254–266. <https://doi.org/10.16381/j.cnki.issn1003-207x.2019.1495>
17. X. S. Xiang, J. F. Qiu, J. H. Xiao, X. Y. Zhang, Demand coverage diversity based ant colony optimization for dynamic vehicle routing problems, *Eng. Appl. Artif. Intell.*, **91** (2020), 103582. <https://doi.org/10.1016/j.engappai.2020.103582>
18. R. Ramachandran Pillai, M. Arock, Spiking neural firefly optimization scheme for the capacitated dynamic vehicle routing problem with time windows, *Neural Comput. Appl.*, **33** (2021), 409–432. <https://doi.org/10.1007/s00521-020-04983-8>
19. H. W. Jiang, T. Guo, Z. Yang, L. K. Zhao, Deep reinforcement learning algorithm for solving material emergency dispatching problem, *Math. Biosci. Eng.*, **19** (2022) 10864–10881. <https://doi.org/10.3934/mbe.2022508>
20. J. Q. Fang, H. P. Hou, C. X. Lu, H. Y. Pang, Q. S. Deng, Y. Ye, et al., A new scheduling method based on sequential time windows developed to distribute first-aid medicine for emergency logistics following an earthquake, *PLOS ONE*, **16** (2021), e0247556. <https://doi.org/10.1371/journal.pone.0247556>
21. L. J. Du, X. H. Li, Y. Gan, K. J. Leng, Optimal model and algorithm of medical materials delivery drone routing problem under major public health emergencies, *Sustainability*, **14** (2022), 4651. <https://doi.org/10.3390/su14084651>

22. J. A. Espejo-Díaz, W. J. Guerrero, A multiagent approach to solving the dynamic postdisaster relief distribution problem, *Oper. Manage. Res.*, **14** (2021), 177–193. <https://doi.org/10.1007/s12063-021-00192-1>
23. Y. Suzuki, Impact of material convergence on last-mile distribution in humanitarian logistics, *Int. J. Prod. Econ.*, **223** (2020), 107515. <https://doi.org/10.1016/j.ijpe.2019.107515>
24. B. K. Mishra, K. Dahal, Z. Pervez, Dynamic relief items distribution model with sliding time window in the post-disaster environment, *Appl. Sci.*, **12** (2022), 8358. <https://doi.org/10.3390/app12168358>
25. J. Ochelska-Mierzejewska, A. Poniszewska-Marańda, W. Marańda, Selected genetic algorithms for vehicle routing problem solving, *Electronics*, **10** (2021), 3147. <https://doi.org/10.3390/electronics10243147>
26. Y. B. Li, H. Soleimani, M. Zohal, An improved ant colony optimization algorithm for the multi-depot green vehicle routing problem with multiple objectives, *J. Cleaner Prod.*, **227** (2019), 1161–1172. <https://doi.org/10.1016/j.asoc.2021.107655>
27. M. A. Islam, Y. Gajpal, T. Y. ElMekkawy, Hybrid particle swarm optimization algorithm for solving the clustered vehicle routing problem, *Appl. Soft Comput.*, **110** (2021), 107655. <https://doi.org/10.1016/j.asoc.2021.107655>
28. J. K. Xue, B. Shen, A novel swarm intelligence optimization approach: sparrow search algorithm, *Syst. Sci. Control Eng.*, **8** (2020), 22–34. <https://doi.org/10.1080/21642583.2019.1708830>
29. Y. X. Duan, C. Y. Liu, Sparrow search algorithm based on Sobol sequence and crisscross strategy, *J. Comput. Appl.*, **42** (2022), 36–43. <https://doi.org/10.11772/j.issn.1001-9081.2021010187>
30. L. F. Yue, R. N. Yang, Y. J. Zhang, Y. Yu, Z. X. Zhang, Tent chaos and simulated annealing improved moth-flame optimization algorithm, *J. Harbin Inst. Technol.*, **51** (2019), 146–154. <https://doi.org/10.11918/j.issn.0367-6234.201811027>
31. L. Abualigah, A. Diabat, Advances in sine cosine algorithm: A comprehensive survey, *Artif. Intell. Rev.*, **54** (2021), 2567–2608. <https://doi.org/10.1007/s10462-020-09909-3>
32. C. Gan, W. H. Cao, M. Wu, X. Chen, A new bat algorithm based on iterative local search and stochastic inertia weight, *Expert Syst. Appl.*, **104** (2018), 202–212. <https://doi.org/10.1016/j.eswa.2018.03.015>
33. J. Q. Wang, M. X. Zhang, H. H. Song, Z. W. Cheng, T. Z. Chang, Y. S. Bi, et al., Improvement and application of hybrid firefly algorithm, *IEEE Access*, **7** (2019), 165458–165477. <https://doi.org/10.1109/access.2019.2952468>
34. X. Lv, X. D. Mu, J. Zhang, Z. Wang, Chaos sparrow search optimization algorithm, *J. Beijing Univ. Aeronaut. Astronaut.*, **47** (2020), 1–10. <https://doi.org/10.13700/j.bh.1001-5965.2020.0298>
35. C. L. Zhang, S. F. Ding, A stochastic configuration network based on chaotic sparrow search algorithm, *Knowl. Based Syst.*, **220** (2021), 106924. <https://doi.org/10.1016/j.knosys.2021.106924>

36. G. Yu, H. Wang, H. Z. Zhou, S. S. Zhao, Y. Wang, An efficient firefly algorithm based on modified search strategy and neighborhood attraction, *Int. J. Intell. Syst.*, **36** (2021), 4346–4363. [https://doi.org/ 10.1002/int.22462](https://doi.org/10.1002/int.22462)
37. M. M. Solomon, Algorithms for the vehicle routing and scheduling problems with time window constraints, *Oper. Res.*, **35** (1987), 254–265. [https://doi.org/ 10.1287/opre.35.2.254](https://doi.org/10.1287/opre.35.2.254)



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