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Scheduling Optimization of Mobile Emergency Vehicles Considering Dual Uncertainties

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Abstract: Compared with the traditional operation mode of emergency vehicles, the mobile emergency vehicle is regarded as a new type of emergency facility carrier with the features of variable locations, flexible mobility, and intelligent decision-making. It can provide an effective solution to reasonably respond to the uncertain risks of sudden disasters. Focusing on meeting the maximum demand for materials and services in disaster areas, this paper proposes a scheduling model of mobile emergency vehicles with dual uncertainty of path and demand. The model, solved by an integer-coding hybrid genetic algorithm, aims to obtain minimum mobile emergency scheduling cost and time by transforming the multi-objective problem into a single-objective problem. The "5.12" Wenchuan earthquake is used as an example to validate the model and solving method. The results show that the model can reduce the impact of uncertain risks and improve the scientific logic of emergency strategies and deployments based on the actual crisis scenario. It benefits from introducing mobile emergency vehicles and optimizing their scheduling process.

Keywords: sudden disaster; mobile emergency; vehicle scheduling; uncertainty risk

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1. Introduction

In recent years, the frequency and destruction range of sudden natural disasters have been increasing. Large-scale road damage and mass casualties are not uncommon. In disaster-affected areas, there is always an urgent need for a large number of emergency supplies and various rescue services in a short period of time. During a disaster, how to schedule emergency supplies and services more quickly and efficiently to the affected areas is the core task of emergency management. However, since traditional emergency vehicles are only used to support the operation mode of the vehicle, it has been challenging to meet the demand for emergency material distribution and rescue. Transportation path damage, demand fluctuations, and other uncertainties further limit traditional emergency services. The introduction of mobile emergency facilities, which can accurately carry out various emergency measures in a short time, has become the first choice to enhance the response capability of emergency services. As the carrier of all kinds of emergency engineering equipment, the mobile emergency vehicle has the advantages of variable flexibility and precision positioning. It not only supports emergency response plans and executes emergency services quickly but also provides quick feedback after emergency results. In addition, the scheduling model of mobile emergency vehicles can more effectively deliver emergency supplies and extra equipment to implement rescue missions. Most scholars define emergency vehicle scheduling as a branch problem of the emergency logistics network optimization system. Thus, based on different research perspectives, current studies can be divided into three categories: emergency scheduling with uncertainty factors, scheduling optimization with uncertainty emergency scenarios, and mobile emergency routing considering uncertainty.

In terms of emergency scheduling with uncertainty factors, Bozorgi [1] introduced post-disaster emergency demand location uncertainty as a characteristic of the emergency vehicle distance minimization model and obtained the optimal routing for relief logistics with changing demand. Focusing on minimizing the vehicle waiting time and total system cost, Zhong [2] conducted risk-averse optimization of the disaster relief facility location and solved the problem of reasonable vehicle allocation with stochastic demand. Taking the risk of transportation materials as a starting point, Feng [3] proposed an inventory location model with a variable-weighted algorithm for flammable, explosive, toxic, and harmful emergency materials. Paying attention to fuzzy information and road network damage risk, Wang [4] proposed a multi-period optimization model of emergency material allocation under uncertain conditions. The model improved the rescue effect, minimized disaster losses, and achieved a reasonable allocation of emergency materials. Aiming at the open location-routing problem of green multi-facilities, Araghi [5] paid attention to the restrictions of emergency demand changes and traffic conditions on vehicle types and then obtained the vehicle routes with minimized pollution. By summarizing the previous research results and evaluating the reliability of the emergency logistics network with an expert group, Jiang [6] demonstrated that the emergency logistics coordination system and the emergency material supply system have higher uncertainty risks than the emergency distribution system and information system.

In terms of scheduling optimization with uncertainty emergency scenarios, Li [7] proposed a scenario tree based on conditional probability to define the correlation between primary and secondary disasters, which reduced the analysis difficulty in unifying the scale and level of disasters and the possibility of secondary disasters. Henceforth, more scholars began to study the dual uncertainty in all kinds of emergency scenarios, but only a few preliminary research results were obtained. For example, taking supply risk and demand uncertainty into account, Safaei [8] adopted an objective programming method to minimize the difference between two emergency service goals. Sun et al. [9] proposed a framework combining cumulative prospect theory and evolutionary game theory to analyze the emergency strategy formulation model of rescuers. The framework integrated the bounded rationality of rescuers and the uncertainties of secondary disasters to select the optimal emergency logistics path. According to the demand uncertainty of allocating emergency facilities and decision-making services in different emergency response stages, Cavdur et al. [10] put forward a corresponding stochastic programming model based on different post-disaster scenarios. It implemented the allocation of temporary disaster response facilities. Afterward, based on adequate information during decision-making, Maharjan [11] developed a multi-objective location-allocation model for emergency supply and distribution. The model is more focused on the uncertainty of disaster location and the inaccuracy of damage degree information.

In terms of mobile emergency routing considering uncertainty, some research works were concerned about the configuration, efficiency, and realization of mobile emergency facilities. For example, Taheri et al. [12] provided a comprehensive framework for mobile emergency facilities in the transportation network. They introduced the spatial and temporal models of the emergency transportation network and the interaction between the location of facilities and the emergency network. In recent years, scholars have only begun to explore the scheduling problem of mobile emergency routing. In order to seek a reasonable team size and position for emergency facilities, Li [13] designed a two-stage programming model and obtained a robust optimization solution for the emergency mobile facility fleet. Then, based on the characteristics of emergency uninterrupted, Li [14] proposed an emergency mobile facility routing model to maximize the emergency service demand by allocating mobile facilities reasonably. With the support of the Internet of Things, mobile emergency systems can capture emergency information changes in real time when dealing with various uncertain risks. Thus, the multiple vacations (MVs) policy, mobile edge computing [15], start-up threshold (ST) policy [16], and uncrewed aerial vehicles (UAVs) were emerged in mobile emergency facilities due to their mobility and autonomy.

Obviously, the comprehensiveness of information enhances the capacity of emergency response. However, the uncertainty of emergency scenarios is still unavoidable, which stimulates the study of uncertainty. Nahavandi [17] put forward a hierarchical structure model with a combined genetic algorithm. The model solved the uncertain emergency location-routing problem with higher efficiency. Zhang [18] presented an uncertain multi-objective location-routing programming model. It is constructed for emergency response with consideration of travel time, emergency relief costs, and carbon dioxide emissions via uncertainty theory. Yu [19] recognized that both randomness and uncertainty should be considered in the preparation stage of these disasters. He used stochastic optimization and robust optimization to deal with the randomness of the affected areas and the uncertainty of the disaster intensities. Aiming at improving the resilience of the distribution system and analyzing the influence of uncertainties on the post-disaster emergency recovery process, Wan et al. [20] proposed a multi-time-step rolling optimization strategy based on model predictive control, which shortened the path for the repair and the total duration of recovery. After reviewing the papers published on emergency logistics management, Kundu [21] pointed out that it is critical to ensure that an effective and efficient emergency logistics management system is in place to meet any uncertainties.

Throughout most of the existing research, mobile emergency vehicle scheduling models have been widely discussed. In particular, there are numerous models and processing algorithms that have been developed with minimum cost, shortest duration, and widest service scope. Nonetheless, most of them are not willing to consider the uncertainty of different factors because of the complexity it brings. Moreover, the introduction of mobile emergency mode systems and infrastructure work is still in the preliminary exploration stage. There is a lack of optimal mobile vehicle scheduling schemes considering the effectiveness of emergency services, emergency response time, and emergency cost. For the government and auxiliary agencies of emergency services, it is important to explore more effective scheduling strategies for mobile emergency units to maximize life and property savings. Optimized mobile emergency scheduling with double uncertainties can shorten rescue time, expand rescue scope, and increase rescue quantity. It can also enrich the framework of mobile emergency systems and provide a solution for reasonable scheduling of emergency resources.

Aiming to minimize mobile emergency costs and time with double uncertainties, this paper presents a scheduling optimization model of mobile emergency vehicles based on the mobile emergency features of vehicle flexibility, autonomy, intelligence, etc. The path uncertainty and demand uncertainty were measured by path integrity and demand disturbance variation, respectively. After transforming the multi-objective problem into a single-objective problem, the model was solved by an integer-coding hybrid genetic algorithm. Finally, the emergency data of the "5.12" Wenchuan earthquake were taken as an example to verify the validity and applicability of the scheduling optimization model.

2. Model Construction

2.1. Problem Description

In order to quickly respond to the emergency needs of the "golden period of emergency", mobile emergency network should be promptly built around the disaster area in the early stages of a disaster. This network should be centered where mobile emergency vehicles gather and cover a specific affected area. Compared with the traditional construction mode of emergency services, as shown in Figure 1 and Table 1, mobile emergency realizes the flattening, expansion, and intelligent upgrading of the emergency system. The infrastructure and data network in the system are enhanced to provide rapid response, global service and unified feedback. Problems, such as inflexibility supply and inefficiency transportation, are eliminated and replaced by flexible mobility, risk evaluation, and advanced emergency service.

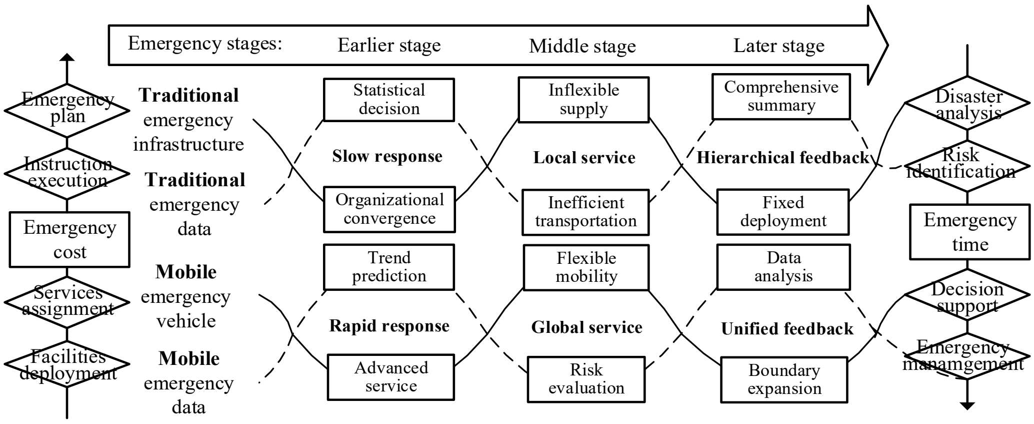

Figure 1. Comparison of traditional emergency system and mobile emergency system.

Table 1. Difference between traditional emergency system and mobile emergency system.

System Dimension	Traditional Emergency	Mobile Emergency
Infrastructure	Immobile	Intelligent, mobile
Data	Unidirectional, mass data	Multisource, big data
Command	Mess, trivial, lack of operability	Comprehensive, specific, intelligent
Response	Slow assignment	Rapid and agile distribution
Feedback	Hierarchical	Directly, unified
Service	According to a pre-arranged plan	On-demand, regional autonomy
Effectiveness	Cursory, delayed	Precise, timely, satisfying

As shown in Figure 1, there are two mainlines for emergency response. One of the mainlines means that government conducts facilities deployment, service assignment, instruction execution, and emergency planning to reduce the emergency cost. The other of the mainlines represents that government endeavor to minimize emergency response time through disaster analysis, risk identification, decision support, and emergency management. As for traditional architecture, the traditional emergency infrastructure and data can only support statistical decision and organizational convergence. This leads to slow emergency response in the earlier stage (pre-disaster). In the middle stage, traditional emergency architecture can only provide a local service via inefficient transportation and inflexible supply facilities. And due to the comprehensive summary and fixed deployment, the emergency service results have to be fed back hierarchically. Hence, traditional emergency architecture have bottlenecks in minimizing emergency response time and cost. As for mobile emergency architecture, it provides a mass of mobile emergency data to form an advanced service and support trend prediction, which greatly improve the response speed in the earlier stage. This kind of superiority can extend to the middle stage to offer a global service with flexible mobility and risk evaluation. In the later stage (post-disaster), the mobile emergency architecture will implement unified feedback through its data analysis ability after boundary expansion.

Furthermore, since mobile emergency vehicles are easy to move, materials and vehicles from different mobile emergency centers can be shared and utilized to help each other, so that the emergency support function is more powerful. However, the process of disaster evolution is very complex, and its damage is difficult to predict accurately, which brings many uncertainties in emergency response. Thus, when determining the operation mode of mobile vehicles, it is necessary to consider the uncertain risks inevitably caused by the unique attributes of sudden disasters. In order to dynamically adjust according to external uncertain conditions, such as road damage risk and demand change, the established mobile emergency scheduling system takes the collection center of mobile emergency vehicles as the focal point. In addition, the following assumptions are proposed to increase the degree of agreement between the model and the reality of mobile emergency response:

Assumption 1: *The transportation capacity for supply distribution of all mobile emergency vehicles is homogeneous.*

Assumption 2: *Each mobile emergency vehicle can only serve one demand point within the upper limit of its capacity. The location of vehicles and demand points can be obtained by GPS or mobile phone.*

Assumption 3: *The resources of each mobile emergency response center can be freely complementary.*

2.2. Uncertainty Risk Measurement

The randomness and destructiveness of sudden disasters determine that mobile emergency vehicle scheduling has many uncertain characteristics. Compared with the daily vehicle scheduling, its uncertainties are generally manifested as emergency path uncertainty, data uncertainty, personnel uncertainty, and demand uncertainty, etc. The path uncertainty and demand uncertainty are closely related to mobile emergency vehicles, which determine the mechanism and goal of scheduling. Thus, this paper proposed an uncertainty-based mobile emergency vehicle scheduling model that focuses on path and demand uncertainty. The objective of the model is to minimize the cost and time of mobile emergency service. In order to effectively characterize these two types of uncertainty, we adopted the following metric method.

(1) Path uncertainty measurement during the decision-making period of mobile emergency vehicle scheduling

Disaster inevitably leads to a certain degree of damage to the road, and traffic congestion caused by disasters will further limit the speed of vehicles. Considering that mobile emergency vehicles are equipped with GPS navigation devices, it is easy to obtain the location of the vehicle and the distance from the destination at any time. Therefore, the main impact on the rescue routing is the road conditions. We can use path integrity to concretely represent the path damage. The stronger the path integrity, the shorter the passage time, the faster the average speed, and the longer the generalized path distance. In addition, path complexity refers to road intersections, overpasses, or areas prone to daily traffic accidents. Because transportation cost and time are strongly related to road conditions in an emergency logistics system, Formula (1) usually is adopted to define the unit logistics cost and single transportation time of mobile emergency vehicles on the premise of introducing path integrity and complexity. Here, the symbol "*" can be k or u, representing the process of emergency material distribution or the process of emergency rescue. That is, c_{ij}^{k} and c_{ij}^{u} are the unit transportation costs of two different processes under path uncertainty conditions. t_{ij}^{k} and t_{ij}^{u} are the single transportation times correspondingly. In Formula (1), α_{ij} represents the path complexity from point i to point j. It is defined as the number of loops from the departure point i to the destination j in a given area and can be measured by McCabe metric. β_{ij} represents the path integrity from point i to point j. α_{ij}/β_{ij} denotes the path influence coefficient. Moreover, β_{min} is the lower limit of the path integrity of this segment. When the path integrity is lower than this value, the path will not be considered an alternative route. Thus, when path uncertainty is merged into the scheduling optimization model, the cost of emergency service c_{ij}^{*} and the corresponding time consuming t_{ij}^{*} are obviously affected by the path influence coefficient. The higher the path complexity or the lower the path integrity, the higher the emergency service cost and time consumption. In addition, if he path integrity β_{ij} is lower than β_{min}, it means that the demand point cannot be reached, so c_{ij}^{*} and t_{ij}^{*} are infinite.

$$c_{ij}^{*} = \begin{cases} \frac{c_{ij}^{*}\alpha_{ij}}{\beta_{ij}}, \beta_{ij} > \beta_{min} \\ +\infty, \beta_{ij} \leq \beta_{min} \end{cases}, i \in I, j \in J \ t_{ij}^{*} = \begin{cases} \frac{t_{ij}^{*}\alpha_{ij}}{\beta_{ij}}, \beta_{ij} > \beta_{min} \\ +\infty, \beta_{ij} \leq \beta_{min} \end{cases}, i \in I, j \in J \tag{1}$$

(2) Demand uncertainty measurement

In the initial stage of emergency service following the occurrence of a sudden disaster, the change in the demand of emergency supply is untraceable. Many factors make it difficult to determine the need for emergency supplies in disaster areas. Moreover, there is a contradiction between the fairness principle of emergency scheduling and the dynamic characteristics of disaster evolution. Therefore, it is difficult to estimate the relief needs and material requirements at each demand point, since the demand point changes dynamically. Fortunately, in the mobile emergency service system, we can easily obtain the location of the demand point by mobile communication. Thus, Formula (2) is often adopted to estimate requirements for different emergency supplies. In the formula, $\overline{d_j^{k,u}}$ represents the nominal value of the demand for type k emergency materials or rescue services at the demand point j. $d_j^{\hat{k},u}$ represents the maximum fluctuation away from the nominal value. In the actual process of mobile emergency vehicle scheduling, if $d_j^{k,u} = \overline{d_j^{k,u}}$, this indicates that the model does not predict enough change in demand point, and the vulnerability of the model is amplified. On the contrary, if $d_j^{k,u} = \overline{d_j^{k,u}} + d_j^{\hat{k},u}$, this means the scheduling model becomes a fully robust model. Of course, the range of changes in demand for various materials is unlikely to approach the maximum, and in this case the decision is meaningless. Therefore, as shown in Formula (3), the relatively robust optimization method is adopted. The control parameter $\gamma_j^{k,u}$ is introduced to control the degree of uncertainty of emergency material demand and rescue service demand in the disturbance interval. When $\gamma_j^{k,u} = 0$, the $d_j^{k,u} = \overline{d_j^{k,u}}$ problem is transformed into a non-robustness problem. In other cases, $\gamma_j^{k,u}$ within the interval [0, 1] controls the range of demand disturbances. However, due to the constant change in demand, it is hard to obtain an accurate value of the parameter $\gamma_j^{k,u}$ in the short term. Therefore, a reasonable estimation of $\gamma_j^{k,u}$ can be performed according to historical emergency event data with the same magnitude. If no historical data are available, the parameter $\gamma_j^{k,u}$ can be estimated by $(\mathrm{Max}d_j^{k,u} - \mathrm{Min}d_j^{k,u})/\mathrm{Max}d_j^{k,u}$. Here, $d_j^{k,u}$ comes from the dataset that can currently be collected.

$$d_j^{k,u} \in \left[\overline{d_j^{k,u}}, \overline{d_j^{k,u}} + d_j^{\hat{k},u}\right], j \in J, k \in K, u \in U \tag{2}$$

$$\gamma_j^{k,u} = \frac{\left|d_j^{k,u} - \overline{d_j^{k,u}}\right|}{d_j^{\hat{k},u}}, j \in J, k \in K, u \in U \tag{3}$$

2.3. Mobile Emergency Vehicle Scheduling Model Considering Dual Uncertainties

Although different disaster scenarios cannot affect the underlying logic standard of mobile emergency vehicle scheduling, all kinds of external conditions still influence the scheduling scheme design of mobile emergency vehicles. Moreover, the particular risk of each sudden disaster will affect the decision preference of the mobile emergency vehicle scheduling model. With reference to the modeling processes by Bozorgi [1] and Li [22], the overall scheduling factors of mobile emergency vehicles from the emergency center to the disaster area are explored based on Section 2.1.

Considering the dual uncertainties, the scheduling optimization model for mobile emergency vehicles focuses on scheduling mobile emergency vehicles to disaster areas for providing emergency services. The objective of the model is not only to find the balance point between the scheduling time advantage and the cost advantage of a mobile emergency vehicle so as to maximally protect the lives and properties of the affected people but also to achieve a win–win situation of timely rescue and effective control of emergency costs.

Since the mobile emergency center has the characteristics of rapid planning, fast feedback, and flexible assignment, the cost of the front-end transfer and replenishment of mobile emergency vehicles can be ignored. Thus, the scheduling model of mobile emergency vehicles must consider the behavior of mobile emergency vehicles only after leaving the emergency center. Furthermore, when finding the optimal value of the total objective function, the total scheduling cost C and the total time T of mobile emergency vehicles should be considered with equal importance. Here, the total emergency cost C consists of the fixed cost C_1, transportation cost C_2, preparation cost C_3 and penalty cost C_4. The fixed cost $C_1 = \sum_i f_i X_i$ denotes the construction cost and various preparation costs of the mobile emergency center for mobile emergency service. The transportation cost $C_2 = \sum_{ijku} (z_{ij}^k n_{ij}^k c_{ij}^k + z_{ij}^u n_{ij}^u c_{ij}^u)$ includes the total cost of emergency material distribution and emergency rescue vehicles transferring from the mobile emergency center to the demand point. The initial cost $C_3 = \sum_{ju} js_j^u$ refers to the additional cost consumed in the early stages when emergency rescue vehicles arrive at the disaster area and carry out various rescue work according to the on-site rescue needs. The penalty cost $C_4 = \sum_{jku} (\theta_j^k \lambda_j^k + \theta_j^u \lambda_j^u)$ represents the direct and indirect losses caused by the failure of various emergency supplies or rescue services to reach the demand point. As for the total emergency time T, it is composed of transportation time T_1, development time T_2 and punishment time T_3. The transportation time $T_1 = \sum_{ijk} z_{ij}^k t_{ij}^k + \sum_{iju} z_{ij}^u t_{ij}^u$ refers to the cumulative transportation time of emergency material distribution and emergency rescue vehicles. The development time $T_2 = \sum_{iju} z_{ij}^u t_j^u$ refers to the cumulative preparation time for rescue work after the arrival of emergency rescue vehicles at the demand point. The penalty time $T_4 = \sum_{jku} (\theta_j^k \lambda_j^k + \theta_j^u \lambda_j^u)$ is similar to the penalty cost and constrains the model development with the goal of efficient scheduling and meeting the emergency demand as much as possible. The scheduling optimization model of mobile emergency vehicles is described by Formulas (4)–(14).

$$\begin{aligned} min(Z_C) &= min(C_1 + C_2 + C_3 + C_4) \\ &= min(\textstyle\sum_i f_i X_i + \sum_{ijku} (z_{ij}^k n_{ij}^k c_{ij}^k + z_{ij}^u n_{ij}^u c_{ij}^u) + \sum_{ju} js_j^u + \sum_{jku} (\theta_j^k \lambda_j^k + \theta_j^u \lambda_j^u)) \end{aligned} \tag{4}$$

$$\begin{aligned} minZ_T &= min(T_1 + T_2 + T_3) \\ &= min(\textstyle\sum_{ijk} z_{ij}^k t_{ij}^k + \sum_{iju} z_{ij}^u t_{ij}^u + \sum_{iju} z_{ij}^u t_j^u + \sum_{jku} (\theta_j^k \lambda_j^k + \theta_j^u \lambda_j^u)) \end{aligned} \tag{5}$$

$$s.t.\ n_{ij}^k + n_{ij}^u \le h_i^{\max k,u}, \forall i \in I, j \in J, k \in K, u \in U \tag{6}$$

$$n_{ij}^k + n_{ij}^u \ge \gamma_j^{k,u} \hat{d_j^{k,u}} + \overline{d_j^{k,u}}, \forall i \in I, j \in J, k \in K, u \in U \tag{7}$$

$$y_i^{k,u} = \sum_{jku} (n_{ij}^k + n_{ij}^u), \forall i \in I, j \in J, k \in K, u \in U \tag{8}$$

$$\sum_{ijk} z_{ij}^k = 1, \sum_{iju} z_{ij}^u = 1, \forall i \in I, j \in J, k \in K, u \in U \tag{9}$$

$$\sum_i x_i \ge 1, \forall i \in I \tag{10}$$

$$\beta_{ij} > \beta_{\min}, \forall i \in I, \forall j \in J \tag{11}$$

$$y_i^{k,u} \ge 0, \forall i \in I, \forall k \in K, \forall u \in U \tag{12}$$

$$n_{ij}^k \ge 0, n_{ij}^u \ge 0, \forall i \in I, \forall j \in J, \forall k \in K, \forall u \in U \tag{13}$$

$$X_i \in \{0,1\}, z_{ij}^k \in \{0,1\}, z_{ij}^u \in \{0,1\}, \forall i \in I, \forall j \in J, \forall k \in K, \forall u \in U \tag{14}$$

In the model, Formulas (4) and (5) are objective functions, and Formulas (6)–(14) are constraints. The objective function (4) minimizes the scheduling cost of mobile emergency vehicles, which is the sum of fixed costs, transportation costs, preparation costs, and penalty costs. The objective function (5) minimizes the scheduling time of mobile emergency vehicles, which includes transportation time, development time, and punishment time. Constraint (6) indicates that the sum $n_{ij}^k + n_{ij}^u$ of all kinds of demands in the mobile emergency system should not exceed the upper limit of the system reserve $h_i^{maxk,u}$. It represents a ceiling on the availability of emergency supplies and services, regardless of how mobile emergency vehicles are deployed between mobile centers.

Constraint (7) describes that, under the premise of introducing the demand uncertainty measurement scheme, meeting the demand of each demand point should still be a prerequisite for the optimal overall objective of the model. Constraint (8) represents that when the mobile emergency center provides emergency materials or emergency services to the disaster area, the number of vehicles and materials stored $y_i^{k,u}$ is equal to the amount of outflow $\sum_{jku}(n_{ij}^k + n_{ij}^u)$. Constraint (9) indicates that a mobile emergency center only meets a certain kind of demand at each demand point. Constraint (10) represents that at least one mobile emergency center participates in this mobile emergency. The constraint (11) indicates that the lower limit of path integrity is constrained in the process of path uncertainty measurement. The constraints (12) to (14) are decision variable constraints.

3. Solution Algorithms

3.1. Objective Function Processing

In the above multi-objective model, the two sub-objective units are not consistent. However, for emergency management decision-makers, the time objective and cost objective should be considered together in the actual emergency vehicle scheduling process. Therefore, the percentage dimensionless method is introduced to streamline the subsequent calculation and eliminate the unit difference. By allocating the weighted value of the sub-objective, the problem is transformed from a multi-objective function to a total objective function. Assume that Z_C^{min} and Z_T^{min} are the nominal minimum of mobile emergency cost and the nominal minimum of mobile emergency time, respectively; the total objective function can be transformed into the following formula:

$$minZ = 100w_1\left(\frac{Z_C}{Z_C^{min}}\right) + 100w_2\left(\frac{Z_T}{Z_T^{min}}\right), w_1 + w_2 = 1 \quad (15)$$

3.2. Genetic Algorithm Solution

The above mobile emergency vehicle scheduling problem is NP-hard, since it is a branch of the mobile facility routing problem (MFRP) [23]. It cannot obtain an accurate solution using the branch and bound algorithm. We tried to utilize three algorithms to solve the model. Compared with particle swarm optimization (PSO) [24], ant colony optimization (ACO) [25] and the genetic algorithm (GA) [26] both have the ability in optimizing various complex problems in a simpler way. Compared with PSO and ACO, the GA more easily deals with the uncertainty problem [27]. And according to the summarization by Alhijawi [28], the genetic algorithm (GA) has many significant advantages, such as strong global search, fewer parameters, and fast solving speed [29]. These characteristics are conducive to obtaining the minimum mobile emergency time and the optimal cost with a relatively simple algorithm structure. Considering the complexity of the transport path and material quantity, the search process of the GA requires the whole population to move toward the optimal area evenly. Therefore, referring to the algorithm models of Bozorgi [1] and Li [12], we designed an integer-coding hybrid genetic algorithm to retrieve all feasible solutions and prevent local optimal solutions from converging quickly. The flow chart of the genetic algorithm is shown in Figure 2.

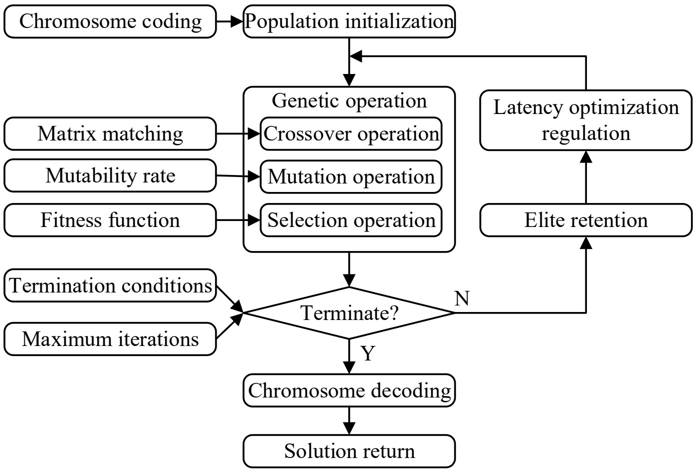

Figure 2. The flow chart of the genetic algorithm.

Step 1: The chromosomal code. Since the solutions of the model are all positive integers, we adopt natural number coding to represent chromosomes instead of decision variable. Assume that the number of mobile emergency centers in the mobile emergency vehicle scheduling system is a, and the number of demand points is b, then the number of optimal paths between the mobile emergency centers and demand points is $c = ab$. Supposing that all the disaster areas need some kind of emergency materials or emergency services to different degrees, the chromosome coding length can be determined as $(\alpha + \beta)c$. Here, α denotes the number of emergency materials involved, and β denotes the type of emergency rescue services. Correspondingly, the code level is related to the name of each demand point, and the code value is related to the number of materials or rescue services.

Step 2: Algorithm initialization settings and fitness value. For the actual mobile emergency vehicle scheduling scenario, the initial population size N is set to $|I||J||K|$, and the maximum number of iterations $T_{\max}$ is defined as N^2. Then, the Randi function is used to randomly generate N mobile emergency vehicle scheduling schemes that meet the emergency needs. And the corresponding path transport volume of each scheme is coded according to the chromosome coding requirements. Considering that the model is described by a minimization problem, the fitness function F_n^t can be designed as the inverse of the objective function, namely the fitness value of the n chromosome in the t generation is the inverse of Z_n^t divided by the sum of all inverse of Z_n^t of each chromosome. It is worth mentioning that the penalty function may reduce the survival probability of unqualified solutions. In this case, the value of the initial population size should double.

$$F_n^t = \frac{1/Z_n^t}{\sum_n (1/Z_n^t)} \tag{16}$$

Step 3: Genetic manipulation and termination conditions. Due to the randomness of the roulette bet and crossover, individuals with higher fitness on the parental chromosome have a certain probability of being eliminated and optimized, resulting in a decline in the population's average fitness. To solve this problem, the elite retention strategy is adopted in the chromosome selection process to preserve the top 10% of the parental population. That is, 10% of the population from the previous generation is directly copied to the next generation, and optimization individuals are retained to accelerate convergence. As shown in Figure 3, a uniform is selected as the crossover strategy. In other words, a 0–1 matrix matching chromosome length is randomly generated, and two chromosomes are selected for crossover according to gene position. If the corresponding position of the gene is 0, the status quo remains. If the gene's position is 1, the points on the two chromosomes are swapped to form a new chromosome. As shown in Figure 4, the mutation strategy is to randomly select two genes on the chromosome for mutation while strictly controlling the mutability rate. Finally, if the number of iterations reaches T_{max} or there is not much difference between the top two chromosomes, the algorithm terminates and outputs the optimal solution. When the algorithm encounters the latency optimization problem, it is generally due to the homogeneity of chromosomes produced by crossover operation or mutation operation. The simple solution is to preserve more 5% elite chromosomes of the previous generation. A further efficient approach is to generate a more suitable 0–1 matrix according to fitness function, but it may lead to higher complexity of the algorithm.

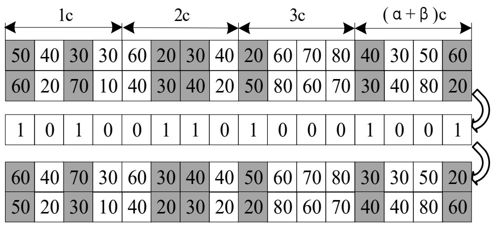

Figure 3. Chromosomal chiasma.

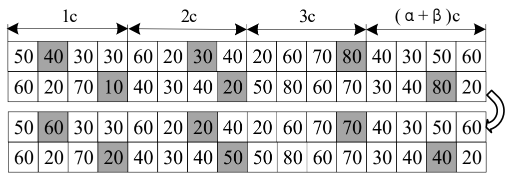

Figure 4. Chromosome variation.

4. Analysis of Examples

In order to verify the adaptability of the mobile emergency vehicle scheduling model for sudden disasters under uncertain conditions, A simulation was conducted by referring to the disaster information related to the "5.12" Wenchuan earthquake. It supposes that four mobile emergency centers and 10 disaster areas are utilized for the mobile emergency response system. The four mobile emergency centers were selected and numbered as $I_1 - I_4$ near the urban transportation hubs of Chengdu City, Guanghan City, Deyang City, and Mianyang City. The 10 heavily affected points, represented by Wenchuan County, Maoxian County, Beichuan County, Mianzhu City, Shifang City, Pingwu County, An County, Pengzhou City, Dujiangyan City, and Qingchuan County, are identified and numbered as $J_1 - J_{10}$. The mobile emergency material distribution vehicle can provide three main types of emergency materials: medical, living materials K_2, and special materials K_3. The mobile emergency rescue vehicle can provide two types of emergency services: excavation and medical rescue services K_5. The material capacity of the mobile emergency center is directly related to the city's layout scale, transportation facilities, and economic situation. Therefore, the location and information of each mobile emergency center are shown in Table 2. The material needs in the affected areas directly refer to the official media reports after the Wenchuan earthquake. By taking the severity of the disaster as the primary standard and referring to the urban population density of the disaster area, the demand quantity information for the disaster area is estimated as shown in Table 3. Before the mobile emergency vehicle arrives at the disaster area, the unit transportation cost of the mobile emergency vehicle is positively correlated with the transportation distance and transportation time. Table 4 shows the unit transportation cost and the single transportation time between each demand point. When mobile emergency rescue vehicles arrive at the affected areas, the cost of preparing emergency rescue services is related to the number of services available. The unit preparation cost of K_4 and K_5 is CNY 800 per item and CNY 1000 per item, respectively. And the unit development time is 15 min per item and 20 min per item, respectively.

Table 2. Mobile emergency center information table.

No.	Construction Costs/CNY	Emergency Material Capacity			Emergency Rescue Service	
		K_1	K_2	K_3	K_4	K_5
I_1	200,000	220	1000	900	500	450
I_2	200,000	900	900	800	550	400
I_3	200,000	900	900	600	450	450
I_4	200,000	1000	800	900	550	350

Table 3. Emergency demand information of disaster-affected areas.

No.	Material Demand			Rescue Demand		No.	Material Demand			Rescue Demand	
	K_1	K_2	K_3	K_4	K_5		K_1	K_2	K_3	K_4	K_5
J_1	400	400	400	200	200	J_6	400	300	300	200	150
J_2	400	400	400	200	200	J_7	400	300	300	150	150
J_3	400	400	300	200	200	J_8	300	300	300	150	150
J_4	400	400	300	200	150	J_9	300	300	300	150	150
J_5	400	300	300	200	150	J_{10}	300	300	300	150	150

Table 4. Unit transportation costs between mobile emergency centers and disaster areas.

No.	*I1*			*I2*			*I3*			*I4*		
	c_{ij}^k/CNY	c_{ij}^u/CNY	$t_{ij}^{k,u}$/min	c_{ij}^k/CNY	c_{ij}^u/CNY	$t_{ij}^{k,u}$/min	c_{ij}^k/CNY	c_{ij}^u/CNY	$t_{ij}^{k,u}$/min	c_{ij}^k/CNY	c_{ij}^u/CNY	$t_{ij}^{k,u}$/min
J_1	141	94	28	141	94	28	147	98	140	153	102	160
J_2	159	106	180	159	106	180	159	106	180	141	94	28
J_3	177	118	240	159	106	180	156	104	170	144	96	130
J_4	135	90	100	31	82	60	117	78	40	31	82	60
J_5	132	88	90	117	78	40	117	78	40	34	84	70
J_6	195	130	300	180	28	250	177	118	240	168	24	210
J_7	141	94	28	129	86	80	31	82	60	26	76	30
J_8	31	82	60	34	84	70	31	82	60	129	86	80
J_9	31	82	60	34	84	70	129	86	80	135	90	100
J_{10}	183	30	260	165	22	200	159	106	180	153	102	160

Firstly, to verify the model's effectiveness, the genetic algorithm is set with the following conditions: initial population size $N = 200$, the maximum number of iterations $T_{max} = 40000$. According to References [15,30], the crossover probability and mutation probability are initialized as $P_1 = 0.9$, $P_2 = 0.1$. In addition, the optimal values of mobile emergency cost and time are set to $Z_C^{min} = 5612800$ and $Z_T^{min} = 1540300$, respectively. In the solution process, GA search and convergence speed is fast, showing good stability in several experiments. After 10 experiments under the same conditions, the floating range of the optimal cost value Z_C^{min} is within 20,000, and the floating range of the optimal time value Z_T^{min} is within 5000. When the importance degree of mobile emergency cost and mobile emergency time is set to be the same $w_1 = w_2 = 0.5$, the optimal solution of the mobile emergency vehicle scheduling model is $Z = 100.02$, $C = 5614400$ and $T = 1540300$ minutes. In the above process, 107 material distribution vehicles and 37 rescue and rescue vehicles are involved in the mobile emergency work. The average cost of each mobile emergency vehicle is $\overline{C} \approx 38989$, and the average time is $\overline{T} \approx 10697$. It can be seen that although the optimal values of the two single objectives are challenging to achieve at the same time, the multi-objective model can well solve the contradiction between the sub-objectives. The compromise solution achieves the optimization of cost deviation as far as possible based on ensuring the minimization of time.

The specific transportation paths of all types of K are shown in Figure 5. The path and demand uncertainty factors are controlled to verify the effectiveness of the mobile emergency vehicle scheduling model considering dual uncertainties. Suppose that the overall road condition deteriorates gradually; for example, the path complexity α_{ij} increases from 1.00–1.20 with step size 0.05, and the path integrity β_{ij} decreases from 1.00–0.80 with phase synchronization length. In other word, the path influence coefficient α_{ij}/β_{ij} is separately set to 1.00 (1.00/1.00), 1.11 (1.05/0.95), 1.22 (1.10/0.90), 1.35 (1.15/0.85), and

1.50 (1.20/0.80). The scheduling results are shown in Figure 6. The overall decrease in road condition inevitably leads to a synchronous increase in the scheduling cost and time of mobile emergency vehicles. However, under different road conditions, the values of emergency costs and emergency time are relatively balanced: the overall optimal Z is within a reasonable range, which shows that the model considers the fairness of cost and time allocation. It is worth noting that in the process of the path impact coefficient rising, compared with the determinacy model, the increased ratio of mobile emergency scheduling time is similar to the value of the path impact coefficient. However, the increased proportion of mobile emergency scheduling costs is relatively slow. This means that emergency decision-makers should pay more attention to the time lag of the scheduling scheme of mobile emergency vehicles when considering the negative impact brought by route factors and give more weight to the emergency scheduling time when the road condition worsens.

As for the demand uncertainty factor, the maximum disturbance value $d_j^{\hat{k},u}$ is set to 50 and 100, respectively, and the example results are obtained when the control parameters $\gamma_j^{k,u}$ are 0.1, 0.2, 0.3, 0.4, and 0.5, respectively. As shown in Table 5, the optimal solution values for mobile emergency scheduling cost and time increase with the increase in demand uncertainty. Under the premise of the same maximum disturbance value $d_j^{\hat{k},u}$, the minimum distribution cost and the shortest distribution time have an increasing trend with the increase in the control coefficient $\gamma_j^{k,u}$. Moreover, when the control coefficient $\gamma_j^{k,u}$ is equal, the larger disturbance value will inevitably increase the model results. This means that the emergency decision-making can choose the control coefficient according to the actual demand floating range when dealing with the uncertainty demand further to determine the emergency center configuration and vehicle scheduling scheme.

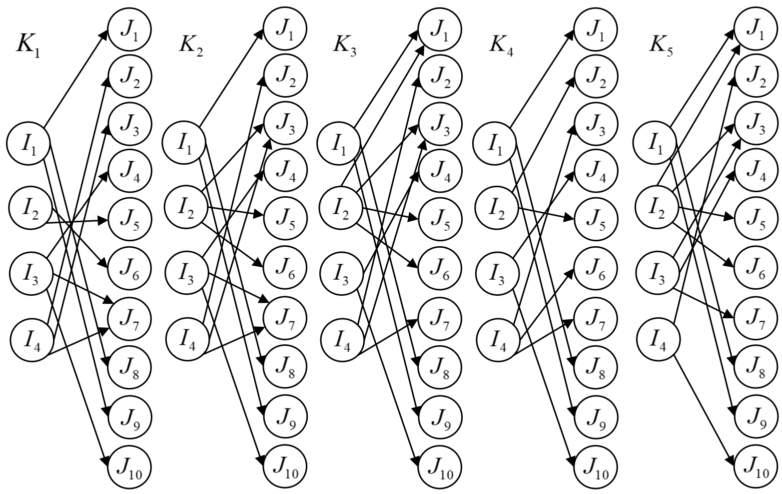

Figure 5. Determination of the optimal deployment path of the mobile emergency.

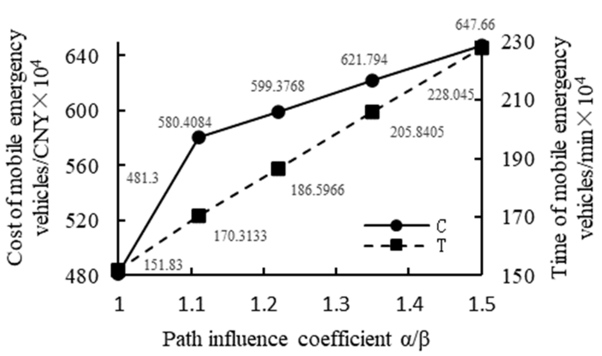

Figure 6. Change in mobile emergency cost and time for different paths.

Table 5. Mobile emergency costs and time for different demand disturbances.

$\gamma_j^{k,u}$	$d_j^{\hat{k},u}$	*C*/*CNY*	*T*/min
0.1	100	5,675,028	1,672,230
	200	5,707,355	1,720,270
0.2	100	5,714,462	1,713,100
	200	5,709,418	1,707,840
0.3	100	5,722,309	1,718,520
	200	5,842,387	1,851,920
0.4	100	5,763,942	1,761,510
	200	5,908,082	1,879,060

Because of the randomness and strong destructiveness of sudden disasters, it is necessary to explore the comprehensive impact of dual uncertainties on the mobile emergency vehicle scheduling model based on considering the two types of uncertainties separately. In order to test the reliability of the model, four types of sudden disaster scenarios were designed. The first type is the scenario with weak path and demand uncertainties, $\alpha_{ij}/\beta_{ij} = 1.11$, $d_j^{\hat{k},u} = 100$. The second type of scenario is the scenario with strong path uncertainty and weak demand uncertainty, $\alpha_{ij}/\beta_{ij} = 1.35$, $d_j^{\hat{k},u} = 100$. The third scenario has weak path uncertainty and strong demand uncertainty, $\alpha_{ij}/\beta_{ij} = 1.11$, $d_j^{\hat{k},u} = 200$. The fourth scenario is the scenario with strong path and demand uncertainties $\alpha_{ij}/\beta_{ij} = 1.35$, $d_j^{\hat{k},u} = 200$. When the dual uncertainty factors rise simultaneously, the increase in the total cost and time of mobile emergency response will be much higher than the result of a single-factor change. As shown in Figures 7–10, the differentiated scenarios and various stages in the mobile emergency process can be mapped according to the corresponding conclusions of the above systems. Different control parameters will lead to the model's preference in terms of cost and time minimization. On the premise of the same external conditions, the changes in demand factors produce more intuitive perturbations to the model results than the path factors. Therefore, when carrying out mobile emergency vehicle scheduling, human resources and material resources should be tilted to the demand points with substantial demand changes to ensure the balanced development of mobile emergency vehicle scheduling within the global scope. For the severely affected areas with high dual uncertainty factors, it is necessary to comprehensively plan the deployment of emergency resources to guarantee their timely arrival and prevent the surge in the total cost and time of local points from causing irreversible damage to the mobile emergency vehicle scheduling network.

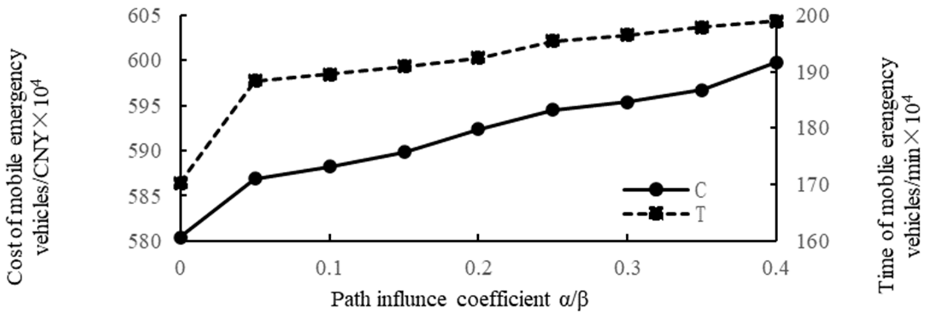

Figure 7. Variation of mobile emergency cost and time in first scenario.

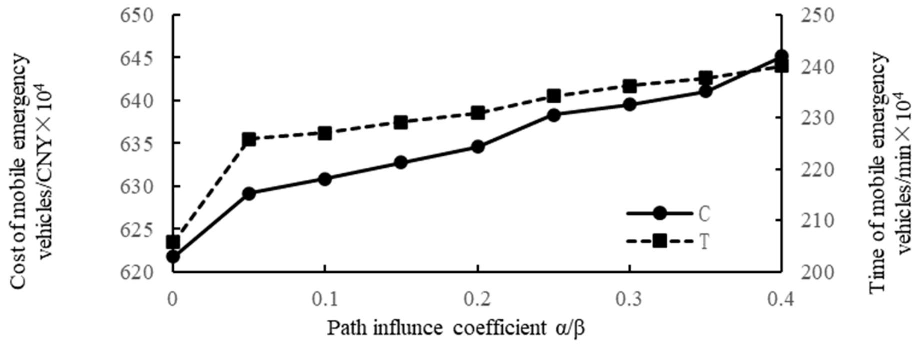

Figure 8. Variation of mobile emergency cost and time in second scenario.

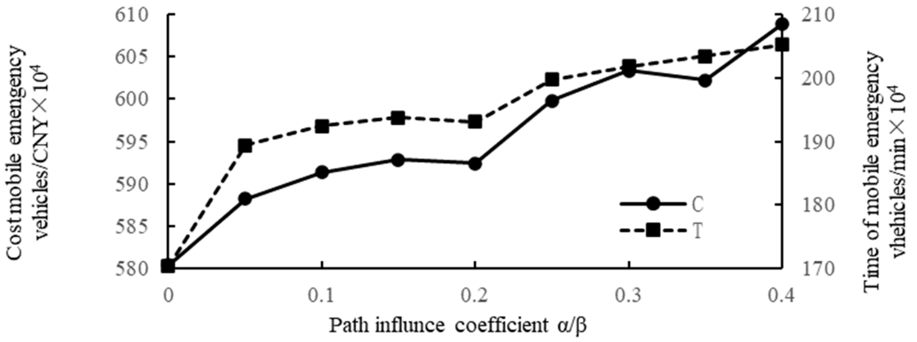

Figure 9. Variation of mobile emergency cost and time in third scenario.

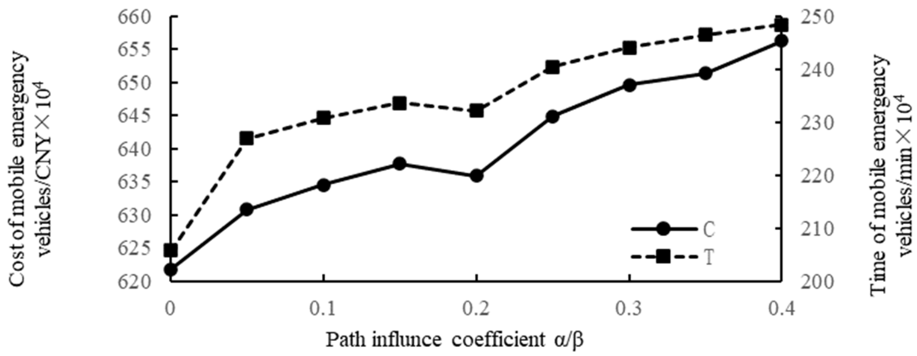

Figure 10. Variation of mobile emergency cost and time in fourth scenario.

5. Conclusions

With the increasing frequency and damage intensity of sudden disasters, the traditional emergency mode has made it difficult to provide accurate and efficient emergency services. The emergence of mobile emergency mode undoubtedly provides an opportunity for upgrading and transforming the emergency system. As the core part of mobile emergency response, the mobile emergency vehicle scheduling mode shows various advantages in facility flexibility and planning intelligence compared with the traditional emergency response. Especially in the face of the uncertain impact caused by disasters, the mobile emergency vehicle scheduling model, considering dual uncertainties, provides a new way to reduce the uncertainty risk and maintain the rationalization of vehicle scheduling cost and time.

To verify the superior performance of mobile emergency vehicle scheduling under uncertainty conditions, a vehicle scheduling of mobile emergency is proposed with two most intuitive impacts: path uncertainty risk and demand uncertainty risk. These uncertainty factors are measured by path complexity, path integrity, and demand disturbance variation. Considering the difference in data orders of magnitude, the model of multi-objective programming is transformed into a single-objective optimal value problem. Then, a genetic algorithm is used to solve the problem and ensure the scheduling logic of each mobile emergency vehicle is feasible. Finally, taking the "5.12" Wenchuan earthquake as an example, the paper verifies the scientificity and superiority of the mobile emergency vehicle scheduling model. Further, the two kinds of influence of key uncertainty factors on the scheduling process of mobile emergency vehicles are discussed. After analyzing the four types of differentiated scenarios, decision suggestions about mobile emergency vehicle scheduling and overall emergency resource deployment are given as follows. (1) The changes in demand produce more impact on mobile emergency vehicle scheduling than the path factors. Thus, it is very important to obtain the change in demand information in time to improve the efficiency of emergency response. (2) The influence of path uncertainty on mobile emergency cost and time shows a linear trend with a quite low slope. That is, improvement in road conditions does not significantly improve emergency serviceability. (3) the minimum distribution cost and the shortest distribution time increase obviously with the control coefficient. This shows that eliminating the uncertainty of data can effectively enhance emergency decision-making ability. Although path uncertainty and demand uncertainty are considered in the vehicle scheduling optimization model of mobile emergency, there are many uncertainty factors that need to be analyzed, such as data transmission uncertainty, disaster evolution uncertainty, and material damage uncertainty. The next step can introduce more uncertainty factors into mobile emergency scheduling to enhance the practicability of the model. Another issue worth investigating is the optimal number and location of emergency resource centers.

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Abbreviations

The following definitions of symbols are made clear for the sake of description:

Symbols:

I:	set of various mobile emergency centers.
J:	set of demand points.
K:	set of emergency materials that can be transported by mobile emergency vehicles.
U:	vehicle type set of mobile emergency.
f_i:	fixed cost of moving the emergency vehicle assembly center i.
c_{ij}^k, c_{ij}^u:	unit transportation cost of mobile emergency vehicles for material distribution and for rescue from point i to point j.
s_j^u:	field preparation cost of category u mobile emergency rescue vehicle at point j.

t_{ij}^k, t_{ij}^u:	single transport time of mobile emergency material distribution vehicles and emergency rescue vehicles from point i to point j.
t_j^u:	rescue operation time of class u mobile emergency rescue vehicle from the point j.
$h_i^{\max k,u}$:	the upper limit of the total number of emergency materials i in a category k or the upper limit of emergency rescue services in a category u that can be provided by each mobile emergency center in the system.
$d_j^k.d_j^u$:	the demand for emergency materials and emergency rescue at the demand point j.
θ_j:	unmet number of various emergency needs at demand point j.
λ_j:	penalty coefficient of all kinds of unmet demands at the demand point j.
Decision variables:	
X_i:	if the mobile emergency center at the place i is selected to participate in mobile emergency response, then $X_i = 1$; otherwise, $X_i = 0$.
$y_i^{k,u}$:	mobile emergency center i mobile emergency supplies and mobile emergency rescue services reserves.
z_{ij}^k:	if the mobile emergency center at i is selected to supply emergency materials to the demand point j, then $z_{ij}^k = 1$; otherwise, $z_{ij}^u = 0$.
z_{ij}^u:	if the mobile emergency center at i is selected to rescue emergency objects at the demand point j, then $z_{ij}^u = 1$; otherwise, $z_{ij}^u = 0$.
n_{ij}^k:	the amount of category k emergency supplies transported from the mobile emergency center i to the disaster area j.
n_{ij}^u:	the number of types k of emergency rescue services provided from mobile emergency centers i to the disaster area j.

References

1. Bozorgi Amiri, A.; Akbari, M.; Dadashpour, I. A routing-allocation model for relief logistics with demand uncertainty: A Genetic algorithm approach. *J. Ind. Eng. Manag. Stud.* **2022**, *8*, 93–110.
2. Zhong, S.; Cheng, R.; Jiang, Y.; Wang, Z.; Larsen, A.; Nielsen, O.A. Risk-averse optimization of disaster relief facility location and vehicle routing under stochastic demand. *Transp. Res. Part E Logist. Transp. Rev.* **2020**, *14*, 102015. [CrossRef]
3. Feng, J.R.; Gai, W.-M.; Li, J.-Y.; Xu, M. Location selection of emergency supplies repositories for emergency logistics management: A variable weighted algorithm. *J. Loss Prev. Process Ind.* **2020**, *6*, 104032. [CrossRef]
4. Wang, Y.; Sun, B. Multiperiod optimal emergency material allocation considering road network damage and risk under uncertain conditions. *Oper. Res.* **2022**, *22*, 2173–2208. [CrossRef]
5. Araghi, M.E.T.; Tavakkoli-Moghaddam, R.; Jolai, F.; Molana, S.M.H. A green multi-facilities open location-routing problem with planar facility locations and uncertain customer. *J. Clean. Prod.* **2021**, *28*, 32343.
6. Jiang, P.; Wang, Y.; Liu, C.; Hu, Y.-C.; Xie, J. Evaluating critical factors influencing the reliability of emergency logistics systems using multiple-attribute decision making. *Symmetry* **2020**, *12*, 235. [CrossRef]
7. Zhang, J.; Liu, H.; Yu, G.; Ruan, J.; Chan, F.T. A three-stage and multi-objective stochastic programming model to improve the sustainable rescue ability by considering secondary disasters in emergency logistics. *Comput. Ind. Eng.* **2019**, *13*, 265–274. [CrossRef]
8. Safaei, A.S.; Farsad, S.; Paydar, M.M. Emergency logistics planning under supply risk and demand uncertainty. *Oper. Res.* **2020**, *20*, 1437–1460. [CrossRef]
9. Sun, W.; Zhu, C.; Li, H. Evolutionary game of emergency logistics path selection under bounded rationality. *Socio-Econ. Plan. Sci.* **2022**, *202*, 101311. [CrossRef]
10. Cavdur, F.; Kose-Kucuk, M.; Sebatli, A. Allocation of temporary disaster response facilities under demand uncertainty: An earthquake case study. *Int. J. Disaster Risk Reduct.* **2016**, *1*, 159–166. [CrossRef]
11. Maharjan, R.; Hanaoka, S. A credibility-based multi-objective temporary logistics hub location-allocation model for relief supply and distribution under uncertainty. *Socio-Econ. Plan. Sci.* **2020**, *7*, 100727. [CrossRef]
12. Taheri, B.; Safdarian, A.; Moeini-Aghtaie, M.; Lehtonen, M. Distribution system resilience enhancement via mobile emergency generators. *IEEE Trans. Power Deliv.* **2020**, *36*, 2308–2319. [CrossRef]
13. Li, J.; Lai, K.K.; Lin, Q. Robust Optimization Solution to Emergency Mobile Facility Fleet Size and Location. *Math. Probl. Eng.* **2019**, *2019*, 7161204. [CrossRef]
14. Li, J.; Lai, K.K.; Fu, Y.; Shen, H. Robust optimization approach to emergency mobile facility routing. *Sci. Prog.* **2021**, *104*, 0036850420982685. [CrossRef]
15. Zaman, S.K.U.; Jehangiri, A.I.; Maqsood, T.; Umar, A.I.; Khan, M.A.; Jhanjhi, N.Z.; Shorfuzzaman, M.; Masud, M. COME-UP: Computation offloading in mobile edge computing with LSTM based user direction prediction. *Appl. Sci.* **2022**, *12*, 3312. [CrossRef]

16. Fang, Z.; Wang, J.; Ren, Y.; Han, Z.; Poor, H.V.; Hanzo, L. Age of information in energy harvesting aided massive multiple access networks. *IEEE J. Sel. Areas Commun.* **2022**, *40*, 1441–1456. [CrossRef]
17. Nahavandi, B.; Homayounfar, M.; Daneshvar, A.; Shokouhifar, M. Hierarchical structure modelling in uncertain emergency location-routing problem using combined genetic algorithm and simulated annealing. *Int. J. Comput. Appl. Technol.* **2022**, *68*, 150–163. [CrossRef]
18. Zhang, B.; Li, H.; Li, S.; Peng, J. Sustainable multi-depot emergency facilities location-routing problem with uncertain information. *Appl. Math. Comput.* **2018**, *33*, 506–520. [CrossRef]
19. Yu, W. Pre-disaster location and storage model for emergency commodities considering both randomness and uncertainty. *Saf. Sci.* **2021**, *14*, 105330. [CrossRef]
20. Wan, H.; Liu, W.; Shi, Q.; Zhang, Y.; Wang, Y.; Zhang, S. Multi-time-step rolling optimization strategy for post-disaster emergency recovery in distribution system based on model predictive control. *CSEE J. Power Energy Syst.* **2022**, 1–11. [CrossRef]
21. Kundu, T.; Sheu, J.B.; Kuo, H.T. Emergency logistics management—Review and propositions for future research. *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *16*, 102789. [CrossRef]
22. Li, J.; Fu, H.; Lai, K.K.; Ram, B. Optimization of Multi-Objective Mobile Emergency Material Allocation for Sudden Disasters. *Front. Public Health* **2022**, *1*, 927241. [CrossRef] [PubMed]
23. Halper, R.; Raghavan, S. The mobile facility routing problem. *Transp. Sci.* **2011**, *45*, 413–434. [CrossRef]
24. Rana, S.; Sarwar, M.; Siddiqui, A.S.; Gupta, P. Particle Swarm Optimization: An Overview, Advancements and Hybridization. *Optim. Tech. Eng. Adv. Appl.* **2023**, *202*, 95–125.
25. Faisal, M.; Albogamy, F. Ant Colony Optimization Algorithm Enhancement for Better Performance. In Proceedings of the 2023 IEEE World AI IoT Congress (AIIoT), Seattle, WA, USA, 7–10 June 2023; Volume 202, pp. 701–710.
26. Mrad, M.; Bamatraf, K.; Alkahtani, M.; Hidri, L. A genetic algorithm for the integrated warehouse location, Allocation and Vehicle Routing Problem in a Pooled Transportation System. *Int. J. Ind. Eng. Theory Appl. Pract.* **2023**, *30*. [CrossRef]
27. Majumder, S.; Saha, B.; Anand, P.; Kar, S.; Pal, T. Uncertainty based genetic algorithm with varying population for random fuzzy maximum flow problem. *Expert Syst.* **2018**, *35*, e3064. [CrossRef]
28. Alhijawi, B.; Awajan, A. Genetic algorithms: Theory, genetic operators, solutions, and applications. *Evol. Intell.* **2023**, *202*, 1–12. [CrossRef]
29. Goswami, R.D.; Chakraborty, S.; Misra, B. Variants of Genetic Algorithms and Their Applications. In *Applied Genetic Algorithm and Its Variants: Case Studies and New Developments*; Springer Nature Singapore: Singapore, 2023; Volume 202, pp. 1–20.
30. Cui, S.; Liu, S.; Tang, X.; Zhu, T. Emergency material allocation problem considering post-disaster impact. In Proceedings of the 2019 8th International Conference on Industrial Technology and Management (ICITM), Cambridge, UK, 2–4 March 2019; Volume 201, pp. 290–294.