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Article

Multi-Agent Optimization Algorithms for Emergency Logistics Networks and Their Applications in Public Health Emergencies

Xiaowei Wu * and Jun Tian

School of Environment and Civil Engineering, Dongguan University of Technology, Dongguan 523808, China
* Corresponding authors: wxw@dgut.edu.cn

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Abstract: This paper investigates the multi-agent optimization algorithms for emergency logistics networks and their applications in public health emergencies. With the acceleration of urbanization and the increasing frequency of emergencies, the optimization of urban network structures for large-scale emergency rescue resource distribution has become increasingly important. Multi-Agent Systems (MAS), known for their flexibility, robustness, and autonomy, have been widely applied in the research of emergency rescue resource distribution. This study introduces a multi-level coverage function for facility location, establishes a multi-objective stochastic programming model for facility location-allocation without capacity constraints, and designs an optimization solution based on genetic algorithms. Through empirical analysis using the collaborative layout of medical material reserve hubs in 33 towns and districts of Dongguan City as a case study, the effectiveness of the model and algorithm is verified. The results show that the optimized emergency logistics network can achieve efficient and fair resource distribution in public health emergencies while considering cost-effectiveness. This research provides theoretical support and practical guidance for the optimal design of emergency logistics networks.

Keywords: emergency logistics networks; multi-agent systems; optimization algorithms; public health emergencies; genetic algorithms; facility location-allocation; multi-objective stochastic programming

1. Introduction

In recent years, with the acceleration of urbanization and the increasing frequency of emergencies, the optimization of urban network structures for large-scale emergency rescue resource distribution has attracted increasing attention [1–4]. As an emerging intelligent technology, Multi-Agent Systems (MAS) have been widely applied in the research of emergency rescue resource distribution due to their flexibility, robustness, and autonomy in complex systems [5–7]. However, despite some progress in existing research, there are still many deficiencies in the optimization of large-scale urban network structures. Internationally, MAS has been successfully applied in various emergency scenarios [8]. For example, Zhejiang University proposed a decision-making system for emergency medical evacuation based on multi-agent reinforcement learning, which realized efficient resource allocation through collaboration among agents. In terms of emergency material distribution, Rabiei et al. proposed a multi-objective optimization model combining a fuzzy reasoning system for post-disaster vehicle route planning and material allocation [9]. In China, the application of MAS in emergency logistics has also made significant progress. Despite the great potential of MAS in emergency rescue resource distribution, there are still some deficiencies in existing research [10–12]. First, the scalability of MAS faces challenges in large-scale urban networks, especially in dealing with complex urban environments, where the optimization of computing resources and the problem of latency need to be solved urgently. Second, most existing research is based on pre-processed datasets and simulated environments, lacking the ability to integrate real-time data streams (such as IoT data). In the practical application of emergency rescue resource distribution, the research on human-agent interaction mechanisms is relatively weak and lacks effective support. At the same time, existing research is insufficient in considering the impact on the environment and social equity, making it difficult to achieve comprehensive optimization in resource allocation. Finally, most research findings lack validation in real urban environments, and their adaptability and reliability in dynamic environments still need further assessment.

2. Optimization of Collaborative Layout of Emergency Logistics Networks under the COVID-19 Pandemic

Emergency material reserve hubs are crucial infrastructures for conducting emergency operations following public health emergencies. Adhering to the principle of “local management and multi-level collaboration,” China’s emergency management departments have been working on optimizing the layout of emergency logistics networks. This study introduces a multi-level coverage function for facility location, aiming to ensure fairness, cost-effectiveness, and satisfaction of emergency demands. A multi-objective stochastic programming model for facility location-allocation without capacity constraints is established to optimize the multi-level collaborative layout of emergency logistics networks. Moreover, a genetic algorithm-based solution that considers both fairness and cost-effectiveness is proposed.

2.1. Construction of Collaborative Emergency Logistics Network Model

(1) Model Assumptions

To abstract the problem and construct a reasonable model, the following assumptions are proposed:

1) Emergency material distribution follows a “many-to-many” model, meaning one reserve hub can be responsible for multiple demand points, and a demand point can be supplied by multiple reserve hubs, ensuring that all demands are fully met.

2) Emergency reserve hubs of different levels have different minimum storage requirements, with no capacity constraints.

3) Different coverage levels correspond to different coverage rate weights.

4) Emergency reserve hubs of different levels and coverage levels have different coverage rates.

5) The transportation distance between candidate reserve hubs and demand points is a fixed value.

6) Transportation costs consist of fixed and variable costs. Fixed costs include vehicle usage and inspection costs, while variable costs are proportional to the distance traveled.

2.2. Genetic Algorithm Design

The multi-level collaborative layout optimization model for emergency logistics networks is essentially a location-allocation model, which has been proven to be an NP-hard problem. When the problem size is small, commercial solvers such as CPLEX and Gurobi can be used to solve it. However, for larger problem sizes, these solvers struggle to obtain optimal solutions within an acceptable timeframe. Heuristic algorithms can help decision-makers obtain relatively optimal solutions within a certain time frame. Genetic algorithms, known for their wide search range and ability to avoid local optima, have been applied to solve large-scale location-allocation problems.

2.2.1. Basic Principles of Genetic Algorithms

Genetic algorithms follow the natural law of “survival of the fittest” and are search algorithms based on natural selection and population genetics. By simulating the reproduction, crossover, and mutation processes in natural selection and genetics, individuals in the population gradually evolve towards the optimal solution. The basic process includes the following components:

Encoding: The first step in genetic algorithms is to convert decision variables into a coding format suitable for computer programming. Common chromosome encoding methods include binary, real-number, and matrix encoding. Different gene combinations in the chromosome represent different solutions, and appropriate encoding methods facilitate crossover and mutation operations, guiding the population towards the optimal solution.

Fitness Function: The fitness function is the criterion for evaluating the quality of individuals in the population. Typically, the objective function is set as the fitness function. By decoding the chromosome and calculating the corresponding fitness value, individuals can be ranked, and high-quality individuals have a higher probability of being passed on to the next generation.

Genetic Operators: These include selection, crossover, and mutation.

Algorithm Termination Conditions: Genetic algorithms cannot guarantee the optimal solution. Therefore, termination conditions must be set to output the current satisfactory solution. These conditions can be: (1) reaching a fixed number of generations for genetic operations; (2) the optimal solution remaining unchanged for a fixed number of generations after iteration; or (3) the algorithm running for a fixed amount of time.

2.2.2. Chromosome Encoding and Decoding

(1) Encoding Rules for Solutions

In genetic algorithms, each chromosome represents a feasible solution, which is a sequence. The length of the sequence is equal to the number of nodes (hub points and non-hub points) in the entire Dongguan area. The chromosome (sequence) uses 0-1 encoding. A value of 1 indicates that the point is a hub point, while 0 indicates a non-hub point. The total number of 1s in the chromosome represents the total number of hub points.

(2) Decoding Rules for Solutions

As mentioned earlier, each chromosome is a feasible solution. The sequence numbers with 0 represent non-hub points, while those with 1 represent hub points. The sequence numbers of hub points and non-hub points are counted separately to form sets of hub point sequence numbers and non-hub point sequence numbers. To determine which non-hub points are covered by each hub point, a hub point allocation algorithm is used, as detailed later.

2.2.3. Hub Point Allocation Algorithm

Iterate through the set of non-hub point sequence numbers. For each non-hub point, calculate the distance to all hub points and select the hub point with the shortest distance. Store the non-hub point sequence number, the corresponding hub point sequence number, and the distance in an array. By iterating through all non-hub point sequence numbers in this manner, a hub point allocation plan corresponding to the current solution is obtained.

2.2.4. Fitness Function

(1) Basic Principle

In genetic algorithms, the fitness function is typically the basis for population evolution. The fitness value of an individual is calculated to evaluate its quality. A higher fitness value indicates better adaptation. The goal of this project is to maximize the minimum coverage level of the emergency logistics location layout while minimizing the expected total cost.

(2) Calculation of the Fitness FunctionThe fitness function is calculated using the following formula is as shown in Eq. (1):

$$w_1\left(\sum_{i=1}^{n_1}\frac{D_i}{v} + +n_2t_0\right) + w_2\left(\sum_{i=1}^{n_2} D_i * cost + n_2cost_0\right) \tag{1}$$

where:$w_1 and w_2$are the weight values for time and cost, respectively;$n_1$is the number of non-hub points;$n_2$is the number of hub points;v is the delivery speed;$t_0$is the hub point delivery time;$cost$ is the unit distance cost;$cost_0$ is the hub point construction cost;$D_i$is the distance from the non-hub point to the corresponding hub point.

2.2.5. Genetic Operators

(1) Selection Operator

The algorithm uses tournament selection to pick individuals for the next generation. Specifically, a number of individuals (tour-size) are randomly selected from the population, and the individual with the best fitness function value is chosen. This process is iterated until the total number of selected individuals reaches pop-size.

(2) Crossover Operator

The algorithm performs crossover operations on the selected individuals. Specifically, assuming two chromosomes, pop1 and pop2, are involved in crossover, a random crossover point x is generated. Information from 1 to x of pop1 and from x+1 to num of pop2 is combined to form a new chromosome child1. Similarly, information from x+1 to num of pop2 and from 1 to x of pop2 is combined to form another new chromosome child2.

(3) Mutation Operator

The algorithm performs mutation operations on the individuals after crossover. Specifically, for each individual, a hub point (represented by 1) is randomly selected from the set of hub points and converted into a non-hub point (represented by 0). Simultaneously, a non-hub point is randomly selected from the set of non-hub points and converted into a hub point.

(4) Feasibility Check

The location results must ensure that each demand point is covered by at least one reserve hub. Therefore, crossover and mutation operations may lead to infeasible solutions. According to the actual needs of the problem, the genes of the offspring chromosomes are adjusted to restore feasibility.

3. Empirical Analysis

The suddenness and severity of public health emergencies require the establishment of emergency material reserve hubs of different levels in each administrative area for physical storage. Below, we take the collaborative layout of medical material reserve hubs in 33 towns and districts of Dongguan City as an example for case study to further verify the effectiveness of the above model and algorithm.

3.1. Parameter Settings

The case plans to set up medical protective material reserve hubs in 33 towns and districts of Dongguan City. The distance data between different towns and districts are actual driving distances obtained through Baidu API calls. Since the occurrence scenarios and losses of COVID-19 are difficult to predict, the scenario generation method is used. Referring to the statistical data in the "Guidance Scheme for Public Health Emergency Material Reserve in Dongguan City, Guangdong Province" (hereinafter referred to as the "Scheme"), six demand scenarios covering all towns and districts in the city are randomly generated to determine the demand for medical disposable protective clothing in each scenario. The specific steps are as follows:

(1) Referring to the statistical data in the "Scheme" and the calculation method of the W4 demand for epidemic prevention medical protective materials in each town and district, the reserve demand for medical disposable protective clothing in each town and district is obtained.

(2) The geographical locations of each town and district are abstracted as nodes in the network. It is assumed that in each demand scenario, 1 to 3 nodes will have emergency material demands, and the probability of the number of demand nodes occurring is uniformly distributed.

(3) Statistics on the number of times COVID-19 occurred in 33 towns and districts of Dongguan City from January 1, 2022 to January 1, 2023 are used as the probability of each town and district experiencing an epidemic. Using MATLAB's random number generation function, the hub towns and districts (Hub points) and spoke towns and districts (Spoke points) of Dongguan City's axis-spoke epidemic prevention emergency logistics network are analyzed in detail. Combined with the logistics situation of each town and district, the axis-spoke emergency logistics network is used as the basis for the study. The algorithm operation for generating 7 to 10 hub points, considering the optimal time, cost, and comprehensive time-cost situation, is shown in Figures 1 to 12.

3.2. Solution Results

(1) Time Optimality

Using the optimization solver, when the number of hub points is set to7, the optimal solution with the shortest expected total time is $f1 * = 11.7187$. By substituting this optimal objective value into the fitness function (Equation 1), and implementing the improved genetic algorithm on the MATLAB platform, the optimization solution for the multi-objective problem can be obtained. The final result of the program run is shown in Figure 1, with a fitness value of 10.6534.

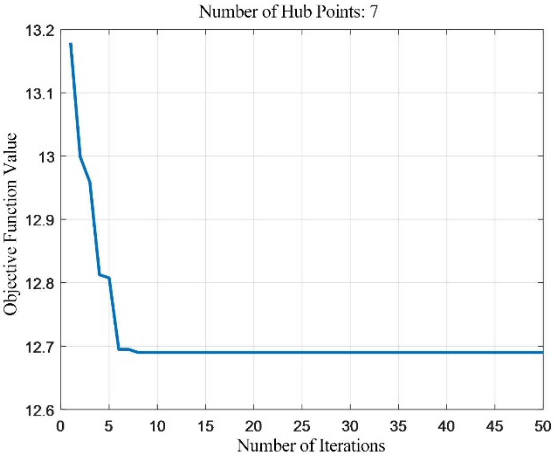

Figure 1. Iteration Graph of Algorithm Solution when Hub Points are 7.

Using the optimization solver, when the number of hub points is set to 8, the optimal solution with the shortest expected total time is f1 ∗= 10.6097. By substituting this optimal objective value into the fitness function (Equation 1), and implementing the improved genetic algorithm on the MATLAB platform, the optimization solution for the multi-objective problem can be obtained. The final result of the program run is shown in Figure 2, with a fitness value of 9.6452.

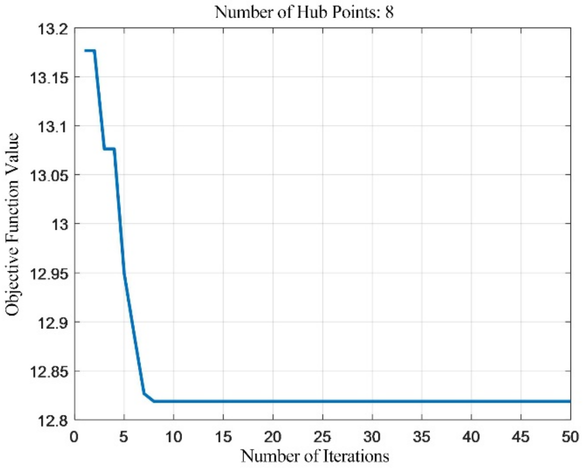

Figure 2. Iteration Graph of Algorithm Solution when Hub Points are 8.

Using the optimization solver, when the number of hub points is set to9, the optimal solution with the shortest expected total time is f1 ∗ = 10.0157. By substituting this optimal objective value into the fitness function (Equation 1), and implementing the improved genetic algorithm on the MATLAB platform, the optimization solution for the multi-objective problem can be obtained. The final result of the program run is shown in Figure 3, with a fitness value of 9.1052.

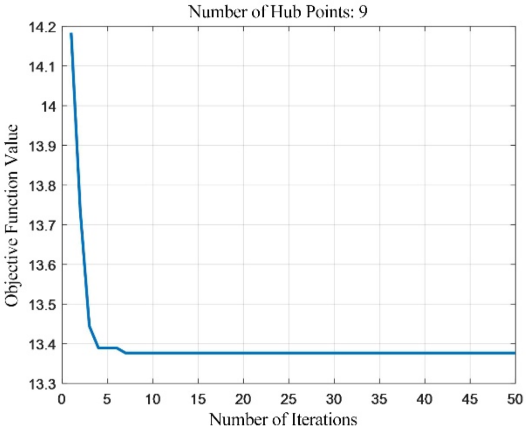

Figure 3. Iteration Graph of Algorithm Solution when Hub Points are 9.

Using the optimization solver, when the number of hub points is set to10, the optimal solution with the shortest expected total time is f1 ∗ = 9.4315. By substituting this optimal objective value into the fitness function (Equation 1), and implementing the improved genetic algorithm on the MATLAB platform, the optimization solution for the multi-objective problem can be obtained. The final result of the program run is shown in Figure 3, with a fitness value of 8.57408.

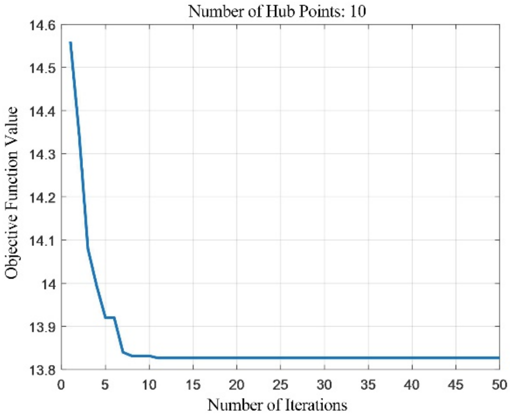

Figure 4. Iteration Graph of Algorithm Solution when Hub Points are 10.

(2) Cost Optimality

Using the optimization solver, when the number of hub points is set to 7, the optimal solution with the shortest expected total time is f1 ∗=5.4. By substituting this optimal objective value into the fitness function (Equation 1), and implementing the improved genetic algorithm on the MATLAB platform, the optimization solution for the multi-objective problem can be obtained. The final result of the program run is shown in Figure 5, with a fitness value of 7.39774.

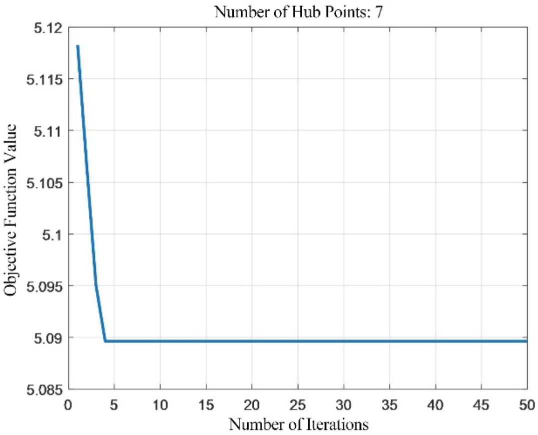

Figure 5. Iteration Graph of Algorithm Solution when Hub Points are 7.

Using the optimization solver, when the number of hub points is set to 8, the optimal solution with the shortest expected total time is f1 ∗ = 5.7023. By substituting this optimal objective value into the fitness function (Equation 1), and implementing the improved genetic algorithm on the MATLAB platform, the optimization solution for the multi-objective problem can be obtained. The final result of the program run is shown in Figure 6, with a fitness value of 7.81136.

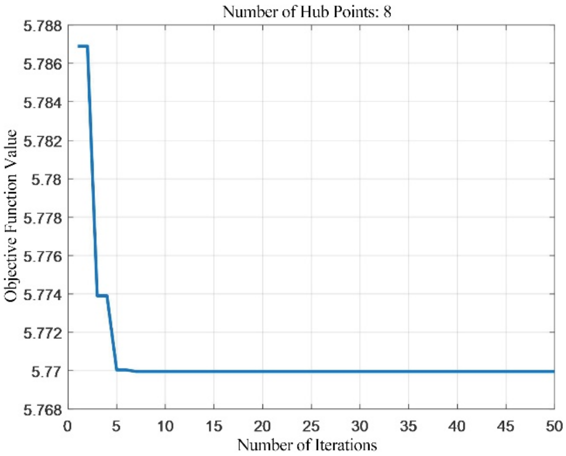

Figure 6. Iteration Graph of Algorithm Solution when Hub Points are 8.

Using the optimization solver, when the number of hub points is set to 9, the optimal solution with the shortest expected total time is f1 ∗ = 6.0668. By substituting this optimal objective value into the fitness function (Equation 1), and implementing the improved genetic algorithm on the MATLAB platform, the optimization solution for the multi-objective problem can be obtained. The final result of the program run is shown in Figure 7, with a fitness value of 8.31073.

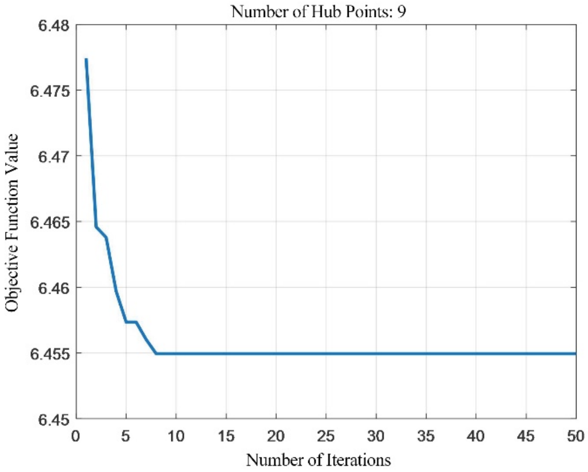

Figure 7. Iteration Graph of Algorithm Solution when Hub Points are 9.

Using the optimization solver, when the number of hub points is set to 10, the optimal solution with the shortest expected total time is f1 ∗ = 6.4642. By substituting this optimal objective value into the fitness function (Equation 1), and implementing the improved genetic algorithm on the MATLAB platform, the optimization solution for the multi-objective problem can be obtained. The final result of the program run is shown in Figure8, with a fitness value of 8.85502.

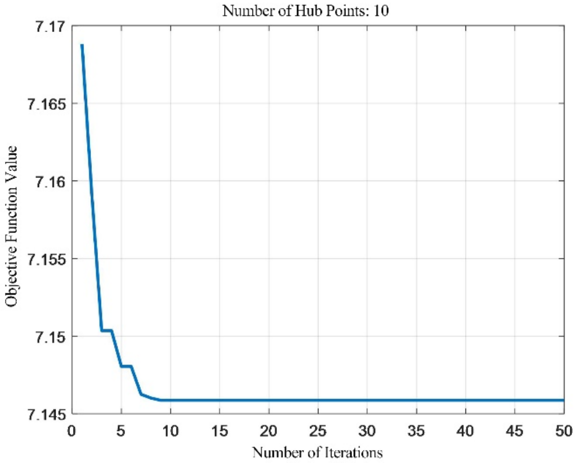

Figure 8. Iteration Graph of Algorithm Solution when Hub Points are 10.

(3) Comprehensive Optimality

Using the optimization solver, when the number of hub points is set to 7, the optimal solution with the shortest expected total time is f1 ∗ = 9.24131. By substituting this optimal objective value into the fitness function (Equation 1), and implementing the improved genetic algorithm on the MATLAB platform, the optimization solution for the multi-objective problem can be obtained. The final result of the program run is shown in Figure 9, with a fitness value of 9.24131.

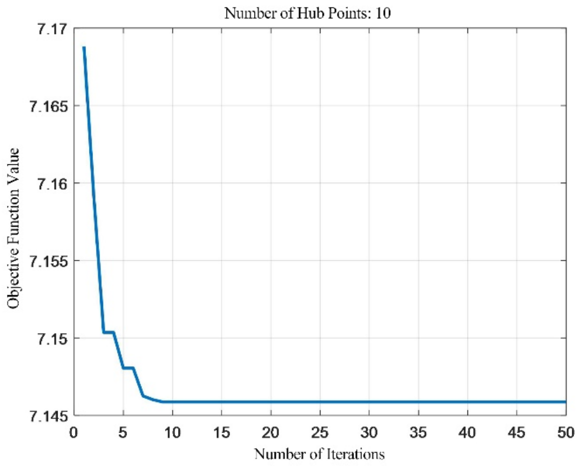

Figure 9. Iteration Graph of Algorithm Solution when Hub Points are 7.

Using the optimization solver, when the number of hub points is set to 8, the optimal solution with the shortest expected total time is f1 ∗ = 8.89377. By substituting this optimal objective value into the fitness function (Equation 1), and implementing the improved genetic algorithm on the MATLAB platform, the optimization solution for the multi-objective problem can be obtained. The final result of the program run is shown in Figure 10, with a fitness value of 8.89377.

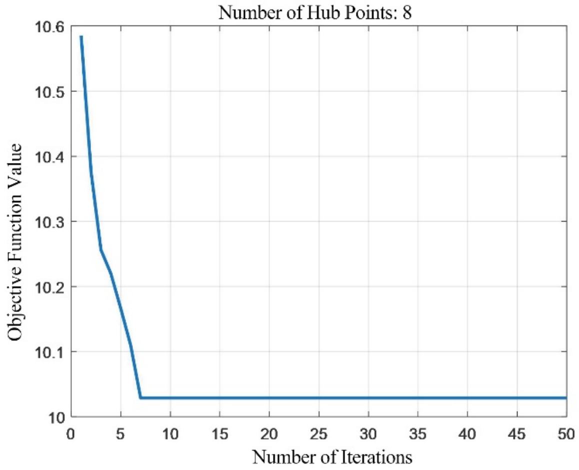

Figure 10. Iteration Graph of Algorithm Solution when Hub Points are 8.

Using the optimization solver, when the number of hub points is set to9, the optimal solution with the shortest expected total time is f1 ∗ = 8.84729. By substituting this optimal objective value into the fitness function (Equation 1), and implementing the improved genetic algorithm on the MATLAB platform, the optimization solution for the multi-objective problem can be obtained. The final result of the program run is shown in Figure 11, with a fitness value of 8.84729.

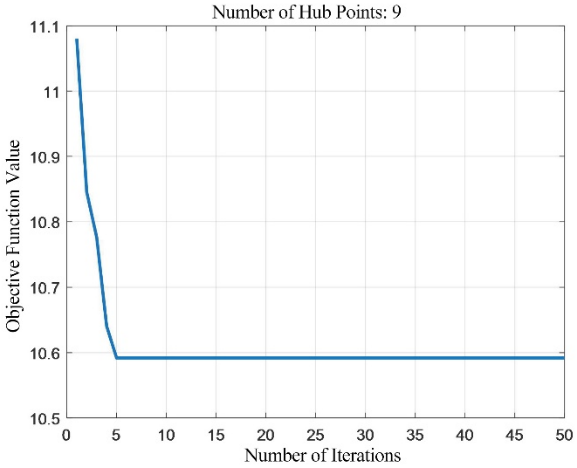

Figure 11. Iteration Graph of Algorithm Solution when Hub Points are 9.

Using the optimization solver, when the number of hub points is set to10, the optimal solution with the shortest expected total time is f1 $*$ = 8.67495. By substituting this optimal objective value into the fitness function (Equation 1), and implementing the improved genetic algorithm on the MATLAB platform, the optimization solution for the multi-objective problem can be obtained. The final result of the program run is shown in Figure 12, with a fitness value of 8.67495.

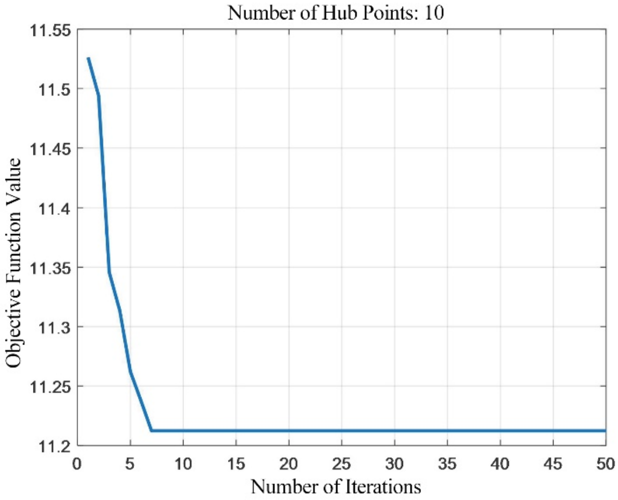

Figure 12. Iteration Graph of Algorithm Solution when Hub Points are 10.

3.3. Analysis of Different Hub Scenarios and Optimization Strategies

(1) Analysis of Time Efficiency

The core objective of the time efficiency analysis is to reduce the total transportation time of emergency materials from supply points to demand points through optimization algorithms and logistics network design, while ensuring the stability and reliability of the network. Specific details are shown in Table 9, and the optimization strategies for the deployment of hub and non-hub points are analyzed in Table 1.

Table 1. Performance Metrics for Different Numbers of Hubs.

Indicator	**7** Hubs	**8** Hubs	**9** Hubs	**10** Hubs
Maximum Response Time (hours)	11.9042	10.7503	10.2072	9.5268
Average Response Time (hours)	11.7187	10.6097	10.0157	9.4315

Coverage of Remote Towns and Districts (%)	85%	90%	95%	98%

Key Conclusions:

Time-Sensitive Scenarios: Prioritize 10 hubs, with the maximum response time being 9.5268 hours.Diminishing Marginal Returns:When the number of hubs increases from 7 to 9:The maximum response time is significantly reduced by 1.697 hours.The average response time is reduced by 1.703 hours.When the number of hubs increases from 9 to 10:The maximum response time is significantly reduced by 0.6804 hours.The average response time is reduced by 0.5842 hours.

(2) Cost Structure Analysis

The core objective of the cost structure analysis is to effectively optimize the cost structure of Dongguan's hub-and-spoke epidemic prevention emergency logistics network, enhance operational efficiency and competitiveness, and provide strong support for the rapid delivery of emergency materials. Specific details are shown in Table 2.

Table 2. Cost-Optimal Scenarios for Different Numbers of Hubs.

Indicator	7 Hubs	8 Hubs	9 Hubs	10 Hubs
Fixed Costs (ten thousand yuan)	3.5	4	4.5	5
Transportation Costs (ten thousand yuan)	1.9	1.7023	1.5668	1.4642
Total Costs (ten thousand yuan)	5.4	5.7023	6.0668	6.4642

Key Conclusions:

Fixed Cost Dominance: The addition of each new hub increases fixed costs by approximately 300,000 yuan (for site and equipment). Transportation Cost Savings: Increased hub density reduces the average transportation distance, but the marginal benefits decrease (e.g., a 9% reduction in transportation costs when increasing from 8 to 9 hubs, and only a 5% reduction when increasing from 9 to 10 hubs).

(3) Comprehensive Optimality Analysis

In Dongguan's hub-and-spoke epidemic prevention emergency logistics network, the core objective of comprehensive optimality, considering both time and cost, is to achieve efficiency and cost-effectiveness in the delivery of emergency materials through optimized logistics network layout, resource allocation, and transportation management. Specific details are shown in Table 3.

Table 3. Comprehensive Optimality Scenarios for Different Numbers of Hubs.

Indicator	7 Hubs	8 Hubs	9 Hubs	10 Hubs
Time Weight (0.6)	11.6295	10.5995	10.0069	9.4265
Cost Weight (0.4)	5.3989	5.6798	6.0621	6.4479
Comprehensive Score	9.13726	8.63162	8.42898	8.23506

Note: Comprehensive Score = 0.6 × Time Normalized Value + 0.4 × Cost Normalized Value (lower score is better)

Key Conclusions:

Optimal Balance Point: 7 Hubs (Comprehensive Score 9.13726), balancing efficiency and cost-effectiveness.Extreme Scenario Adaptation:Time Priority: Choose 10 Hubs (during epidemic outbreak periods). Cost Priority: Choose 7 Hubs (for routine epidemic prevention).

4. Summary

The algorithm design of this project first constructs a multi-level coverage function, optimizing the minimum coverage level and the expected total cost under multi-level coverage to build a multi-objective stochastic programming model for multi-level collaborative location of emergency reserve hubs. Secondly, based on the characteristics of the decision variables in the model, a genetic algorithm combining 0-1 encoding and real-number encoding is designed. To solve the multi-objective problem, the dual-objective dimensions are eliminated, and the improved genetic algorithm embeds the material allocation schemes for each scenario. Finally, taking the location of the reserve hub for medical disposable protective clothing in Dongguan City, Guangdong Province, as an example, the effectiveness of the proposed algorithm is verified, and the impact of changes in demand on the location results and various costs is discussed. The management insights and implementation strategies for Dongguan's hub-and-spoke epidemic prevention emergency logistics network need to comprehensively consider time, cost, and urgency of demand. By constructing a multi-objective optimization model, reasonably laying out hub and spoke points, introducing an intelligent scheduling system, establishing an urgency assessment system for demand, and adopting robust optimization and multi-stage planning, managers can achieve efficient operation of the emergency logistics network. At the same time, continuous improvement and feedback mechanisms will ensure that the network continuously enhances its performance in a dynamic environment. The main analysis is conducted from three aspects: time optimality, cost optimality, and comprehensive optimality.

(1) The time optimality strategy should focus on "trading spatial density for time efficiency," compressing the time consumption of key links through intelligent scheduling algorithms, multimodal transportation technology, and regional coordination mechanisms, while balancing cost and feasibility. It is recommended that Dongguan prioritize real-time traffic scheduling and drone delivery, and in the medium term, expand regional coordination to form an emergency logistics capability of "one-hour delivery across the entire area."

(2) The cost optimality strategy should focus on "light asset and heavy collaboration," compressing fixed costs through shared facilities, path algorithms, and policy innovations, while setting a response time baseline to avoid excessive sacrifice of efficiency. It is recommended that Dongguan prioritize a basic network of 7 Hubs + community-based end delivery, and in the medium term, introduce flexible warehousing and algorithm optimization to form a cost-effective and resilient emergency logistics system.

(3) The comprehensive optimality strategy for Dongguan's hub-and-spoke epidemic prevention emergency logistics network needs to consider time, cost, and urgency of demand. Through a multi-objective optimization model, hub-and-spoke network structure, intelligent algorithm solution, and dynamic adjustment mechanism, efficient scheduling of emergency materials and reduction of the total system cost can be achieved.

Author Contributions

Xiaowei Wu: Investigation, Funding acquisition, Writing-original draft. Jun Tian: Test results analysis and Review & editing. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Competing Interest

The authors declare no competing interests.

Data Availability statement

Data will be made available on request.

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