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RESEARCH ARTICLE

Optimization of Emergency Supply and Distribution of Fresh Agricultural Products Under Public Health Emergencies

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ABSTRACT COVID-19 is a major public health emergency, the Chinese government adopts pandemic prevention and control measures such as home quarantine in order to block the strong contagiousness of the virus. In order to solve the problem of distribution difficulties due to the limited transportation resources brought by the pandemic and to guarantee the demand of fresh agricultural products for the isolated residents, this study takes the emergency supply as the main objective, and designs three distribution modes, namely, single distribution center, multi-vehicle model based on the classification of temperature zones, and multi-distribution center for isolated communities of different sizes, with the objectives of minimizing the number of vehicles in use, minimizing the average response time, and minimizing the risk of viral infections. A multi-objective optimization model was constructed as the objectives. Then the genetic algorithm is improved by adding destruction operator, repair operator and greedy operation, and the effectiveness of the algorithm is verified through empirical research, and the advantages of the algorithm in convergence speed are compared and analyzed. Finally, different distribution methods are suggested for the number of communities of different sizes. This study can provide a scientific basis for government departments to formulate an optimized decision-making plan for the emergency supply and distribution of fresh agricultural products under public health emergencies.

INDEX TERMS Fresh produce, emergency supply, multi-objective optimization, improved genetic algorithm (IM-GA).

I. INTRODUCTION

COVID-19 has been spreading globally since early 2020. Considering that the new coronavirus is highly transmissible and infectious, the Chinese government has taken control measures in Wuhan, Shanghai and other cities where the pandemic is severe, and residents have been asked to quarantine at home to prevent the further spread of the pandemic. However, the transportation and supply of fresh produce is severely constrained by the lack of timeliness, limited resources of distribution personnel and vehicles, and the susceptibility of people to infection during the distribution process in the context of the closure and control [1]. For this reason, in the context of transportation personnel and capacity constraints, how to design a reasonable and efficient vehicle distribution program for fresh agricultural products to ensure the supply of food needs of residents in closed communities is of great significance in stabilizing people's livelihoods and eliminating panic in residential areas [2].

The occurrence of public health emergencies often triggers widespread social concern and urgent needs, and the problem of imbalance in relief resources often occurs [3]. Most of the previous studies have focused on medical supplies and relief materials [4], [5], [6], [7], while fresh agricultural products, as necessities of life, are facing unprecedented challenges in the supply chain and logistics system [8], [9]. Fresh

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agricultural products have their special properties, such as short shelf life and perishability, which require that they will be distributed from the storage center to the isolated residents in the shortest possible time, while their emergency distribution in the context of public health events has been little studied. In the face of emergencies such as pandemics, safeguarding the public's food supply and food safety has become a top priority, and the emergency supply of fresh produce is crucial to safeguarding the basic livelihood of residents [10]. In the event of a public health incident, due to measures such as pandemic prevention and control, the transportation, storage and distribution of fresh agricultural products need to be more efficient and precise, taking into account the constraints of manpower, material and financial resources, and the coordinated use of warehousing facilities, the rational planning of the path of distribution vehicles, and the control of temperatures in the transportation of factors such as the quality of fresh agricultural products and the ability to supply them are directly impacted. Some scholars [11] point out that the government should play a role in solving the problems of supply-demand imbalance, transportation constraints, and personnel safety risks, and some scholars [12] believe that the government should reasonably coordinate with the suppliers on the basis of contracts to improve the efficiency of emergency response and reduce procurement costs. However, no matter which way to solve the problem, it is necessary to design a scientific and reasonable optimization plan for fresh produce distribution to protect the daily needs of residents.

In previous studies, a variety of emergency logistics models have been constructed in different contexts. Garrido and Aguirre [13] presented a modeling framework to assist decision makers in strategic and tactical planning for effective relief operations after an earthquake's occurrence. Wang and Ma [14] established a dual-objective mixed-integer nonlinear planning model for the problem of siting of emergency facilities and distribution of materials in the urban emergency logistics system, with the objectives of minimizing the time for emergency rescue and maximizing the rate of satisfaction of the demand for emergency materials. Cao [15] divided the operation of the emergency logistics system into four different phases, the daily management phase, the emergency activation phase, the smooth operation phase, and the aftercare phase, and constructed an optimization model for the emergency logistics network. Yoruk et al. [16] examined the problem of siting and replenishment of neighborhood disaster stations, with the primary goal of locating disaster stations, which would minimize the maximum distance between the post-disaster staging area and the nearest disaster station, and the second goal of creating routes that would minimize the total transportation costs during the material replenishment process. Aviation emergency relief has become one of the most effective means of natural disaster relief due to its flexibility and timeliness [17], and the joint delivery of drones and vehicles has been used for emergency delivery [18], Lu et al. [19] applied a cooperative truck delivery model synchronized with drones to humanitarian logistics, considering the impact of time-varying weather conditions on synchronized delivery from two dimensions: drone safety and drone delivery efficiency. Zhang et al. [20] established a multi-objective dynamic demand splitting distribution emergency material distribution model to enhance the efficiency of emergency material distribution and promote the smooth progress of safety rescue operations under unconventional emergencies. Jiang et al. [21] classified and packaged different categories of fresh produce according to the cold chain temperature of fresh produce, and then established a multi-model vehicle path optimization model.

Since most of the emergency material distribution problems consist of multi-objective and multi-decision variables, with high solution complexity, belong to mixed-integer linear programming problems, and are NP-hard problems, which are difficult to be solved by using exact algorithms, intelligent optimization algorithms for solving the emergency material allocation problem have an advantage in solving the emergency material distribution problem. Wang et al. [22] constructed a three-objective optimization mathematical model in order to minimize the total operation cost, total delivery time and the number of vehicles, and proposed a multi-objective adaptive large-neighborhood segmentation search algorithm to find the Pareto optimal solution. Qi and Hu [23] established a mathematical model for emergency cold chain logistics scheduling including vehicle loss, refrigerated consumption and cargo damage over time based on the minimum time for emergency cold chain logistics resource scheduling. Many scholars [24], [25], [26], [27] have improved the standard optimization algorithm and achieved good results. Some scholars also combine the two algorithms to solve the problem, Zhang and Xiong [28] proposed a hybrid algorithm that integrates the immune algorithm and the ant colony algorithm with the research objectives of maximizing the rate of food demand satisfaction and minimizing the total food distribution cost and distribution time. In order to solve the problem of maritime emergency material distribution, Peng et al. [29] designed a hybrid algorithm of ant colony and forbidden search to solve the model, and analyzed it together with the example of Bohai Sea area to verify the effectiveness of the model and algorithm. Wang et al. [30] developed an efficient Adaptive Large Neighborhood Search (ALNS) algorithm, and it was shown that the ALNS algorithm was able to produce high-quality solutions within a reasonable computation time. Zheng et al. [31] used the shortest total distribution distance as the objective function to establish a mathematical model of mixed-integer linear programming, and introduced the crossover operation of the genetic algorithm, the destructive operator and the restorative operator of the large-neighborhood search algorithm into the brainstorming optimization algorithm, which enhances the diversity of the solutions while moving the solutions towards the optimal direction. Table 1 shows the studies related to the emergency logistics optimization problem.

TABLE 1. Studies related to emergency logistics optimization problems.

Literature	Time window	Distribution center	Objective function	Approach
Zhou et al.[32]	√	multiple	operating cost	Hybrid multi-population GA
Zhen et al.[33]	-	multiple	travel time	Hybrid PSO and GA
Tan et al.[1]	√	single	system cost	IP-PSO
Govindan et al.[34]	-	multiple	operating cost & pollution risk	Fuzzy goal programming approach
Wang et al.[35]	-	multiple	cost, time and number of vehicles	Improved reference point-based NSGA -III

In addition, emergency logistics is not only a part of emergency management system, but also an important link of disaster relief and disaster reduction [36], the key point of efficient rescue is to reasonably design vehicle routes and determine the amount of emergency supplies, and path optimization, as a key component of the optimization algorithm, focuses on planning the optimal driving path for vehicles, which is expected to significantly improve the efficiency of emergency logistics for fresh agricultural products. Under public health emergencies, road blockades, traffic control and other factors make path planning more complicated. Through effective path optimization, vehicle travel time can be reduced, delivery time shortened, and the ability of emergency supply preservation improved. Liu and Qian [37] proposes an optimization model for material dispatch in emergency events using a non-dominant sorting algorithm for vehicular communication. Hsu and Chen [38] focused on the time factor for medium-term deliveries based on differences in temperature requirements, while short-term deliveries optimized the loading of delivery vehicles for orders and developed a decision strategy for the minimum number of vehicles and the fastest departure time for multi-temperature co-distribution.

In reality, due to the unpredictability of the pandemic, the suddenness, the impact of a wide range of characteristics, single distribution centers and multi-distribution centers are often used in combination in order to supply the residents with fresh produce demand. The fresh produce resources and vehicle resources of a single distribution center can meet the demand of a small number of residents, and a single distribution center has a single place of supply and a fast response speed; while multiple distribution centers can meet the demand of a certain number of residents, and the "multiple supply points-multiple demand points" model can shorten the distance between the demand point and the distribution center, shorten the distance of distribution, and improve the efficiency of the emergency security of supply [39].Chang et al. [40] took 13 districts and counties in Wuhan City, Hubei Province, China, during the COVID-19 period as the research object, analyzed to determine the optimal siting scheme using the improved PageRank and TOPSIS algorithms, and constructed a model of emergency material scheduling with the objectives of distribution cost and siting cost using the particle swarm algorithm, which solved the problem of multi-distribution center scheduling. Song et al. [41] took the Wenchuan earthquake as the case background, introduced the unfair aversion effect model, quantified the fairness preference psychology of the disaster victims in the disaster area, and constructed the objective function of emergency material allocation with maximized fairness utility and minimized comprehensive logistics cost by comprehensively considering the emergency material dispatching cost, which provided technical support for the decision-making of the emergency material allocation under the scenario of dispersed demand of multi-disaster points and multi-distribution centers at the early stage of disaster. The objective function is constructed to maximize the fair utility and minimize the comprehensive logistics cost.

This paper studies the supply and demand imbalance, transportation restrictions, insufficient vehicle resources, personnel susceptibility to infection and other problems in emergency logistics for fresh agricultural products under public health emergencies, and explores how to deploy resources and optimize vehicle paths to improve the response speed and distribution efficiency of emergency logistics, so as to ensure that fresh agricultural products can quickly reach the hands of residents. The main research content of this paper contains the following points: (1) For the special situation of public health events, an emergency supply preservation and distribution model for urban fresh agricultural products is constructed; (2) The objective of minimizing the risk of viral infection is innovatively added, and the mathematical model is constructed with maximizing the capacity resources, minimizing the average response time and minimizing the risk of viral infection as the emergency relief objectives, and an improved genetic algorithm is designed to solving the optimal distribution scheme; (3) three different distribution schemes are adopted for the number of residents' demands; under small scale, single distribution center single vehicle type distribution is adopted; under medium scale, multi-model distribution based on temperature zone classification is adopted; under large scale, after clustering algorithm clustering, multi-distribution center distribution is adopted.

II. PROBLEM FORMULATION AND MODELING

A. PROBLEM FORMULATION

In the event of a public health incident, in order to guarantee the supply of fresh produce to residents of the sealed community, it is necessary to adopt a non-contact unified purchasing and distribution method, the specific process of which involves the community organization where the sealed residents are located collecting information on the needs of the residents and transmitting it to the distribution center, which distributes the purchased and donated supplies from other areas to each community using a unified distribution method, and volunteers from each community delivering the Fresh produce is delivered to each resident's home, which improves distribution efficiency and reduces the risk of pandemic spread. For this reason, how to efficiently dispatch distribution resources and design a scientific and reasonable vehicle distribution program is crucial to ensuring the supply of fresh produce to residents.

B. EMERGENCY SUPPLY AND DISTRIBUTION MODEL DESIGN

The hypothetical rescue logistics network considered in this study involves three members: rescue providers, rescue distribution centers, and resident demand areas, forming a three-tier network structure diagram for emergency supplies distribution. The community collects residents' demand information and passes it to the distribution center, which packages fresh produce and loads them in the reverse order of the distribution community, and the distribution vehicle goes to the pandemic control community in accordance with the agreed time window, where the distribution personnel get off the vehicle to complete temperature measurement and help local volunteers complete unloading of the fresh produce, and after the distribution is completed, the distribution vehicle returns to the distribution center to carry out the next distribution. After this distribution, the distribution vehicle returns to the distribution center for the next distribution, and the distribution personnel need to be quarantined for 14 days after completing one day's work to comply with the pandemic prevention and control policy. The emergency supply distribution process is shown in Figure 1.

C. BASIC ASSUMPTION

The complexity of the fresh produce emergency supply problem in the context of pandemic control comes firstly from the weight, freshness compatibility and demand distribution of fresh produce. Secondly, the huge demand and limited transportation resources put more requirements and restrictions on vehicle distribution than usual. Finally, the emergency supply

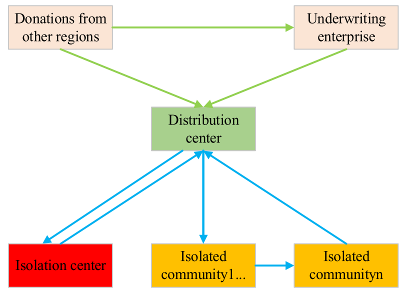


FIGURE 1. Flow chart of emergency supply and distribution.

of fresh produce needs to consider the time urgency and plan the optimal vehicle path. According to the actual demand, the assumptions made in this paper are as follows:

(1) Each vehicle starts at a distribution center

(2) Distribution vehicles travel at an even speed.

(3) Roads between segregated communities are passable.

(4) Distribution vehicles start from the logistics and distribution center, assuming that the vehicle stops at the logistics and distribution center after the maximum mileage or service.

(5) After the scope of distribution is determined, the logistics distribution center only considers the distribution business of community fresh produce.

(6) Each transportation vehicle can serve multiple communities, allowing the vehicle to make multiple deliveries.

(7) The load of each transportation vehicle is known and overloading is not allowed during transportation.

(8) Increasing the number of distribution personnel will reduce the unloading efficiency.

D. MODEL BUILDING

Different from the traditional distribution optimization objective,(the main focus is on cost [42], depletion [23], carbon emissions [43]), the optimization objective of this paper mainly focuses on the short time to keep the supply of pandemic, the number of distribution vehicles and the low risk of pandemic spread, so as to guarantee the demand of fresh agricultural products of the residents with limited resources; therefore, this paper takes the number of distribution vehicles, the average response time, and the risk of viral infection as the objective function, and takes full account of various constraints to model the problem and solve it. The relevant parameter variables used in this paper are shown in Table 2.

1) OBJECTIVE FUNCTION

a: NUMBER OF VEHICLES

Vehicles are limited as an important capacity resource in the context of public health emergencies due to pandemic prevention and control policies, due to the small number of vehicle drivers and road control [44]. The model considers minimizing the total number of dispatched distribution vehicles to pursue the maximization of capacity resource utilization. The expression for minimizing the number of distribution vehicles is as follows:

$$MinZ_1 = \sum\nolimits_{k \in K} y_k \tag{1}$$

TABLE 2. Parameter variables.

notation	mathematical expression
O	Distribution centers
n	Number of isolated communities
K	All vehicles muster
k	A vehicle in the vehicle pool
x_{ij}^k	0-1 variable, 1 if transporter k passes through arc (i,j), 0 otherwise
y_k	0-1 variable, 1 if the hauler transports fresh produce, 0 otherwise
n_k	Communities with distribution by vehicle k
Qi	Demand for community i
Q	Vehicle load
d_{ij}	Distance between community i and community j
L_{max}	Maximum vehicle mileage
t_a	Time of arrival of vehicles in the community
tl	Time of vehicle departure from the community
td	Vehicle inter-community travel time
ts	Vehicle unloading time in the community
η	Efficiency of unloading by unloading personnel
h_{best}	Number of persons at maximum unloading efficiency
h	Actual number of persons unloaded
T	Contact time standard value
H	Standard value for number of unloading personnel
α	Virus transmission coefficient

b: AVERAGE RESPONSE TIME

In order to enhance the rapidity of emergency rescue, some scholars aim to minimize the cumulative waiting time at all affected points [45]. However, in rescue, not only the timeliness but also the fairness should be considere [46], [47]. In this study, the optimization objective is to minimize the average response time(minutes) with the following expression:

$$MinZ_2 = \sum X_{ijk} \sum\nolimits_{k \in K} (t_d + t_s)/n \tag{2}$$

Considering that unloading time is not a simple linear problem, after the number of people unloading is optimized, adding unloading personnel reduces the unloading efficiency by 5-10%. So the unloading time:

$$t_s = \frac{Q_i}{h_{best} \cdot \eta + (h - h_{best}) \cdot \eta \cdot (1 - 5\%)^{h - h_{best}}} \tag{3}$$

c: RISK OF VIRAL INFECTIONS

Due to the rapid spread of viruses under public health emergencies, highly infectious, the longer the distribution personnel in the medium and high-risk areas, the higher the risk of infection with viruses, which is often ignored in previous studies. Therefore, in the process of emergency distribution of fresh produce, minimize the unloading time of emergency vehicles, and reduce the risk of virus infection of distribution personnel while ensuring the timeliness of fresh produce distribution. The expression of minimized virus infection risk is as follows:

$$MinZ_3 = \alpha \sum X_{ij}^k \sum\nolimits_{k \in K} \frac{1}{n} \cdot \frac{t_s}{T} \cdot \frac{h}{H} \tag{4}$$

2) CONSTRAINTS

(1) $\sum_{i=1}^{n} X_{io}^k = K$: Delivery trucks return to the distribution center after delivery;

(2) $\sum_{k=1}^{n} n_k = n$: Distribution area where all communities can receive fresh produce;

(3) $\sum_{i=1}^{n} X_{ij}^k \cdot Q_i \leq Q$: No overloading of vehicles during distribution;

(4) $\sum_{i=1}^{n} \sum_{j=1}^{n} X_{ij}^k \cdot d_{ij} \leq L_{\max}$: The total mileage of the vehicle while engaged in distribution activities shall not exceed the maximum mileage;

(5) $\sum_{i=1}^{n} (X_{ij}^k - X_{ji}^k) = 0$: Ensuring a balanced flow of traffic;

(6) $0 \leq n_k \leq n$: Vehicles can only deliver to the community for which the emergency is secured;

(7) $\sum_{k=1}^{K} \sum_{i=1}^{n} \sum_{j=1}^{n} X_{ij}^k \cdot (t_a - t_l) = 0$: All vehicles deliver to the next community as soon as unloading is complete, ensuring time continuity.

3) WEIGHTS SOLUTION

Considering the complexity of the problem, this paper uses the entropy weighting method to solve the weights of the three objective functions, and first invites six experts in related fields to score the importance of the objective functions (10 points out of 10), and the scoring table is shown in Table 3.

TABLE 3. Scoring table for experts.

Ratings experts	Number of vehicles	Average response time	Risk of viral infections
Expert 1	7	6	8
Expert 2	8	7	6
Expert 3	7	6	8
Expert 4	8	7	6
Expert 5	7	8	9
Expert 6	8	7	9

The entropy weight method solves for the weights with the following formula:

$$r_{ij} = \frac{a_{ij} - \min(a_{ij})}{\max(a_{ij}) - \min(a_{ij})} \tag{5}$$

where a_{ij} is the value in the matrix of the expert scoring table and equation (5) is the data normalization.

$$p_{ij} = \frac{r_{ij}}{\sum_{i=1}^{n} r_{ij}} \tag{6}$$

where n is the number of rows of the matrix, equation (6) calculates the weight of the target in column j in row i

$$e_j = -\frac{1}{\ln n}\sum_{i=1}^{n} p_{ij}\ln p_{ij} \tag{7}$$

Equation (7) calculates the entropy value for each target

$$k_j = \frac{1 - e_j}{\sum_{j=1}^{m}(1 - e_j)} \tag{8}$$

Equation (8) calculates the weights of each objective, and finally the weights of the three objectives are found to be 0.44,0.29,0.27, respectively.

III. ALGORITHM DESIGN

A. ALGORITHM SELECTION

Through the combing of emergency logistics related literature, the application of CiteSpace software to analyze the use of solution algorithms in solving such problems was obtained, as shown in the subject line in Figure 2 (the larger the text represents the more application of such solution algorithms), and in solving this kind of NP-hard problems, intelligent optimization algorithms are the first choice, and the most applied is the Genetic Algorithm, with Ant Colony algorithms being next in importance.

In this paper, genetic algorithm(GA) and ant colony algorithm(ACO) are chosen to solve the problem, and the genetic algorithm is improved to verify the feasibility and robustness of the algorithm through examples.

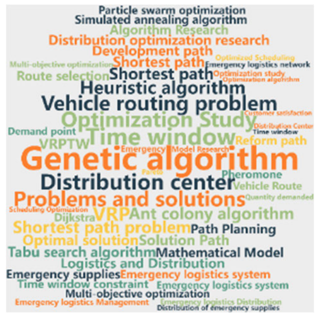


FIGURE 2. Research topic terms related to emergency logistics solving algorithms.

B. IMPROVED GENETIC ALGORITHM

The standard genetic algorithm has poor local search capability and poor optimization results in large-scale search. In this paper, we improve the genetic algorithm by adopting the ideas of "destruction" and "repair" in Large Neighborhood Search (LNS) in the local search operation, and design the destruction operator to remove several communities in the route from the current solution, and then use the repair operator to reinsert the removed communities back into the destroyed solution to enhance its global search and large-scale search capability.

1) ENCODING AND DECODING

The key step in solving using genetic algorithm is how to encode the chromosome, concise encoding helps to improve the speed of solving, so this paper adopts the integer encoding method. Assuming that there are now 5 isolated communities and a maximum of 3 vehicles are allowed to carry out the distribution of fresh produce, it is encoded as 1263475, where 6 and 7 represent the distribution centers, and it converts 12345 into 3 segments, i.e., it is divided into 3 paths (0 represents the distribution centers).

2) FITNESS FUNCTION

The objective function was used as the fitness function and individual fitness function values were calculated.

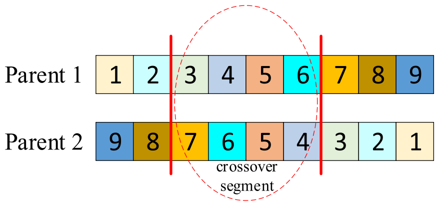


FIGURE 3. Cross-segmentation.

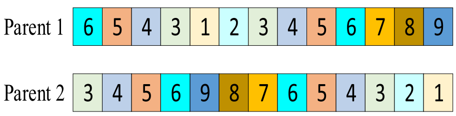


FIGURE 4. Parent graph after crossover.

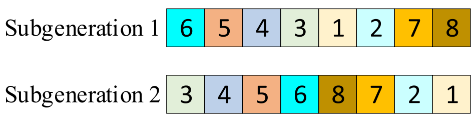


FIGURE 5. Subgenerational graph after crossover.

3) INITIALIZATION OF POPULATIONS

The algorithm uses real number coding to randomly generate a feasible solution as the initial population within the interval constraints.

4) ROULETTE SELECTION OPERATION

The roulette selection operating formula is as follows:

$$P(a_i) = \frac{F(a_i)}{\sum_{i=1}^{A} F(a_i)} \tag{9}$$

where F(ai) is the fitness of individual i,P(ai) is the probability of individual i being selected

5) CROSS-OPERATION

The crossover method used in this paper is as follows, assuming that there are two parent individuals as follows, at which point two crossover positions x_1 and x_2 are randomly selected, such as $x_1 = 3$,$x_2 = 6$,then the crossover fragment is shown in Figure 3.

Move the cross segment of parent 2 to the front of parent 1, and similarly move the cross segment of parent 1 to the front of parent 2, then these two parent individuals are shown in Figure 4.

The second duplicated gene was deleted from front to back to form two zygotic individuals, as in Figure 5.

6) MUTATION OPERATION

The mutation operation is very important for optimization search and evolution and can be used to jump out of the trap of locally optimal solutions when the optimization process is trapped in a locally optimal solution. The mutation operation is performed bitwise, i.e., mutating the content of a particular bit. The mutation operation can be carried out after the exchange operation, which can randomly select a bit for one of the paired individuals and then mutate it according to the mutation probability. The mutation operation is shown in Figure 6.

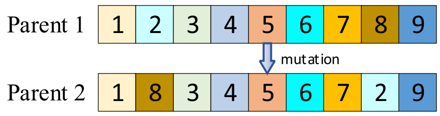


FIGURE 6. Schematic representation of paternal variation.

7) LOCAL SEARCH OPERATION

The local search operation designed in this paper adopts the ideas of "destruction" and "repair" in LNS. The destruction operator is used to remove several communities in the route from the current solution, and then the repair operator is used to reinsert the removed communities back into the destroyed solution.

The destruction operator removes a number of relevant distribution communities according to the following equation

$$R(i,j) = 1/\left(d'_{ij} + u_{ij}\right) \tag{10}$$

$$d'_{ij} = \frac{d_{ij}}{\max d_{ij}} \tag{11}$$

where d_{ij}' is the value that will be normalized in the range of [0, 1]; d_{ij} is the Euclidean distance between communities i and j; u_{ij} is whether i and j are on the same path or not, and if i and j are on the same path it is 0, otherwise it is 1.

From the above formula, it can be seen that the larger R(i,j) is, the larger the correlation between community i and community j is. On the basis of the above correlation formula, assuming that the number of communities is N, the number of communities to be removed is q, and the random element is D, the pseudocode of the destruction operator is shown in Table 4.

The repair operator is to insert the removed community back to the position that minimizes the total distance traveled by the vehicle as much as possible while satisfying the loading constraints and the time window constraints. The repair operator pseudocode is shown in Table 5.

8) GREEDY OPERATION

Through the algorithm solution can be derived to complete the emergency distribution task under the scientific and reasonable distribution vehicle path, but taking into account the reality of the limited resources, each path only by a dedicated vehicle alone distribution is often impractical. Therefore, through the greedy operation on the distribution path for the combination of operations, so that the vehicle in the completion of a path of distribution tasks back to the logistics center, in the time window allows within the re-sanitization of loading to complete other paths of distribution tasks. The greedy operation design is shown in Table 6.

TABLE 4. Destruction operator pseudocode.

Destructive operator

Inputs: current solution S (distribution scheme), number of communities to be removed q, random element D

Output: destroyed solution Sd, set of removed communities I

Randomly select the community i_{seed} from the solutions S, and it will be placed in the set I

$while\ |I| < q\ do$

Randomly select community i_{seed} from set I

Sort the communities that are in the current solution S but not in set I in the following way:

$i < \mathrm{j} \Rightarrow R(i_{curr}, LT_i) < R(i_{curr}, LT_j)$, The sorted result is then stored in the sorted sequence L

Calculate the serial number of the randomly selected community $r \leftarrow \lceil rand^D |L| \rceil$(rand is a random number from 0 to 1, $|L|$ is the number of communities in the set, $\lceil\ \rceil$ denotes upward rounding)

$I \leftarrow I \cup \{L_k\}$

end while

Remove the community in set I from S to obtain the corrupted solution Sd

return S

Finally, the improved genetic calculus is shown in Figure 7.

IV. EMPIRICAL RESEARCH AND ANALYSIS OF RESULTS

A. SINGLE VEHICLE TYPE DISTRIBUTION FOR SINGLE DISTRIBUTION CENTER

This is a strategy for efficiently distributing supplies in small-scale emergencies through one distribution center depot and one model of vehicle. Designed to quickly meet emergency needs and optimize route planning to ensure that supplies are quickly delivered to their destinations, this kind of emergency logistics vehicle dispatch optimization can act quickly to provide emergency support to disaster areas.Its distribution model is shown in Figure 8.

1) DATA SOURCES

In this paper, 20 isolated communities in Shanghai during the pandemic prevention and control period were selected as the research object, and the geographic coordinate information of each point was obtained through the Gaode map, and the latitude and longitude conversion was carried out to obtain the relative coordinates of each community, and the information of each community is shown in Table 7.The relative location of the distribution center is at (12,12), the unit of km, and the service time is from 08:00 to 18:00.Nos.1-20 in Table 7 are the 20 isolated communities. The distance between each community is in km, the demand of vegetables, fruits, meat and aquatic products is in kg, considering the emergency situation of distribution, the weight limit of emergency vehicles is 20,000kg; this study does not set a specific time window for each community, the time window of all the communities is set from 9:00am to 17:00am, and the fresh agricultural products delivered in this time period meet the food safety and timeliness requirements. The time window is set from 9:00 am to 17:00 pm in all communities.

2) PARAMETER SETTINGS

The running environment of the algorithm in this paper is Intel Corei5-9300H@2.4GHz and the memory is 16GB. In this paper, taking into account the actual situation, the number of unloading people h in each isolated community in the study is 8-12 people, the number of people at the maximum unloading efficiency is 8 people, and the unloading efficiency is 20 kg per person per minute. The virus transmission coefficient is taken as 0.1; the standard value of contact time T is taken as 30 min, and the standard value of the number of unloading personnel H is taken as 20 people.The parameter settings of the algorithm are shown in Table 8.

3) RESULTS OF THE SOLUTION

In the case of community size of 20, the algorithm solves better, no violation of the constraints of the time window and vehicle weight limit, requires 1 distribution vehicle to

TABLE 5. Repair operator pseudocode.

Restoration of the operator
Inputs: the solution Sd after destruction, the set of removed communities I Output: repaired solution S (distribution scheme) 1 $S \leftarrow S_d$ 2 $while\,\|I\| > 0\ do$ 3 Calculate the minimum insertion objective function value $Z = \min_{k\in K} \Delta f_{i,k}$ and the corresponding insertion back path number r_i and the insertion back position pos_i on that path for each community in I. $\Delta f_{i,k}$ is the distance increment added after inserting community i into path k to minimize the increase in the objective function under the constraints, and if there is no path in the current solution that can accept the community, then a new path is created to accept community i 4 Select the community i_m with the largest objective function value Z from I, i.e., select the community with the largest minimum insertion objective function from I 5 Plug the community i_m back into the position in S on the r_{i_m} path, i.e., the community i_m is inserted back into the position that minimizes the insertion objective function. 6 $I \leftarrow I \setminus \{i_m\}$, Removing community i_m from I 7 end *while* 8 return S

TABLE 6. Pseudocode for path reorganization greedy operation.

Greedy operation
Inputs: distribution time per route, working time window of the logistics center Outputs: number of delivery vehicles required, route per vehicle 1 Create an array to store all trip delivery paths, each including their time required 2 Sort the distribution paths according to the time of the distribution paths and prioritize the paths with shorter times 3 Initialize number of vehicles = 1 4 Initialize a variable indicating the remaining working time of the current distribution center, set to W 5 Initialize a variable indicating the time required for the already scheduled path, set to p 6 Distribution paths with long times select distribution paths in order from the sorted list of distribution paths and place them in the distribution center working time and update the remaining time 7 Whenever the remaining time is insufficient to accommodate the next distribution path, add a vehicle and reinitialize the remaining working time of the current distribution center as W 8 Repeat steps 6 and 7 until all distribution paths have been processed

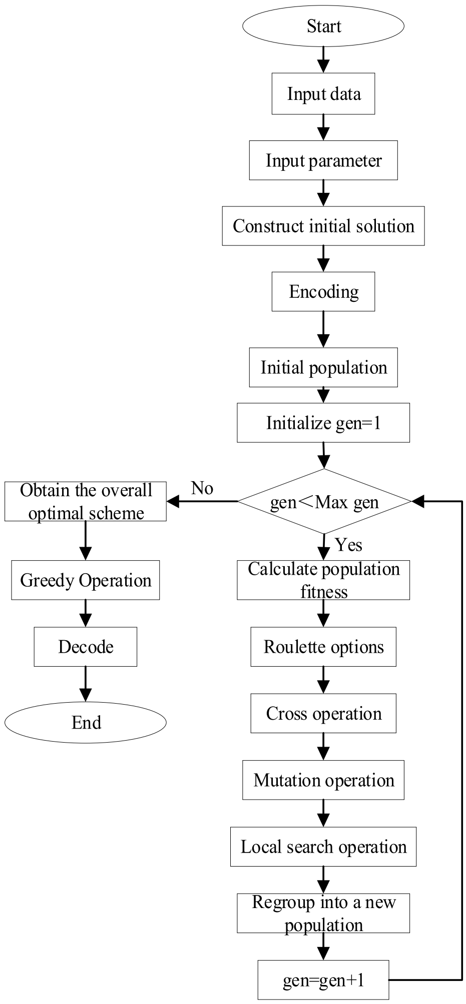


FIGURE 7. Flowchart of the improved genetic algorithm.

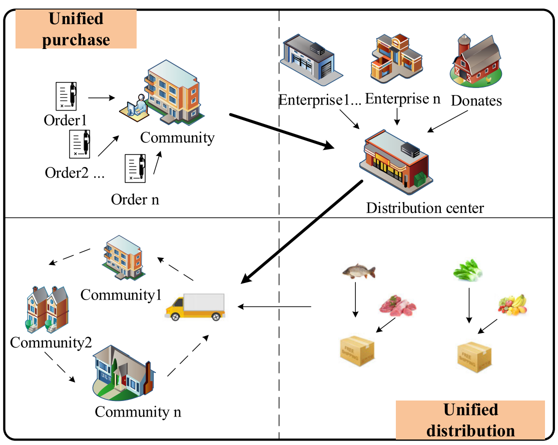


FIGURE 8. Single vehicle type distribution for single distribution center.

undertake 3 trips of distribution tasks, the average response time of the site to complete the distribution task is 15.3 minutes, and it takes 5.1 hours to complete the distribution task, which verifies the rationality and feasibility of the algorithm. Its vehicle distribution path planning is shown in Figure 9, and the specific optimization results are shown in Table 9.

In order to verify the feasibility and robustness of the proposed algorithms in this study, a comparative study is carried out in communities of 30, 50, and 80 scale simulation cases respectively, assuming that the number of people in each community is 2,000-8,000, and the demand for fresh produce per person per day is 1.5-2 kg. The solution results of the three algorithms are shown in Table 10.

As shown in Table 10, under different number of segregated communities, the three algorithms solve the same number of paths under 30 and 50 scale arithmetic, but IM-GA outperforms under 80 scale arithmetic. Under the 30 scale example, the three algorithms use the same number of vehicles, and under the 50 and 80 scale examples, IM-GA outperforms both ACO and GA, and the average response time optimization is better than both GA and ACO algorithms. In terms of average response time, IM-GA outperforms ACO and GA in different cases, and in the optimization process, IM-GA algorithm is more capable of reaching the optimal solution with a lower number of iterations, and has a higher robustness in different scale cases. In terms of virus infection risk, IM-GA also slightly outperforms ACO and GA in different scale cases. In addition, in terms of running time, IM-GA's running time for finding the optimal solution is better than that of GA and ACO, and the IM-GA algorithm is able to solve the problem of unified distribution of fresh agricultural products within a reasonable time, which is scientific and feasible for solving the practical problems.

B. MULTI-VEHICLE DISTRIBUTION BASED ON TEMPERATURE ZONE CLASSIFICATION

The special nature of fresh produce determines that it needs to meet certain temperature and humidity conditions during transportation and storage. In the process of fresh produce distribution, in order to ensure the freshness of fresh produce, emergency distribution vehicles need to set up different transportation temperatures, the appropriate temperature of fruits and vegetables is 10 °C, the appropriate temperature of meat and aquatic products is 0 °C, vegetables, fruits and meat, aquatic products due to the appropriate temperature consistent with the common transportation, will be segregated from the community residents' demand for orders according to the 0 °C and 10 °C is divided into two categories for distribution. The temperature zone classification packing distribution for the arithmetic example of 4.1 is shown in Figure 10.

The temperature zone classification packaged vehicle distribution path is shown in Figure 11. Specific vehicle distribution schemes for the two zoning types are shown in Table 11.

The basic data of this part of the study use the demand of fresh agricultural products of the residents of 20 isolated districts in Shanghai during the pandemic prevention and control period as mentioned above, and the improved genetic algorithm designed in this paper is used to solve the problem, and the algorithm solves the problem with better effect, which

TABLE 7. Isolated community fresh produce demand information.

Communities	Position	Vegetables	Fruits	Meats	Fishes	Time window
1	(17.77,11.51)	1629	1157	984	497	(09:00,17:00)
2	(29.31,2.88)	1133	880	739	331	(09:00,17:00)
3	(19.81,5.06)	823	586	547	202	(09:00,17:00)
4	(18.30,11.60)	762	528	509	177	(09:00,17:00)
5	(18.01,1.41)	1352	1088	874	423	(09:00,17:00)
6	(20.22,0.03)	640	413	434	126	(09:00,17:00)
7	(14.76,31.35)	1083	833	708	311	(09:00,17:00)
8	(15.69,0.89)	825	589	549	203	(09:00,17:00)
9	(21.67,2.61)	399	184	200	110	(09:00,17:00)
10	(24.06,3.26)	872	632	577	223	(09:00,17:00)
11	(16.82,13.13)	665	436	449	136	(09:00,17:00)
12	(22.35,4.71)	550	327	278	188	(09:00,17:00)
13	(17.60,11.10)	993	747	652	273	(09:00,17:00)
14	(17.86,14.42)	705	475	475	153	(09:00,17:00)
15	(19.48,12.11)	424	207	200	135	(09:00,17:00)
16	(29.28,20.88)	807	570	537	195	(09:00,17:00)
17	(24.51,14.15)	658	429	445	133	(09:00,17:00)
18	(15.40,18.22)	467	248	227	153	(09:00,17:00)
19	(14.87,26.88)	846	608	561	212	(09:00,17:00)
20	(9.87,8.38)	853	615	565	215	(09:00,17:00)

TABLE 8. Parameter settings for the three algorithms.

Algorithm name	Description of symbols	Parameter settings
ACO	Number of ants m	50
	Pheromone importance factor α	1
	Heuristic function importance factor β	3
	Pheromone volatilization factor ρ	0.85
	Updating pheromone concentration constants Q	5
	Maximum number of iterations Maxgen	400
GA/ IM-GA	Initial population N	50
	Probability of Crossover p_c	0.9
	Probability of mutation p_m	0.05
	Generation gap GGAP	0.9
	Maximum number of iterations Maxgen	400

verifies the reasonableness and feasibility of the algorithm. A total of one 0°C cold chain vehicle and one 10°C cold chain vehicle are needed to complete the distribution task in two temperature zones. The average response time of the 0°C cold chain vehicle is 8.4 minutes, and it takes 2.8 hours to complete the distribution task; the average response time of the 10°C cold chain vehicle is 11.8 minutes, and it takes 3.9 hours to complete the distribution task. Compared with the temperature-zone preservation and distribution without temperature-zone preservation and distribution, the former is

TABLE 9. Contingency supply path optimization results.

		The optimal vehicle routing
Route	1	0 → 18 → 19 → 7 → 16 → 17 → 15 → 4 → 1 → 13 → 0
	2	0 → 20 → 8 → 5 → 6 → 9 → 10 → 2 → 12 → 3 → 0
	3	0 → 11 → 14 → 0
Vehicle	1	Route 1 → Route 2 → Route 3

TABLE 10. Solution results of the three algorithms for different sizes of arithmetic cases.

Algorithms	Case Size	No. of paths	No. of vehicles	Average response time	Risk of viral infections	No. of iterations	Running time (s)
ACO	30	6	2	29.72	3.26%	264	182.57
	50	10	4	32.26	3.25%	297	335.42
	80	16	6	33.24	3.34%	311	603.25
GA	30	6	2	30.27	3.24%	252	193.84
	50	10	4	30.22	3.22%	264	321.46
	80	16	6	33.42	3.32%	291	579.63
IM-GA	30	6	2	28.38	3.22%	122	156.71
	50	10	3	27.78	3.19%	146	220.30
	80	15	5	27.84	3.28%	185	552.34

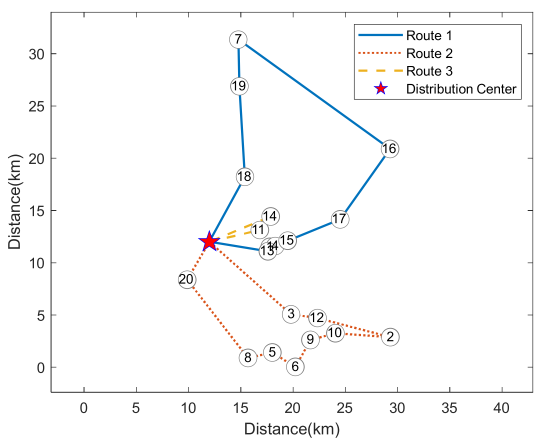


FIGURE 9. Vehicle distribution route planning.

higher than the latter in terms of the occupation of capacity resources, and the former is lower than the latter in terms of the distribution time, and at the same time, the former can better realize the freshness of fresh agricultural products.

In order to compare the feasibility and robustness of the algorithms, a comparative study is also carried out under the community of 30, 50, and 80 scale simulation cases respectively, and the solution results are shown in Table 12.

As can be seen from Table 12, the number of iterations with the corresponding runtime is still better than that of ACO and IM-GA in finding the optimal solution when distributing in sub-temperature zones.

When the community size is 30, the three algorithms have the same number of vehicles in use, and the average response time IM-GA is better than ACO by 4.3% and GA by 5.4%, and in terms of the risk of viral infection, GA and IM-GA are the same and better than ACO.From the perspective of the number of iterations of optimal solutions, the IM-GA is 49.5% of the ACO and 50% of the GA for the distribution of the cold chain vehicles at 10°C, and IM-GA is 24.0% of the ACO and 25.1% of the GA for the distribution of the cold chain vehicles at 0°C. IM-GA is 24.0% of ACO and 25.1% of GA under 0°C cold chain truck delivery.

When the community size is 50, the three algorithms have the same number of vehicles in use, and the average response time IM-GA is better than ACO by 4.3% and GA by 5.4%, and at the risk of viral infection, GA and IM-GA are the same and better than ACO.In terms of the number of iterations of the optimal solution, under 10°C cold chain vehicle distribution, IM-GA is 47.5% of ACO and 46.2% of GA; under 0°C cold chain vehicle distribution IM-GA is 41.0% of ACO and 42.1% of GA; and under 0°C cold chain vehicle distribution IM-GA is 41.0% of ACO and 42.1% of GA. Under the cold chain truck delivery, IM-GA is 41.0% of ACO and 42.1% of GA.

When the community size is 80, the ACO algorithm needs 7 vehicles to complete the distribution task, and the GA

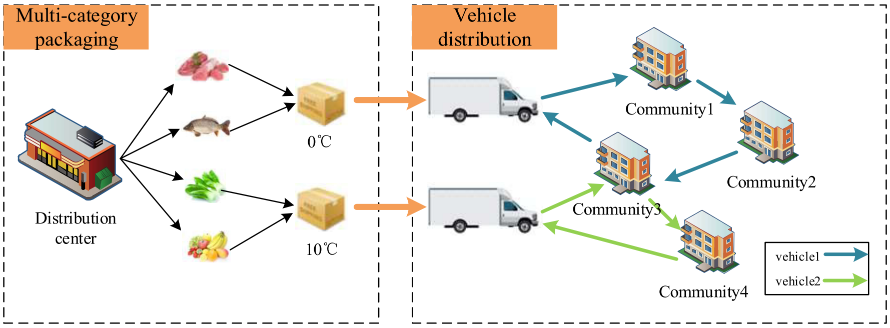
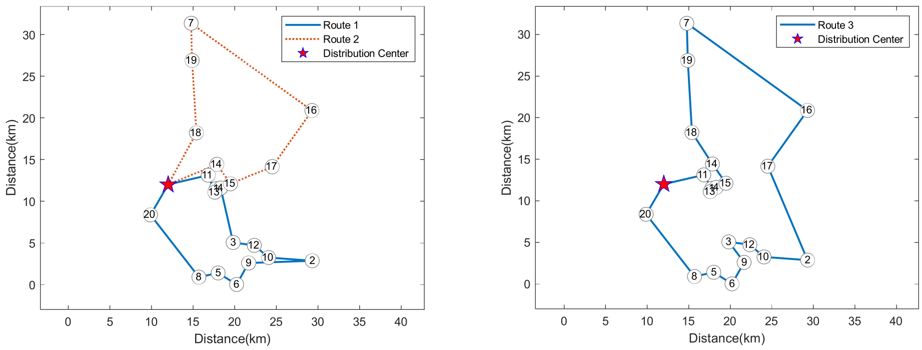


FIGURE 10. Temperature zone categorization packing and distribution.



(a) Vehicle distribution route map for 10°C (b) Vehicle Distribution Route Map for 0°C

FIGURE 11. Temperature zone categorized packaged distribution path map.

TABLE 11. Temperature zone distribution vehicle routing.

Agri-product category			The optimal vehicle routing
Vegetable & Fruit[a]	Route	1	0 → 20 → 8 → 5 → 6 → 9 → 2 → 10 → 12 → 3 → 4 → 1 → 13 → 11 → 0
		2	0 → 14 → 15 → 17 → 16 → 7 → 19 → 18 → 0
	Vehicle	1	Route 1 → Route 2
Meat & fish[b]	Route	3	0 → 11 → 1 → 13 → 4 → 15 → 14 → 18 → 19 → 7 → 16 → 17 → 2 → 10 → 12 → 3 → 9 → 6 → 5 → 8 → 20 → 0
	Vehicle	2	Route 3

algorithm needs 8 vehicles to complete the distribution task, but IM-GA only needs 6 vehicles for distribution, and IM-GA has the smallest average response time, which is 85.6% of the ACO and 85.7% of the GA, and from the number of iterations of the optimal solution, under the distribution of 10°C cold-chain trucks, the solution of IM-GA has the highest efficiency, and the number of iterations is 71.3% of the ACO and 63.9% of the GA. efficiency is the highest, the iteration number is 71.3% for ACO and 63.9% for GA, and the solution iteration number of IM-GA is 79.5% for ACO and 60.7% for GA under the distribution of 0°C cold-chain trucks.

Compared with a single model, the cold chain vehicles of 0°C and 10°C are selected for distribution in the sub-temperature zone, the quality of fresh produce distribution is better guaranteed, and although the number of vehicles has increased, the risk of infection of the average response time virus has been reduced. Under the use of sub-temperature zone distribution, the optimization effect of IM-GA algorithm in the number of vehicles and average response time is still better than GA and ACO algorithms, which once again verifies the high robustness of IM-GA algorithm compared with ACO and GA algorithms in the emergency supply and distribution problem.

TABLE 12. Solution results of the three algorithms for different sizes of instances in the context of distribution in different temperature zones.

Algorit -hms	Case Size	Temperature zones	No. of paths	No. of vehicles	Average response time	Risk of viral infections	No. of iterations	Running time (s)
ACO	30	10°C	5	2	23.93	3.22%	194	101.26
		0°C	2	1	13.25	3.21%	192	104.29
	50	10°C	7	3	24.74	3.18%	257	223.12
		0°C	3	2	11.29	3.16%	239	254.90
	80	10°C	12	5	26.25	3.32%	261	472.23
		0°C	4	2	11.55	3.28%	224	562.53
GA	30	10°C	5	2	23.70	3.21%	192	93.17
		0°C	2	1	13.90	3.20%	183	95.28
	50	10°C	7	3	24.33	3.17%	264	201.25
		0°C	3	2	11.46	3.15%	233	223.89
	80	10°C	13	5	25.67	3.31%	291	463.27
		0°C	4	3	12.07	3.27%	293	529.16
IM-GA	30	10°C	5	2	23.18	3.21%	96	82.96
		0°C	2	1	12.40	3.20%	46	83.76
	50	10°C	7	3	22.41	3.17%	122	171.74
		0°C	3	2	10.87	3.15%	98	176.13
	80	10°C	12	4	22.14	3.27%	186	389.90
		0°C	4	2	10.21	3.25%	178	408.44

C. MULTI-DISTRIBUTION CENTER DISTRIBUTION BASED ON CLUSTERING ALGORITHM

In the event of a large-scale public health emergency, the scope of social impact is often very large, and the pandemic prevention and control policy will affect many community residents. Due to the limited throughput capacity of a single distribution center, it is difficult to undertake a large number of community emergency supplies to protect the task, which often requires multiple distribution centers to jointly carry out distribution. Therefore, this paper proposes a multi-distribution center emergency material distribution scheme based on clustering algorithm.

The idea of clustering algorithm is to design optimized distribution routes and improve efficiency by dividing communities into different clusters or groups in order to perform centralized material distribution within each cluster. By dividing neighboring communities into the same clusters for uniform distribution, in order to design and solve a more efficient and reasonable vehicle distribution scheme. In addition, cluster analysis can also consider the size and material demand of each cluster in order to better balance the load of each distribution center, thus improving the overall distribution capacity.

1) CLUSTERING ALGORITHM

K- means clustering is a type of unsupervised learning which is based on center of mass by dividing a set of data into clusters k. This clustering algorithm requires an appropriate number of clusters k because the initial center of mass may change, thus affecting the grouped data with inconsistent results. By applying The Elbow Method, the inflection points of the Sum Squared Error (SSE) curve can be utilized to determine the appropriate number of centers of mass for different

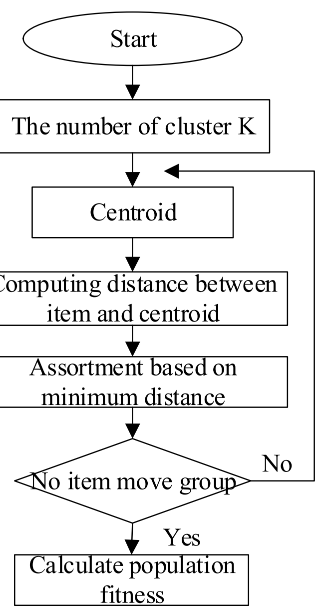
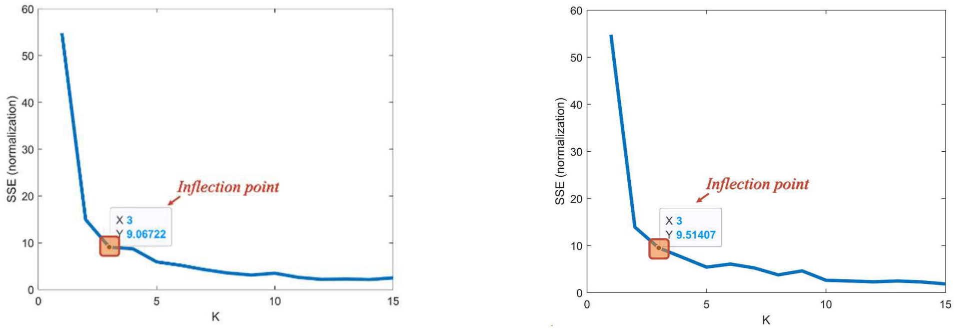
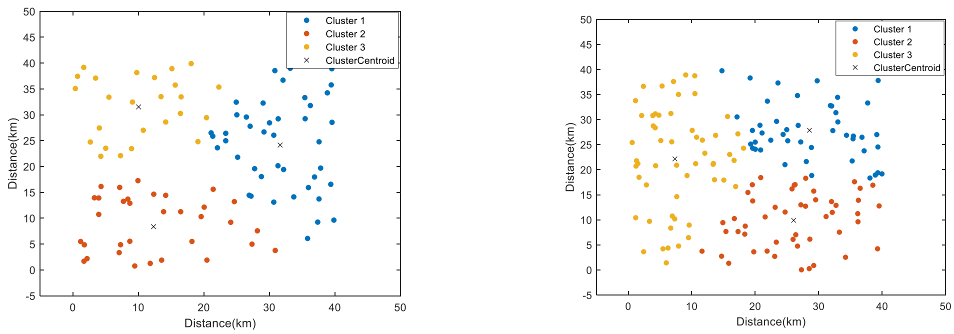


FIGURE 12. Flowchart of K-Means clustering algorithm.



Scale 100 Scale 150

FIGURE 13. The Elbow method for determining the point of inflection.



Scale 100 Scale 150

FIGURE 14. Graph of clustering results.

TABLE 13. Results of the arithmetic example.

Clust-ered	Case Size	No. of paths	No. of vehicles	Average response time	Risk of viral infections	No. of iterations	Running time (s)
Y	100	7;9;5	2;3;1	23.18;22.57; 21.66	3.01%;2.76%; 2.61%	107;124;84	198.25
	150	11;10;9	3;3;2	24.09;21.94; 21.46	2.79%;2.86%; 2.63%	103;112;96	230.32
N	100	21	7	(29.79)	3.04%	266	628.41
	150	30	10	(28.71)	2.97%	289	992.74

values of the number of clusters k. The Elbow Method can be used to determine the appropriate number of centers of mass for different values of the number of clusters.

Given two samples $X = (x_1, x_2, \ldots, x_n)$ and $Y = (y_1, y_2, \ldots, y_n)$, where n denotes the number of features, the Euclidean Distance between two vectors X and Y is denoted as:

$$dist_{ed} = (X, Y) = \|X - Y\| = \sqrt[2]{(x_1 - y_1)^2 + \ldots + (x_n - y_n)^2} \tag{12}$$

where C denotes the center of clustering, if x belongs to the cluster C_i, the Euclidean distance between the two is computed, and the distances from all the sample points to their centroids are worked out and summed up as the sum of squared errors. Sum Squared Error (SSE) is calculated as follows:

$$SSE = \sum_{i=1}^{K} \sum_{x \in C_i} (C_i - x)^2 \tag{13}$$

The flowchart of the clustering algorithm is shown in Figure 12.

2) ANALYSIS OF EXAMPLES

In order to further verify the effectiveness of the IM-GA algorithm in this chapter, 2 groups of medium and large-scale cases are set up respectively, and the demand categories of fresh produce in isolated communities are still vegetables, fruits, meats and seafoods, and according to the previous section on the demand of each community for each category of fresh produce and the distribution of the geographic location of each community, the 100- and 150-size cases are set up, and the demand of fresh produce in each isolated community is generated randomly between [2000, 2500] kg is randomly generated between, the geographic location of each isolated community is generated between [0, 40] km horizontal and vertical coordinates, the rest of the parameters of the arithmetic cases are kept consistent with the previous section, in order to avoid chance, each group of cases are tested five times, and the average of the five results is taken to test the performance of the algorithm, and the results of the specific case test are shown in Table 12. The elbow method determines the inflection points as in Figure 13 and the clustering results as in Figure 14.

As can be seen from Table 13, under the solution of large-scale arithmetic cases, the use of clustering algorithm to divide the community distribution range has a better optimization effect. When the community size is 100: in terms of the number of vehicle distribution, it is 14.3% better than unclustered; in terms of the average response time, it is 24.6% better than unclustered; in terms of the risk of viral infection, all three distribution centers are better than unclustered, but one is higher than unclustered. When the community size is 150: 20.0% better than unclustered in number of vehicles distributed; 21.6% better than unclustered in average response time; and all three distribution centers are also better than unclustered in viral infection risk. It can be concluded that in the case of large-scale distribution, the distribution effect after clustering is significantly better than that of non-clustering. In addition, in terms of the number of algorithm iterations and running time, the post-clustering also shows obvious advantages.

In emergencies such as public health emergencies, this emergency material distribution scheme based on the k-means clustering algorithm can optimize the use of distribution resources, improve the speed of arrival of materials, and minimize the waste of resources while safeguarding the needs of the community. Through reasonable clustering and distribution route planning, limited resources can be utilized scientifically and reasonably to ensure timely and efficient distribution of materials to meet the basic needs of community residents, and this study can provide a scientific basis for the government and other organizations to formulate the optimization of emergency supply and distribution of fresh agricultural products in response to emergencies such as the COVID-19.

V. CONCLUSION

In this paper, under the scenario of emergency supply in public health events, based on the perspective of the government and other organizational management departments, and with the research object of meeting the order demand for fresh agricultural products of the residents in medium and high-risk areas under the pandemic prevention and control policy, and taking the example of the emergency supply of fresh agricultural products during the Shanghai COVID-19 pandemic, the unified distribution of fresh agricultural products is investigated, and the risk of cross-infection is innovatively introduced as the optimization objective, taking the risk of viral infection into consideration of the insufficient personnel and the long-time gathering of the personnel in pandemic. Considering the risk of cross-infection brought by insufficient personnel and long-time gathering of personnel under the pandemic, we innovatively introduced the optimization objective of viral infection risk and constructed a distribution optimization model. On this basis, three different emergency supply distribution modes are designed under public health emergencies, and the problem is solved by the improved genetic algorithm and greedy algorithm, which results in the vehicle resources required under different distribution modes and the time needed to complete the distribution task. Meanwhile, this paper also verifies that the improved genetic algorithm has better convergence and robustness than the unimproved genetic algorithm and ant colony algorithm.

Among the three distribution schemes: the single distribution center distribution scheme is applicable to the number of small-scale communities, and the government is able to use simple resources to make a quick response; the temperature zone categorized distribution is adapted to the number of medium-sized communities, with higher requirements for the type of vehicles, and under the same scale of demand, the distribution of the sub-temperature zones can better guarantee the quality of the fresh agricultural products; and the distribution of the multi-distribution centers based on the k-means clustering algorithm is able to reasonably utilize the limited resources to improve the distribution efficiency and distribution capacity, and to better satisfy the residents' needs for the fresh agricultural products.

This paper considers the constraints of capacity resources, gives the optimal distribution program for different distribution, when the vehicle resources are more, for the degree of urgency of the emergency can increase the vehicle resources, which in turn reduces the average response time, such as section IV-A3, a single vehicle for distribution takes 5.1 hours, but when the number of vehicles is 2 only takes 2.8 hours, which can significantly reduce the average response time, the government can be based on their own vehicle The government can flexibly deploy the resources to achieve the distribution optimization.

The empirical study in this paper focuses on large cities such as Shanghai, where the capacity reserve is more adequate, so for similar medium and large cities, the distribution method of emergency supply protection in this paper can be borrowed in the face of a pandemic. However, for some cities in less developed regions, it may be difficult to allocate all the capacity resources and supplies, and then we can consider expanding the scope of the time window to improve the utilization rate of the capacity resources.

There are some shortcomings in this study, such as: (1) this paper only studied the first level of distribution in the context of emergency supply, and in the future, we can consider the multilevel distribution model; (2) we did not design the degree of urgency of the demand, and according to the degree of urgency of the demand for distribution; (3) this paper considers the fresh agricultural products of the distribution center to meet the demand for the distribution area, and in the future, we can consider the distribution of distribution centers when the amount of the distribution center is insufficient, and the distribution center of more than one for collaborative distribution.

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