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Optimization Model and Algorithm of Logistics Vehicle Routing Problem under Major Emergency

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Abstract: The novel coronavirus pandemic is a major global public health emergency, and has presented new challenges and requirements for the timely response and operational stability of emergency logistics that were required to address the major public health events outbreak in China. Based on the problems of insufficient timeliness and high total system cost of emergency logistics distribution in major epidemic situations, this paper takes the minimum vehicle distribution travel cost, time cost, early/late punishment cost, and fixed cost of the vehicle as the target, the soft time window for receiving goods at each demand point, the rated load of the vehicle, the volume, maximum travel of the vehicle in a single delivery as constraints, and an emergency logistics vehicle routing problem optimization model for major epidemics was constructed. The convergence speed improvement strategy, particle search improvement strategy, and elite retention improvement strategy were introduced to improve the particle swarm optimization (PSO) algorithm for it to be suitable for solving global optimization problems. The simulation results prove that the improved PSO algorithm required to solve the emergency medical supplies logistics vehicle routing problem for the major emergency can reach optimal results. Compared with the basic PSO algorithm, the total cost was reduced by 20.09%.

Keywords: emergency logistics; vehicle routing problem optimization; soft time window; improved particle swarm optimization algorithm; major epidemic situation

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1. Introduction

Emergency logistics usually refers to a special kind of logistics management activity that is arranged for the emergency dispatch of daily necessities, rescue materials, and personnel in response to natural disasters or catastrophic emergencies. Emergency logistics is a vital part of the emergency response system. Optimizing emergency vehicle routes is the key to the fast, accurate, and stable operations of emergency logistics activities. It is an important part of emergency logistics. Major national emergency events include public health events, geological disasters, and major natural disasters. For example, during the COVID-19 pandemic, Wuhan's strategy of closing the city has posed great challenges to urban emergency logistics.

When a major emergency occurs, emergency logistics must respond in time, deliver emergency supplies to the demand point, and meet the various needs of the demand point as soon as possible. One of the necessary and difficult requirements is to optimize the vehicle path and to deliver the required materials within the specified time under the emergency. The main problem to be solved in optimizing the emergency logistics vehicle path is the designated location. The obvious difference from traditional vehicle path optimization is that emergency vehicle path optimization focuses more on the characteristics of timeliness and accuracy [1,2]. For example, Yan, et al. [3] explored the optimal path strategy that trucks with drones can choose in the face of emergencies and situations. To ensure the accuracy of path selection, the mathematical model considers the time window function and the uncertainty of random attack. To minimize the total time for private enterprises and the government to participate in the distribution of relief materials, Wang and Huang [4] proposed a vehicle routing problem (VRP) model that considered the difference between the starting and ending points of the vehicles and the departments. Ribeiro et al. [5] focused on the path optimization problem of UAVs (Unmanned-Aerial-Vehicles), accurately performing search and rescue under time constraints and constrained equipment in emergency and post-disaster scenarios.

The problem can be summarized as certain demand and starting points [6]. Knowing the demand and the position coordinates of each demand point, how to meet the constraints will enable choosing the most suitable path to return to the starting point [7]. When applied to actual scenarios, many types of VRP are derived [8], including VRP with time windows [9], open VRP [10], green VRP [11], emergency VRP [12], and other extension issues [13].

This paper significantly contributes to the literature in several aspects. First of all, we give the corresponding solutions according to the operation of the enterprise after the emergency event. The scheduling of vehicle traffic volume and vehicle number in the distribution center is studied following the existing reference route optimization scheme. Second, this paper studies emergency medical supplies' vehicle routing optimization problem. By considering the different aspects of government entities and enterprises in the emergency supply chain, we design an improved particle swarm optimization (IPSO) algorithm to assist enterprises in the safe and rapid transportation of medical items. The research results provide a complete and quick solution for the path optimization of the medical emergency supply chain. The findings of this study not only help to reduce the time cost and transportation cost of enterprises in routing selection, but also provide a certain policy reference for decision makers and provide a methodology for other countries and regions.

2. Literature Review

2.1. Emergency Logistics Information System Decision-Making

Information systems play a critical role in emergency decision-making [14], particularly in logistics [15]. Farzaneh, et al. [16] developed an integrated emergency system decision support framework [17] with three interdependent recovery operations for the online coordination of disaster response phases, including damage assessment, road recovery, and relief allocation. The data are shared instantly with the developed online model to prioritize the recovery process of blocked roads. Zhao et al. [18] studied a constraint-based emergency task termination strategy for the normal operation and defect existence stages of tasks [19]. In emergency incidents, decision makers can also derive the operational stability of the system and the overall economic loss; combined with a vector evaluation genetic algorithm (VEGA), this study developed a model for solving emergency prediction allocation [20]. Zhao et al. [21] proposed a solution model and algorithm for balancing task failure probability and economic benefits. Some scholars have focused on the system's early warning information [22], abort strategy [23], or joint optimization [24].

2.2. Emergency Logistics Distribution and Material Distribution

Agardi, et al. [25] constructed a VRP model for most scenarios applied by a variety of classic cases, and demonstrated the system's designated transportation tasks in case studies. Because of the sudden outbreak of the epidemic [26], adequate medical supplies must be made available in a timely fashion [27]. However, most existing research [28] focuses on physical reserve inventories, and some authors consider reserve production capacity [29]. This study is the first to take capital reserves other than physical stocks into account. Reducing dependence on safety stocks [30] and increasing dependence on capital reserves are important in limiting the risk of elimination. Liu et al. [1] explored a hybrid multidimensional universe optimization algorithm (DE-IMOV) for solving the humanitarian supply chain VRP problem in urban distribution scenarios. The constraints include material distribution priority and vehicle load. Cerrone and Sciomachen [31] focused on sustainable urban freight distribution, using models to select vehicle types and quantities based on socioeconomic and environmental factors. In addition, the maximum duration of each route was required to be limited since the beginning of the COVID-19 pandemic to ensure that vehicles used for delivery are regularly kept clean [32]. To minimize the total time of private enterprises and the government to participate in the distribution of relief supplies, Wang and Huang [4] used a VRP model during emergencies [33]. Considering the differences in the vehicle's starting point, general logistics VRP, vehicle departments, etc., the model introduced vehicle capacity constraints, time windows, and other constraints close to the actual needs of emergency rescue [34]. Islam et al. [35] constructed a clustering vehicle routing problem (CluVRP) based on the customer category. To address the specific problem, a new hybrid element heuristic algorithm was proposed to solve CluVRP by combining PSO and variable neighborhood search (VNS). A multi-objective mixed integer nonlinear programming (MINLP) model with uncertainty can be constructed by considering the disaster relief center (RC), demand point (DP), transport item (RI), and relief materials. In the pre-disaster response, the location and quantity of RC and its pre-set inventory level are determined [36]. After a disaster, the number of RIs to be delivered to DP and the number of vehicles required based on the distribution plan are to be determined [37].

2.3. Emergency Logistics Technology Implementation and Personnel Optimization

The novel coronavirus infection and its health consequences have disproportionately affected the global socio-economic vulnerable groups. This research [38] aims to analyze the relationship between socio-economic conditions and the production of antibodies in population-based samples in Geneva, Switzerland. Xu, et al. [39] generated the general selection mechanism, which consisted of selecting or aggregating elite and high-potential solutions from single-objective problems and aggregating and transferring knowledge storms from resolved tasks. Many studies on the VRP with time windows (VRPTW) have confirmed the great universality of the SMO framework. Yan, et al. [3] attempted to explore the truck [40] and the UAV's optimal path and termination strategy under random attack. The target's time window is considered in the truck-drone route [41], truck suspension strategy, and random attack to solve the shortcomings of small UAV loads, in addition to short working hours [42]. It can also conduct preliminary investigations in the emergency management or the military to obtain disaster or enemy information and explain the rescue procedure (RP). We usually set the system state to avoid task failure or accident to avoid system data loss or benefit loss. Existing work has modeled the RP triggered by emergency mission failure or the RP triggered by the system state, but not both [43]. Another study contributes to system reliability analysis with multiple heterogeneous data by jointly modeling two types of RPs [44]. Although much research has focused on task abort rules (MAR) for different types of systems, the issue of product storage systems has not been discussed in previous works [45].

Few studies have focused on the optimization of vehicle paths under major epidemics. Existing research on the route optimization of emergency logistics vehicles provides the basis for this research, but further research and optimization are urgently needed for the route optimization of emergency logistics vehicles involved with major emergency [46]. An emergency vehicle path optimization model with a soft time window is established, and convergence speed improvement strategies, particle search improvement strategies, and elite retention improvement strategies are introduced by considering the various factors which affect emergency logistics vehicle path optimization in a major epidemic environment. An improved PSO algorithm is used, and the effectiveness of the algorithm is verified through an example.

To fill multiple research gaps, this paper designs the priority of medical material distribution according to the urgency of customer demand, carries out vehicle route planning according to the scheduling of an enterprise distribution center, and considers the facility construction situation, resource allocation ability and vehicle scheduling quantity of the enterprise. The integer programming model of path optimization with the goal at total transportation cost and satisfaction is presented. An improved PSO algorithm is advanced by combining PSO and expanding the elite population. The stability and superiority of the model and algorithm are verified by a basic test and empirical simulation.

3. Emergency Logistics Vehicle Path Optimization Model

In the early stages of an epidemic, the provincial and municipal Red Cross Societies are usually responsible for the deployment and distribution of emergency supplies. After the emergency supplies are concentrated in the distribution center, they need to be delivered to the demand site in a timely and accurate manner within the specified time range according to the specific demand variety and quantity of each demand site. Therefore, how to quickly formulate vehicle loading and distribution routes is a major consideration and is a key issue that emergency logistics need to solve. The objective is to take the minimum vehicle travel cost, time cost, early/late penalty cost, and fixed cost of departure, considering the soft time window of receipt, rated load of the vehicle, volume, maximum mileage of a single delivery of the vehicle, and each demand. The goods of the point can only be delivered by one vehicle with constraints to construct an emergency logistics vehicle path optimization model for major epidemics.

Some areas often encounter the problem of insufficient resources due to emergency incidents. Before constructing the model, this paper needs to consider the possibility of vehicle and resource allocation to avoid the possibility of vehicle unavailability due to weather and traffic factors.

The model assumptions are as follows:

(1) The penalty function for the demand point being early/late is linear;
(2) The cargo demand at the demand point does not exceed the rated load and volume of the vehicle.
(3) Transportable reserve emergency resources are sufficient.
(4) The number of people driving the vehicle can meet the demand.

The parameters in the model are defined as:

Name i as the Number the goods $i = 1, 2, \ldots, \mathrm{I}$;
Name j as the vehicle number. $j = 1, 2, \ldots, \mathrm{J}$;
Name p, q as demand point number, $p, q = 0, 1, 2, \ldots, \mathrm{K}$;
d_{pq} indicates the distance from demand point p to q;
Name k as the demand point number, $k = 1, 2, \ldots, \mathrm{K}$;
V_i represents the volume of cargo i, unit: m^3;
VV_j represents the maximum mileage of the j vehicle.
Vehicle rated volume: m^3;
CW_{pi} represents the weight of the i cargo at the demand point of p;
VW_j represents the rated load of j vehicle, unit: kg;
M_j represents the maximum mileage of the j vehicle,
VC_j represents the unit transportation cost of the j vehicle in a single transportation process;
TC_j represents unit time cost;
$T_{\max}$ indicates the time it takes to complete a single delivery,
A_{jk} represents the time when vehicle j arrives at demand point k;
ET_k indicates the earliest allowable time in the time window;
LT_k indicates the latest time in the time window;
Z_k represents the penalty cost of the k demand point. Z_z represents cost for unit early arrival; Z_c indicates the unit penalty cost for being late;
C represents the fixed cost of the vehicle unit.

The penalty cost considers the urgency of the delivery of each hospital. If it cannot arrive on time within the time window, the penalty cost is multiplied by the corresponding demand point delivery priority final score α, and $\alpha \in [2,6]$.

Definition of decision variables in the emergency logistics vehicle routing optimization model:

$$x_{jpq} = \left\{ \begin{array}{l} 1, \text{the vehicle } j \text{ goes from point } p \text{ to point } q \\ 0, \text{not} \end{array} \right\}$$

$$y_{jk} = \left\{ \begin{array}{l} 1, \text{the vehicle } j \text{ is delivered to the point } k \\ 0, \text{not} \end{array} \right\}$$

$$z_{ijk} = \left\{ \begin{array}{l} 1, \text{The cargo } i \text{ at the point } k \text{ is delivered by the vehicle } j \\ 0, \text{not} \end{array} \right\}$$

The constructed emergency logistics vehicle path optimization model is as follows:

$$\begin{aligned} \min f = & \sum_{j=1}^{J} \sum_{p=0}^{K} \sum_{q=0}^{K} x_{jpq} d_{pq} VC_j + \sum_{j=1}^{J} TC_j \ * \ T_{\max} \\ & + \sum_{j=1}^{J} \sum_{k=1}^{K} Penalty(p) + \sum_{p=1}^{K} \sum_{j=1}^{J} y_{jk} C \end{aligned} \tag{1}$$

s.t.

$$\sum_{i=1}^{I} \sum_{k=1}^{K} z_{ijk} y_{jk} CW_{pi} \leq VW_j, \forall j = 1,2,3,\cdots, \mathrm{J}; \tag{2}$$

$$\sum_{p=0}^{K} \sum_{q=0}^{K} x_{jpq} d_{pq} \leq M_j, \forall j = 1,2,3,\cdots, \mathrm{J}; \tag{3}$$

$$\sum_{i=1}^{I} \sum_{k=1}^{K} z_{ijk} V_i \leq VV_j, \forall j = 1,2,3,\cdots, \mathrm{J}; \tag{4}$$

$$\sum_{j=1}^{J} y_{jk} = 1, \forall k = 1,2,3,\ldots, \mathrm{K}; \tag{5}$$

$$\sum_{p=1}^{K} x_{j0p} = \sum_{q=1}^{K} x_{jq0}, \forall j = 1,2,3,\cdots, \mathrm{J}; \tag{6}$$

$$Penalty(p) = \begin{cases} \alpha Z_Z \left(ET_k - A_{jk} \right) & A_{jk} < ET_k \\ 0 & ET_k \leq A_{jk} \leq LT_k \\ \alpha Z_C \left(A_{jk} - LT_k \right) & A_{jk} > LT_k \end{cases} \tag{7}$$

$$x_{jpq} \in \{0,1\} p,q = 0,1,2,\ldots, \mathrm{K}; j = 1,2,3,\ldots, \mathrm{J}; \tag{8}$$

$$y_{jk} \in \{0,1\} k = 0,1,2,\ldots, \mathrm{K}; j = 1,2,3,\ldots, \mathrm{J}; \tag{9}$$

$$z_{ijk} \in \{0,1\} i = 1,2,3,\ldots, \mathrm{I}; j = 1,2,3,\ldots, \mathrm{J}; k = 0,1,2,\ldots, \mathrm{K}; \tag{10}$$

Formula (1) indicates that the objective function of the model includes vehicle delivery cost, time cost, early/late penalty cost, and minimum fixed cost of departure; Formula (2) expresses that the total weight of each vehicle loaded does not exceed the rated load of the vehicle; Formula (3) represents that the total distance of each delivery of each vehicle does not exceed the maximum mileage of the vehicle in a single delivery; Formula (4) indicates that the total volume of cargo loaded by each vehicle does not exceed the vehicle capacity; Formula (5) implies that, for each demand point, the goods can only be delivered by one vehicle; Formula (6) shows that the vehicle returns to the distribution center after completing the delivery task; Formula (7) indicates the penalty function of the delivery time being earlier or later than the demand point receiving time window; Formulas (8)–(10) are 0–1 decision variables.

4. Emergency Logistics Vehicle Path Optimization Algorithm

4.1. Improved PSO Mathematical Model

Compared with the traditional particle swarm algorithm, the convergence speed is too fast, the particle movement ability is too poor, and the solution space is too small. The internal logic of the improved algorithm mathematical model is to intelligentize the particles and particle swarms and actively and quickly find the best solution space. The core of the optimal solution lies in the unique particle update strategy and speed change. The improved PSO mathematical model formula is shown in Formula (11)–(18).

The position of particle i is shown in Formula (11) as a potential solution to the optimization problem:

$$X_i = (x_{i1}, x_{i2}, \cdots, x_{id}), i = 1, 2, 3, \ldots, m \tag{11}$$

The velocity of particle i:

$$V_i = (v_{i1}, v_{i2}, \cdots, v_{id}), i = 1, 2, 3, \ldots, m \tag{12}$$

Particle i seeks optimal position:

$$P_i = (p_{i1}, p_{i2}, \cdots, p_{id}),\ i = 1, 2, 3, \ldots, m \tag{13}$$

Population optimization position:

$$G_i = (g_1, g_2, \cdots, g_{id}),\ i = 1, 2, 3, \ldots, m \tag{14}$$

In d-dimensional space, the velocity update formula of particle i is:

$$\begin{aligned} v_{id}^{n+1} = \omega * v_{id}^n + c_1 * r_1 * \left(p_{id}^n - x_{id}^n\right) \\ + c_2 * r_2 * \left(p_{gd}^n - x_{id}^n\right) \end{aligned} \tag{15}$$

In the d-dimensional space, the position update formula of particle i is:

$$x_{id}^{n+1} = x_{id}^n + v_{id}^n \tag{16}$$

Insert an improved particle optimization formula in the d-dimensional space:

$$x_{id}^{n+1} = c_3 * x_{id}^n + c_4 * v_{id}^n \tag{17}$$

In this process, for each particle i, there is:

$$X_i \in [X_{\min}, X_{\max}], V_i \in [V_{\min}, V_{\max}] \tag{18}$$

Among them: ω is the inertia weight, expanding the space of particle exploration to let particles maintain inertia for new exploration. c_1 and c_2 are cognitive constants; c_1 represents particle self-cognition ability, while c_2 represents the cognitive ability of particle swarms. When the cognitive constant is set to a high value, the particles may cross the target area, and generally are not 0. Both c_3 and c_4 represent the particle optimization coefficients. When the particle optimization coefficient is set to a higher value, the particle movement ability is enhanced, while the understanding space is expanded, and the information exchange between the particles and the particle swarm is closer. r_1 and r_2 are two random numbers that vary in the range [0, 1]. The velocity of a certain dimension particle should satisfy $V_i < V_{\max}$, If the iteration process due to particle acceleration $V_i \geq V_{\max}$, the current particle velocity in this dimension will be reset to $V_{\max}$, which determine the distance that can be selected between the current position of the particle and the best position of the particle swarm.

4.2. Improved PSO Implementation Steps

Strategies adopted in the improved PSO include: (1) The convergence speed improvement strategy. We mainly test the basic set of the algorithm and dynamically adjust the parameters in the algorithm settings, such as inertial weight ω and cognitive constants c_1 and c_2, combined with the influence of parameters on the search accuracy and range of the algorithm particle swarm. (2) Particle dynamic search improvement strategy. The particle optimization formula is introduced, and the optimal solution is searched via the intersection of the particle with the individual extreme value with the group extreme value, the particle self-mutation, and the optimization method. (3) Elite retention and improvement strategies. Several bad solutions that do not meet the constraints in the particle intersection can be accepted to help the particles jump out of the local optimum.

The running steps of the algorithm are as follows:

Step 1: We initialize the population, particle initial velocity, particle position, and number of iterations of the algorithm, and set the initial speed of the vehicle and the driving distance limit. We then collect the freight volume data of the customer demand point and classify the delivery cargo. In the process of particle optimization, the update process is formula (19), where v and x are the velocity and position variables at the time of iteration; α and β are scaling factors; ω is an inertia weight factor; r_1 and r_2 are arbitrary values between (0, 1), which is convenient for the random motion of particles to obtain more optimal results; c_1 and c_2 are learning weight factors; *pbest* and *gbest* are individually optimal and globally optimal particles. The algorithm not only preserves the individual and global optimal information, but also has the ability of collaborative search.

$$\begin{gathered} v_{id}(k+1) = \alpha[\omega v_{id}k + c_1 r_1(pb_{id}k - x_{id}k)] + \beta(c_2 r_2 gb_{id}k - x_{id}k) \\ x_{id}(k+1) = x_{id}(k) + v_{id}(k+1) \end{gathered} \tag{19}$$

Step 2: Based on the fitness function, we calculate the fitness value of each particle and traverse the population with the consideration of the location of a distribution center, the number of vehicles, and the matching of the transported cargo. According to the priority of the demand point, the order of the distribution of the cargo is sent to the corresponding vehicle. The inertia weight factor ω is a key index to reflect the velocity of the particle to maintain its motion. When ω decreases with iteration, it converges faster. The higher value of ω in the early stage, the better is the global optimization ability; while the smaller the value in the later stage, the better is the local optimization ability. The process with better search performance and convergence speed is expressed by Formula (20), where $\omega_{\max}$ and $\omega_{\min}$ are the maximum and minimum inertia weight factors, respectively, and $T_{\max}$ is the maximum number of iterations.

$$\omega = \omega_{\max} - \frac{(\omega_{\max} - \omega_{\min})}{T_{\max}}k = \omega_{\min} + \frac{(\omega_{\max} - \omega_{\min})(T_{\max} - k)}{T_{\max}} \tag{20}$$

Step 3: POS and elite retention strategies are introduced in the process of particle iterative update to expand the search range of the particle solution set. If the current fitness is greater than before, the particle and the global optimal values are updated; otherwise, the optimal value is not updated.

Step 4: In the process of particle crossover and substitution, we dynamically update the particle velocity and position. The solution space is reserved, and the evaluation value is stored for the evaluation of the next state. We replace the individual optimal particle and the group optimal particle in accordance with the particle fitness value, and allocate them for the material requirements of the task and the existing vehicle scheduling resources.

If the particle position is better than before, we update and move to Step 5; otherwise, it remains unchanged, and we return to the step 3.

Step 5: By obtaining the task sequence in the latest solution set, we store the cargo sequence number, type and time penalty cost of each vehicle, decode the sum of each particle, and judge whether the constraint condition is satisfied. Based on the rated load and load limit of each vehicle, we evaluate whether it can be used as a feasible solution, and then update the speed and position of the particle swarm through the optimal crossover of the population for the calculation of the objective function.

Step 6: The initial solution results and bad solutions generated by the algorithm are used as the backup solution set. When a bad solution is less than or equal to a current solution, we accept the current solution; otherwise, we accept the bad solution. When the particle motion and search ability decrease, the probability of accepting bad solutions will also be decreased until no bad solution exists. The choice of bad solutions is based on the acceptance probability and the random probability. If the acceptance probability is greater than the random generation probability, we accept the bad solution and update the particle and the optimal solution of the algorithm, then return to step 4; otherwise, we reject it and go to Step 7.

Step 7: We judge whether the algorithm satisfies the termination condition, and whether the maximum number of iterations is reached. If the termination condition is satisfied, the output is returned. If not, we return to Step 3. Finally, the corresponding vehicle routing optimization scheme is obtained, including the vehicle passing through the demand point, the number and type of cargo transported, and the target optimal value.

The algorithm flow diagram is shown in Figure 1.

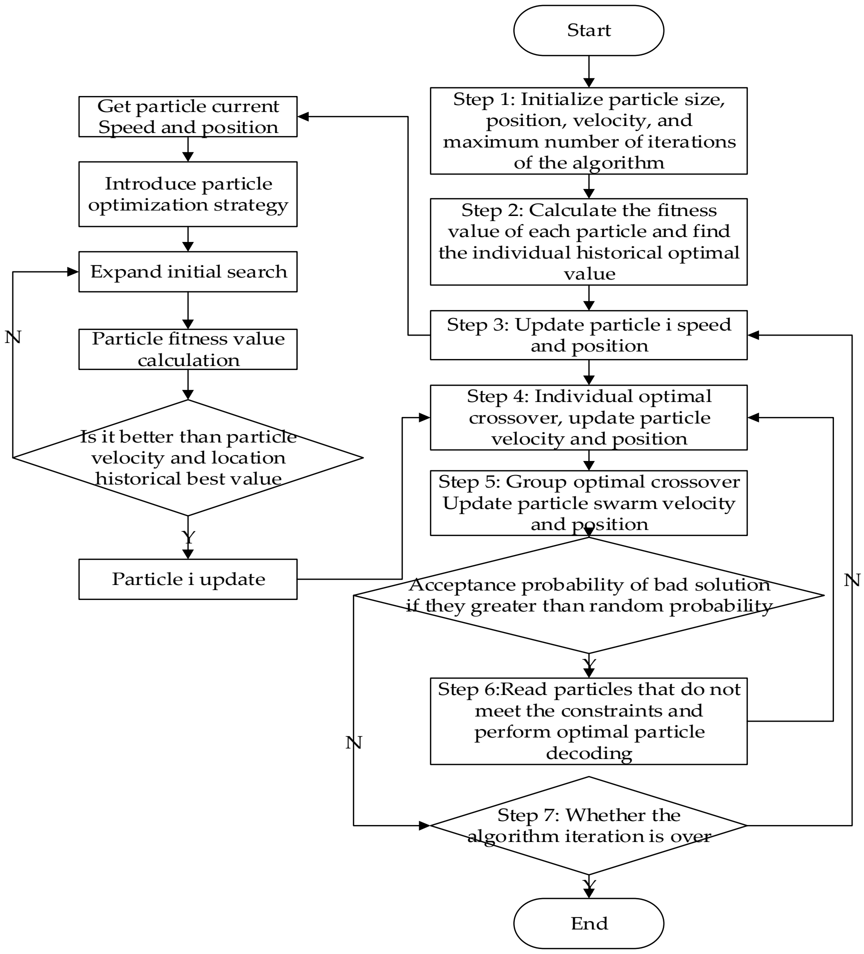

Figure 1. Flow chart of improved PSO.

5. Emergency Logistics Vehicle Path Optimization Empirical Analysis

5.1. Empirical Data Collection and Processing

Taking the emergency delivery of medical supplies in a city at the early stage of the outbreak of the COVID-19 pandemic as an example, the model and algorithm are empirically analyzed. The city had nine designated hospitals at the beginning of the outbreak, and the emergency logistics distribution center was a temporary warehouse of the Red Cross. The original relevant data on a certain day at the beginning of the outbreak are shown in Table 1, and the delivery urgency of the demand point was calculated based on its information [47]. Thus, the relevant decision-making departments can formulate a reasonable and timely emergency material distribution plan. The original data of each hospital include the specific name, jurisdiction, level, number of infections, and confirmed cases in the jurisdiction, number of medical isolations, shortage rate of emergency supplies and medical staff, and the medical point scale.

Table 1. Medical-related information of each hospital.

Number	Infected and Confirmed Cases	Number of Medical Staff	Medical Point Scale	Open Beds	Emergency Supplies Shortage Rate	Population	Infection Growth Rate Compared to the Previous Day
1	4719	4000	13,767	2100	45%	117	0.8%
2	7985	6000	133,333	5200	65%	126	0.5%
3	7985	7000	279,000	3300	41%	126	0.5%
4	1489	2000	14,997	2000	10%	65	0.1%
5	7203	4000	91,813	3000	42%	68	0.7%
6	6692	3283	180,000	2520	38%	52	2.0%
7	7985	800	49,821	1200	55%	126	0.5%
8	6692	1900	14,805	1800	27%	52	2.0%
9	4719	2000	141,795	3000	64%	117	0.8%

We then applied the entropy method to weight the generated data. An evaluation index with positive trend is determined, as the larger value of the index, the better. We use $D+$ and $D-$ to represent the distances between the evaluation object and the positive and negative ideal solutions, and C to represent the degree of closeness between the evaluation object and the optimal solution.

First, given that the indicator data are $X_1, X_2, X_3 \cdots, X_7$, $X_i = \{x_1, x_2, \cdots, x_n\}$ and X_{ij} represents the jth index data of the ith sample, the standardized value of each indicator data $Y_1, Y_2, \cdots, Y_7$ can be calculated as $Y_{ij} = \frac{x_{ij} - \min(x_i)}{\max(x_i) - \min(x_i)}$.

Second, based on the definition explained in information theory, we calculate the information entropy in a set of data $E_j = -\ln(n)^{-1} \sum\limits_{i=1}^{n} p_{ij} \ln p_{ij}$, $p_{ij} = Y_{ij} / \sum\limits_{i=1}^{n} Y_{ij}$, if $p_{ij} = 0$, $\lim p_{ij} \ln p_{ij} = 0$.

Third, by the calculation formula of information entropy, the index information entropy is calculated as $E_1, E_2, \cdots, E_7$. The weight of each indicator through information entropy is then calculated as $W_i = \frac{1-E_i}{7-\sum E_i} (i = 1, 2, \cdots, 7)$, as shown in Table 2.

According to the formula $T_i = \frac{D_i^+}{D_i^+ + D_i^-} (i = 1, 2, \cdots, 7)$, we calculate the relative proximity, C, of each hospital, respectively, and the calculation results are shown in Table 3.

The weighted data generated by the entropy weight method is used for TOPSIS analysis. Seven target indicators include: (1) the number of infections and diagnoses in the jurisdiction, (2) the number of hospital medical staff, (3) the scale of medical points, (4) open beds, (5) the emergency supplies shortage rate, (6) the population in the jurisdiction, and (7) the infection growth rate in the jurisdiction compared to the previous day. Using the TOPSIS method, we first found the positive and negative ideal solutions of the evaluation index, and then calculated the distance values $D+$ and $D-$ of each evaluation object, thus sorting the degree of closeness (C value). According to the sorting results, the distribution urgency β of 9 hospitals was assigned as 1.7, 1.4, 1, 1.9, 1.5, 1.2, 1.6, 1.8, and 1.3. The higher the value, the more urgent.

Table 2. Summary of calculation weight results by entropy.

Item	Information Entropy e	Information Utility Value d	Weight Coefficient w
Number of infected and confirmed cases in the jurisdiction	0.9689	0.0311	6.47%
Number of medical staff in hospital	0.9284	0.0716	14.90%
Medical point scale	0.8347	0.1653	34.37%
Open beds	0.9646	0.0354	7.37%
Emergency supplies shortage rate	0.9611	0.0389	8.10%
Population in the jurisdiction	0.9725	0.0275	5.73%
Infection growth rate compared to the previous day	0.8891	0.1109	23.07%

Table 3. TOPSIS evaluation calculation results.

Number	Positive Ideal Solution Distance (D+)	Negative Ideal Solution Distance (D−)	Relative Proximity (C)	Sort Results
1	91,154.775	524.778	0.006	7
2	50,061.887	41,101.992	0.451	4
3	139.945	91,158.929	0.998	1
4	90,734.77	462.735	0.005	9
5	64,332.702	26,829.336	0.294	5
6	34,028.707	57,131.896	0.627	2
7	78,768.366	12,397.881	0.136	6
8	90,799.98	519.098	0.006	8
9	47,160.149	44,000.695	0.483	3

At the same time, this article sets the corresponding priority according to the nature of the goods and the delivery timeliness requirements of the hospital. The higher the level of the goods, the higher the timeliness requirements and the higher the priority. The goods are divided into three levels. The first-level goods are mainly artificial resuscitators, anesthesia ventilators, non-invasive ventilators, therapeutic ventilators, etc., and the second-level goods include positive pressure isolation gowns, protective masks, goggles, disinfectants, etc. Class III cargo refers to infrared body temperature detectors, electronic thermometers, forehead thermometers, ear thermometers, etc., as shown in Table 4.

The demand information of each demand point (hospital) (average data extracted based on experience) and the receiving time window are shown in Table 5.

Table 4. Goods classification indication.

Material Level	Material Name	Value (μ)
Level 1	Artificial resuscitator, anesthesia ventilator, non-invasive ventilator, therapeutic ventilator, etc.	3
Level 2	Positive pressure isolation gown, protective mask, goggles, disinfectant, etc.	2
Level 3	Infrared body temperature detector, electronic thermometer, forehead thermometer, ear thermometer, etc.	1

Table 5. Demand material information and delivery time window at each demand point.

Number	Demand Supplies Level	Required Material Weight (Kilogram)	Required Material Volume	Receiving Time Window
1	I	60	1.8	9:00–10:00
2	I	45	1.35	7:00–9:00
3	I	135	4.05	6:30–7:30
4	II	90	2.7	13:00–16:00
5	II	45	1.35	15:00–17:00
6	II	120	3.6	17:30–20:00
7	III	75	2.25	18:00–21:00
8	III	90	2.7	21:00–21:50
9	III	150	4.5	19:30–23:00

The final delivery sequence is determined by the urgency of delivery and the level of goods required by the hospital. That is, it is determined by the value corresponding to the 40% emergency delivery level and the value after 60% of the required material level, using the weighting method, written as Formula (21).

$$\alpha = 0.4 * \beta + 0.6 * \mu \tag{21}$$

The final priority order is shown in Table 6.

Table 6. Final priority.

Number	Required Material Level	Delivery Urgency	Final Score	Sort Results
1	3	1.7	2.22	1
2	3	1.4	2.04	2
3	3	1	1.8	4
4	2	1.9	1.94	3
5	2	1.5	1.7	5
6	2	1.2	1.52	6
8	1	1.8	1.48	7
7	1	1.6	1.36	8
9	1	1.3	1.18	9

Setting the serial number of the city's Red Cross temporary warehouse or distribution center to 0, the distance matrix between the distribution center and each demand point (hospital) is shown in Table 7.

Table 7. Distance matrix between the distribution center and the demand points.

Number/Distance	0	1	2	3	4	5	6	7	8	9
0	0	16	6	11	9	7	7	15	7	21
1	16	0	12	8	23	16	16	10	17	5
2	6	12	0	6	13	6	5	9	6	17
3	11	8	6	0	18	8	8	4	10	13
4	9	23	13	18	0	14	13	22	12	28
5	7	16	6	8	14	0	1	10	3	21
6	7	16	5	8	13	1	0	10	2	21
7	15	10	9	4	22	10	10	0	12	13
8	7	17	6	10	12	3	2	12	0	20
9	21	5	17	13	28	21	21	13	20	0

5.2. Simulation Results

This paper uses MATLAB 2017a to program and solve the algorithm, and it was tested on an Intel notebook with a CPU of 2.20 GHz, a memory of 4 GB, and a 64-bit operating system. The basic parameter values are shown in Table 3, and the simulation results are shown in Tables 8 and 9.

Table 8. Simulation parameter.

Parameter	**Value**
Particle size	200 pcs
The maximum number of iterations	200 times
Number of vehicles	5 vehicles
Vehicle rated volume	25 m^3
Vehicle rated load	2.5 t
Vehicle speed	60 km/h
Early arrival fine	40 (RMB [1]/10 min)
Late arrival fine	60 (RMB [1]/10 min)
Total volume of materials to be delivered	24.3 m^3
Total weight of materials to be delivered	0.81 t
Fixed cost	200 RMB [1]/car
The unit transportation cost	5 RMB [1]/cubic meter·km

[1] Note: As this study takes China as the research context, the currency unit is RMB.

We tested the optimization ability of the IPSO algorithm for basic problems. It includes six VRP examples of different sizes of Solomon examples, and the node size includes 50 and 100 categories. Since the IPSO algorithm belongs to the swarm intelligence optimization algorithm, we selected the more classic and excellent performance PSO and genetic optimization (GA), and the new intelligent optimization algorithm solvers that have been widely used in recent years, CPLEX and Gurobi. By comparing it with other similar algorithms, the performance of the IPSO algorithm is verified. The parameters in the setting algorithm are shown in Table 8.

It can be seen from Table 9 that the IPSO algorithm we designed shows good performance in six examples. For example, it is superior to the other two algorithms and two solvers in terms of time cost and penalty cost. From the perspective of the total cost of vehicle transportation, the IPSO algorithm works best.

As shown in Table 10, using the improved PSO algorithm proposed in this paper, the total cost is 2951.3465 RMB, while the total cost calculated by the basic particle swarm algorithm is 3693.7196 RMB, which indicates a savings of 20.09%. Therefore, the emergency logistics vehicle route optimization model and algorithm for major epidemics proposed in this paper are effective.

Table 9. Optimization results of different algorithms.

Solomon Example (Problem Size)	IPSO ALGORITHM			CPLEX			Gurobi			PSO			GA		
	Penalty Cost	Time Cost	Total Cost	Penalty Cost	Time Cost	Total Cost	Penalty Cost	Time Cost	Total Cost	Penalty Cost	Time Cost	Total Cost	Penalty Cost	Time Cost	Total Cost
C101(50)	988.31	3662.50	6450.82	1079.21	4254.21	7333.43	1652.15	4336.08	7888.24	1225.32	4288.31	7613.63	1310.45	4443.65	7904.10
C102(50)	823.89	4017.92	6641.80	1419.64	4195.77	7615.41	1235.54	4006.90	7142.44	1367.54	4068.15	7535.69	841.72	4551.77	7543.50
RC102(50)	1132.36	3780.64	6713.00	956.44	4538.74	7495.18	1176.78	4454.57	7531.36	1711.12	4436.02	8247.14	945.86	4261.65	7357.52
R101(100)	1156.45	3905.72	6862.18	800.41	4698.96	7499.37	1542.47	4098.51	7540.98	1673.84	4324.23	8098.07	1024.87	4054.46	7229.33
R102(100)	1505.38	4262.96	7568.34	1414.78	4761.67	8176.45	1380.88	4069.91	7350.80	1363.94	4099.74	7563.68	1374.46	4542.64	8067.10
RC101(100)	1077.69	4054.60	6932.28	1047.87	5724.00	8771.87	1309.17	4309.76	7518.93	880.79	5451.84	8432.63	901.13	4888.57	7939.70

Table 10. Optimization results of emergency logistics vehicle routing considering the urgency of distribution.

Improve Algorithm Transportation Route	Improved Algorithm Optimal Value	Basic Algorithm Transportation Route	Optimal Value of Basic Algorithm
The transportation route of the first vehicle is: 0→3→0 The transportation route of the second car is: 0→8→1→2→6→0 The transportation route of the third vehicle is: 0→4→7→5→9→0 The transportation route of the 4th car is: 0→0→0 The transportation route of the fifth vehicle is: 0→0→0	2951.3465	The transportation route of the first vehicle is: 0→1→0 The transportation route of the second car is: 0→3→0 The transportation route of the third car is: 0→6→4→0 The transportation route of the fourth car is: 0→9→7→8→0 The transportation route of the fifth vehicle is: 0→5→2→0	3693.7196

5.3. Simulation Sensitivity Analysis

This simulation sensitivity analysis experiment is a controlled variable experiment. Under the premise of controlling other basic parameters unchanged, first, the number of vehicles in the distribution center (1–5 vehicles) are adjusted, then we analyze the influence of the number of vehicles on the objective function value in the model, and obtain the optimal number of delivery vehicles. The specific simulation results are shown in Table 11. The solution space schematic, corresponding total cost and various cost change curves are shown in Figures 2 and 3.

In general, the IPSO algorithm can effectively solve the problem of emergency logistics vehicle path optimization in a major epidemic situation, especially in a variety of different situations, showing the good performance of the improved particle swarm algorithm.

Table 11. Simulation results.

Number of Vehicles	Transportation Route	Fixd Cost	Travel Cost	Penalty Cost	Time Cost	Total Cost
1	The transportation route of the first car is: 0→4→8→→7→5→2→9→6→3→0	200	900	564.7515	1410.98	3075.7315
2	The transportation route of the first car is: 0→1→7→6→3→0 The transportation route of the second car is: 0→4→8→5→2→9→0	400	1055	400.4637	977.2363	2832.7887
3	The transportation route of the first car is: 0→3→0 The transportation route of the second car is: 0→1→8→2→6→0 The transportation route of the third vehicle is: 0→7→5→9→4→0	600	1032	462.8592	788.1208	2882.98
4	The transportation route of the first car is: 0→3→0 The transportation route of the second car is: 0→1→8→2→6→0 The transportation route of the third vehicle is: 0→7→5→9→4→0 The transportation route of the 4th car is: 0→0→0	600	1032	462.8592	788.1208	2882.98
5	The transportation route of the first car is: 0→3→0 The transportation route of the second car is: 0→1→8→2→6→0 The transportation route of the third vehicle is: 0→7→5→9→4→0 The transportation route of the 4th car is: 0→0→0 The transportation route of the 5th car is: 0→0→0	600	1032	462.8592	788.1208	2882.98

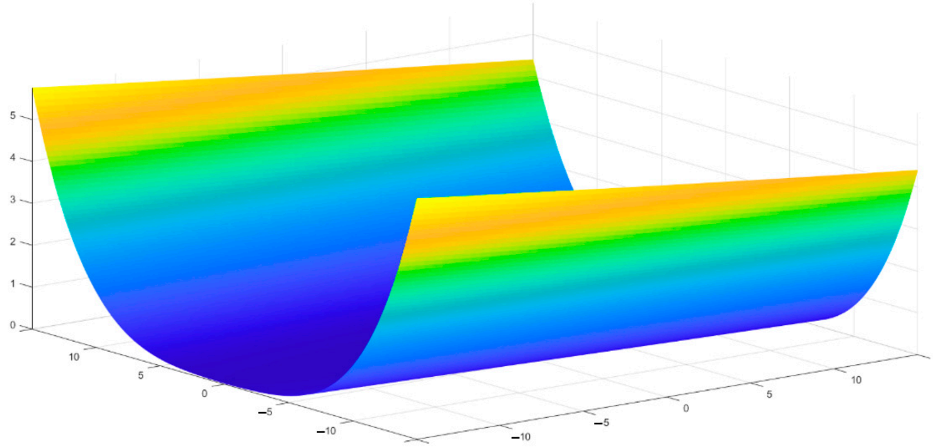

Figure 2. Improved particle swarm algorithm solution space schematic.

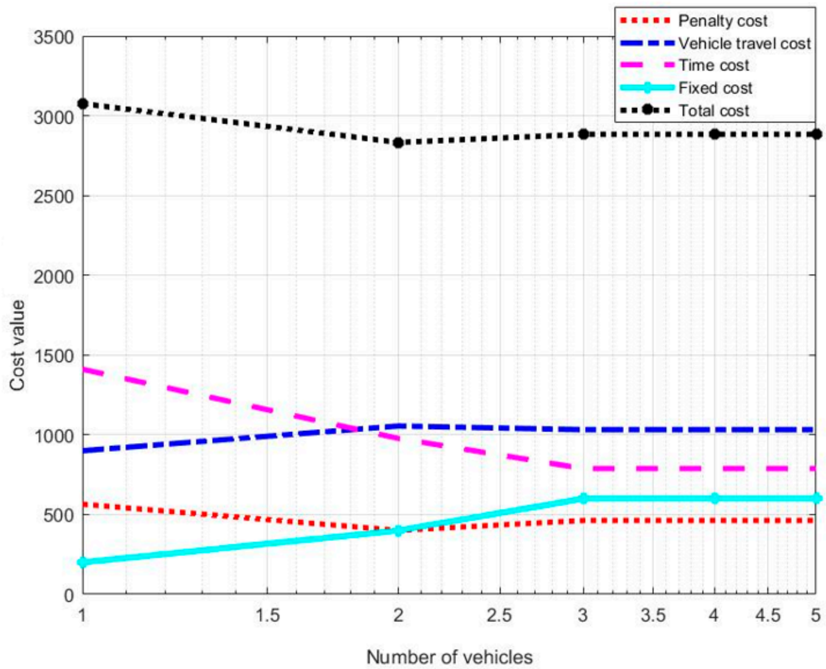

Figure 3. Schematic diagram of cost changes with the number of vehicles.

6. Discussion and Conclusions

6.1. Conclusions

With the development of science in human society, natural disasters, man-made accidents, frequent public health emergencies, and the orderly development of the social economy pose a serious threat to human health and safety. Many large cities will face great disaster risks due to their geographical locations, geological conditions, and other reasons. These disasters include earthquakes, typhoons, floods, public health concerns, and other sudden disasters. They also include environmental disasters caused by human activities, such as land subsidence and desertification [48].

Agardi, Kovacs and Banyai [25] established a general VRP model and demonstrated the number of transport tasks that the system can build by including each component in an emergency urban distribution case [26]. Adequate medical supplies must be put in place quickly [27]. Zhong, Cheng, Jiang, Wang, Larsen and Nielsen [28] focused on the physical inventory of reserves, and some scholars also considered the reserve production capacity [29]. Research has considered capital reserves other than physical stocks for the first time. To limit the risk of elimination, reducing the dependence on safety stock [30] and increasing the dependence on capital reserves should be ensured. Liu, Sun, Pan, Li, An and Pan [1] explored the humanitarian logistics VRP to cope with the adverse effects. Under the premise of the urgent demand for emergency supplies and the higher distribution priority of hospitals in urban areas, a hybrid multidimensional universe optimization algorithm based on differential evolution (DE-IMOV) is posed. Cerrone and Sciomachen [31] focused on sustainable urban freight distribution and presented a variant of VRP, which included some innovative aspects. The objective is to minimize the cost components of the route based on selected vehicles and different city streets, including travel and external costs due to environmental issues.

This paper puts forward a vehicle routing optimization scheme based on emergency events, and considers the time window and penalty functions from the perspective of system optimization. The goal of meeting demand of points and optimizing total distribution costs and total distribution time is achieved with regard to global optimization. This paper proposes an improved PSO algorithm, which has achieved good results in the test set and empirical analyses. Compared with the output scheme of the basic algorithm, the improved PSO algorithm greatly reduces the distribution cost, time cost, and other scheduling resources, and improves the average service level of vehicle distribution centers. Based on the simulation results, the improved PSO algorithm is verified to effectively solve the emergency vehicle scheduling optimization problem with complex constraints.

(1) The results of emergency logistics vehicle routing optimization (as shown in Tables 9 and 10) show that more optimized results can be obtained when using an improved PSO to solve the emergency medical service supplies logistics vehicle routing problem facing major epidemics, compared with the basic particle swarm algorithm;
(2) The simulation results in Table 11 and Figures 2 and 3 show that as the number of vehicles driven increases, the fixed cost of vehicle transportation and the cost of vehicle travel will increase, while the time and penalty costs will decrease accordingly;
(3) By a comparison of Tables 9 and 10, it is found that the improved vehicle routing optimization algorithm considering the urgency of delivery can reduce a certain time cost under the condition of meeting the delivery priority of each demand;
(4) Based on the delivery goods experience data given in the simulation case, the sensitivity analysis shows that the optimal number of vehicles in the distribution center is three when the time cost is the lowest (when the number of vehicles in the distribution center is 4 and 5). The optimal number of vehicles is still 3, as shown in Table 10.

6.2. Limitation

An emergency logistics vehicle path optimization model for major epidemics was constructed and an emergency logistics vehicle path optimization algorithm based on improved PSO that can effectively solve the problems of poor timeliness of emergency logistics distribution and high total cost under the background of major epidemics was designed to meet the objective needs of major epidemics for emergency logistics and distribution.

(1) The simulation examples show that the proposed optimization method can effectively reduce the total cost of emergency logistics. Meanwhile, based on the demand data, the optimal number of vehicles in the distribution center and the distribution priority of each demand can be analyzed. In future research, different types of vehicles can be added, and demand points can also distribute different material needs.
(2) The dynamic real-time traffic data of the road network and the distribution vehicles of different specifications will affect the emergency logistics vehicle routing optimization scheme to a certain extent. Further research can consider real-time traffic factors, such as weather and congestion factors.
(3) Although this paper proposes an IPSO algorithm and verifies its performance in the face of different natural and man-made disasters, the vehicle routing problem faces different constraints and influencing factors that need to be extended further.

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