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Optimization of Urban Fire Emergency Resource Allocation Based on Pre-Allocated Swarm Algorithm

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Abstract: As a high-frequency disaster with potentially devastating consequences, urban fires not only threaten the lives of city residents but can also lead to severe property losses, especially for hazardous chemical leaking scenarios. Quick and scientific decision-making regarding resource allocation during urban fire emergency responses is crucial for reducing disaster damages. Based on several key factors such as the number of trapped individuals and hazardous chemical leaks during the early stages of an incident, an emergency weight system for resource allocation is proposed to effectively address complex situations. In addition, a multi-objective optimization model is built to achieve the shortest response time for emergency rescue teams and the lowest cost for material transportation. Additionally, a pre-allocated bee swarm algorithm is introduced to mitigate the issue of local incident points being unable to participate in rescue due to low weights, and a comparison of traditional genetic algorithms and particle swarm optimization algorithms is conducted. Experiments conducted in a virtual urban fire scenario validate the effectiveness of the proposed model. The results demonstrate that the proposed model can effectively achieve the dual goals of minimizing transportation time and costs. Furthermore, the bee swarm algorithm exhibits advantages in convergence speed, allowing for the faster identification of ideal solutions, thereby providing a scientific basis for the rapid allocation of resources in urban fire emergency rescues.

Keywords: urban fire emergency response; hazardous chemical leakage; emergency weight; multi-objective optimization model; bee swarm algorithm

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1. Introduction

In recent years, urban fires have become a severe social issue. Data from the National Fire and Rescue Administration of China indicate that there have been as many as 450,000 reported fire incidents nationwide, from residential buildings and factories to public gathering places such as hotels and restaurants [1,2]. The multidimensional impacts of fires cannot be overlooked: the fires directly destroy property, including buildings, equipment, and inventories, placing significant economic pressure on individuals, businesses, and government entities. On one hand, the toxic smoke, high temperatures, and combustion products generated by fires severely threaten personal safety, potentially leading to significant casualties. On the other hand, secondary disasters following fires, such as collapses, environmental pollution, and traffic disruptions, further complicate disaster management [3,4]. Therefore, establishing an efficient and scientific urban fire emergency response system and optimizing emergency resource allocation strategies are crucial for enhancing urban disaster prevention and reduction capabilities and mitigating fire-related losses [5].

Emergency resources are mobilized rapidly in response to sudden events (such as fires) to ensure the safety of lives and property and to mitigate the impact of disasters [6,7]. The allocation of emergency resources is based on the real-time conditions at the disaster site, employing scientific planning and appropriate allocation to ensure that various resources are delivered accurately and efficiently to the areas of greatest need, with the aim of maximizing rescue efficiency and minimizing disaster losses [8,9]. The importance of this process is self-evident: it not only pertains to whether critical resources can be delivered to the rescue front lines in the most urgent moments, but also directly relates to the success or failure of rescue operations and the preservation of lives and property. Additionally, it requires making optimal choices under limited resource conditions to avoid unnecessary waste and misuse [10]. Therefore, developing and optimizing the allocation mechanism for emergency resources is a key component in enhancing the overall emergency response capability of cities and even nations, ensuring social safety and stability [11].

In addition, hazardous chemical leakage in urban fires is a highly complex emergency management challenge that requires the development of sound strategies and measures throughout the entire process of prevention, response, and recovery [12]. For hazardous chemical leakage problems, different disposal plans should be developed based on the area of leakage, volatility, and other factors, so as to minimize the loss of people, property, and the environment caused by fires and chemical leakage [13,14].

Modern cities frequently experience threats from fires, with their potential dangers and damages far exceeding those of other urban safety issues like traffic accidents. Over the past two decades in China, the annual direct economic losses caused by fires have consistently exceeded CNY 2.55 billion. Notably, many severe fire incidents in China often lack timely responsive firefighting resources and rescue forces, a situation that urgently needs improvement.

Urban fires, as common sudden disasters, involve an emergency response process that encompasses several key stages, including fire alarms, fire situation assessment, resource allocation, on-site rescue, and follow-up handling, requiring collaboration among multiple departments [15]. The suddenness and unpredictability of fires make resource demand forecasting difficult, leading to delays or waste in resource allocation. [7]. Therefore, optimizing resource allocation strategies to enhance emergency response efficiency and cost-effectiveness has become an urgent issue to address.

In recent years, scholars have conducted extensive and in-depth research on the allocation of emergency response resources for urban fires. In developed countries such as those in Europe and America, researchers rely on mature emergency management systems and continually optimize response efficiency through simulation exercises, detailed case analyses, and other methods. In China, with increasing attention to public safety issues, scholars have focused on optimizing the layout of emergency resources and innovating intelligent allocation algorithms, proposing numerous novel theories and practical methods aimed at enhancing the effectiveness of urban fire emergency responses. Wang et al. [16] concentrated on the challenges of emergency transportation under limited resources and proposed an optimization scheme aimed at achieving both minimum cost and maximum response speed. The highlight of their research lies in fully considering the cooperation and alliance mechanisms between multiple departments, providing new insights for improving overall emergency response efficiency. Addressing the fuzzy problem of demand uncertainty, Yang et al. [17] introduced a post-disaster material demand-forecasting technology based on fuzzy case reasoning. The results show that the proposed method can provide a scientific prediction of the demand for emergency supplies. A hybrid ABC targeting the deteriorating operational characteristics of the distributed flow-shop problem (DFSP) was proposed by Li et al. [18], specifically introducing a new scout bee heuristic that integrates information from global and local optimal solutions, significantly improving research efficiency. An HMaPSO algorithm was designed [19] aiming at solving complex multi-objective optimization problems. They not only validated the effectiveness of the HMaPSO algorithm on DTLZ functions but also successfully applied it to optimize green coal production, maximizing resource utilization. Kaewfak K et al. [20] developed a decision support model using an analytic hierarchy process (AHP) and zero-one goal programing (ZOGP) to determine an optimal multimodal transportation route. This methodology can provide a guidance for effectively determining the multimodal transportation routes to improve the performance of logistics systems. Guo et al. [21] addressed efficiency and accuracy issues in grid resource allocation management, proposing a new algorithm which significantly optimized the resource allocation process and improved allocation efficiency.

It is worth noting that a significant number of scholars in the current research field are committed to addressing issues related to minimizing time and optimizing routes in fire resource allocation. At the same time, researchers like Zhou et al. [22] have turned their attention to the specific needs for fire resources in particular areas, such as those storing hazardous chemicals, exploring the positive role of rational resource allocation in mitigating the risks of fire and explosion incidents in such areas. Lu et al. [23] creatively applied a scenario–response model to resource allocation decisions, focusing on the uncertainties in emergency scenarios within subway systems, effectively enhancing the practical capabilities of subway emergency rescues. Tang et al. [24] focused on the challenges of ambiguity in railway emergency resource allocation, building an optimization model. They innovatively employed a constrained parameter interval method to find quick solutions that achieve Pareto optimality. Chen et al. [25] established a multi-objective optimization model for minimizing the total transportation time, transportation cost, and container usage cost. The results demonstrate that using railway containers and railway transportation as much as possible in route selection can effectively solve the problem of container shortage and balance transportation time and transportation cost. Zheng et al. [26] introduced an improved particle swarm optimization algorithm (IPSO) to address the model, which has been proven to retain a fast convergence rate and achieve outstanding solving accuracy through the experimental study. Niyomubyeyi et al. [27] proposed an improved multi-objective artificial bee colony algorithm (MOABC), which combines random exchange, random insertion methods, as well as a two-point crossover operator and Pareto-based optimization methods.

This paper focuses on the rescue scenarios of urban fire incidents and conducts an in-depth analysis of the complex consequences of multi-disaster coupling emergency response sites and shortages of various emergency resources to address the challenges of emergency resource allocation under conditions of multiple disaster points, multiple rescue points, and multi-disaster coupling.

2. Problem Description and Analysis

In the urban case, there exists a set of accident-prone areas denoted as $D_1, D_2, \ldots, D_h$ and h is the number of areas requiring urgent rescue. A rescue system is established at different supply points c ($c = 1, 2, \ldots, C$), with each supply point containing a collection of rescue stations denoted as $R_1, R_2, \ldots, R_m$, m being the number of rescue stations. Command centers are denoted as $K_1, K_2, \ldots, K_b$, and b signifies the number of command centers.

The quantity of emergency supplies stored for a specific supply point c (c = 1, 2, . . ., C) is represented as number (c_{cb}). Additionally, the amount of emergency supplies stored at each rescue station is denoted as number (c_{cr}).

The scenario (as shown in Figure 1) includes ten rescue points (R_1 to R_{10}), five accident sites (D_1 to D_5), one command center (K), and seven types of core material requirements. Based on the location, resource reserve capacity, and specialization, each rescue point is equipped with different types of rescue supplies, such as fire engines, ambulances, firefighting equipment, and life support equipment. Different accident locations require a corresponding allocation of rescue materials. The types of materials available are shown in Figure 2.

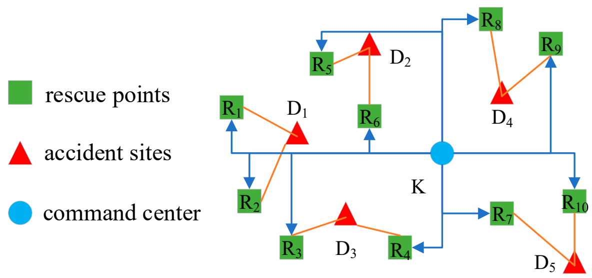


Figure 1. Setting of the emergency rescue scenario.

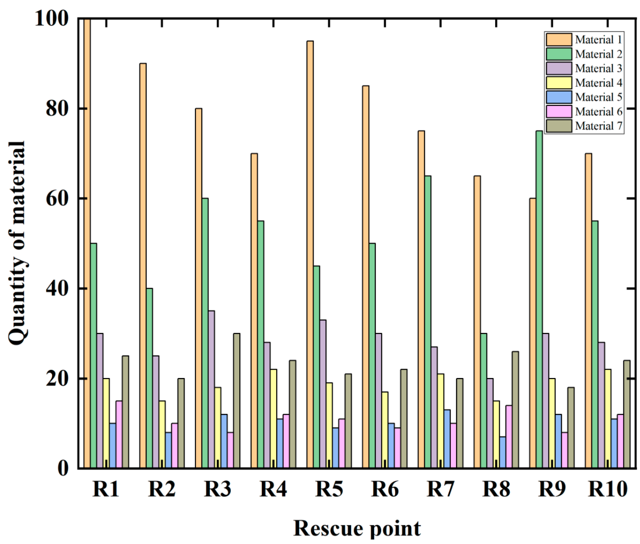


Figure 2. Types of supplies and reserve quantities at the rescue center.

3. Urban Fire Emergency Resource Allocation Model

This section aims to elaborate on the specific design and implementation process of the resource allocation model constructed for emergency responses to urban fires. The model is based on an improved swarm algorithm, which integrates the advantages of genetic algorithms and particle swarm optimization, enhancing the algorithm's directional search capability by adding a pre-allocation step to enable a rapid and efficient deployment of emergency rescue supplies in the event of a fire [28,29]. To build a model that meets practical allocation needs and easy operation, this paper makes the following assumptions:

1. The transit time between rescue points and incident sites is fixed, while the demand for emergency resources at the accident site remains constant throughout the process.
2. In order to address various emergencies that may arise during rescue operations, the quantities of various emergency resources stored on-site are typically greater than the actual needs, ensuring sufficiency and flexibility in emergency response.

3. To reduce transportation costs, the transport of each type of rescue material is managed and delivered by the corresponding rescue team, effectively avoiding waste and redundancy. This arrangement ensures the rationality of resource allocation and prevents the wasting of resources due to duplicative transport.

3.1. Multi-Objective Optimization Model

The rapid spread of fire poses a significant threat to life and property safety; therefore, the time it takes for rescue supplies to arrive is one of the most critical optimization objectives. This paper quantifies this objective as the shortest transportation time for supplies from the rescue points and command centers to all demand points (fire scenes). Specifically, it is assumed that there are multiple fire scenes, each with different demands for supplies and varying levels of urgency. By reasonably planning transportation routes and allocating transport vehicles, the total transportation time for all supplies can be minimized. In addition to ensuring rescue efficiency, reducing transportation costs is also an essential goal that cannot be overlooked. This includes vehicle operating costs, fuel consumption, labor costs, and so on. Various cost factors are taken into account to build an objective function aimed at minimizing the total transportation cost.

$$F_1 = T_k + T_S = \sum_{i=1}^{2}\left(\sum_{j=1}^{m} t_{dr} + \sum_{k=1}^{b} t_{dk}\right) \quad (1)$$

$$F_2 = C_K + C_S = \sum_{i=1}^{2}\left(\sum_{j=1}^{m} C_{cdr} number(C_{cdr}) + \sum_{k=1}^{b} C_{cdk} number(C_{cdk})\right) \quad (2)$$

F_1 represents the total time taken for emergency resource allocation, T_K means the transportation time of materials required to rescue trapped individuals, and T_S indicates the transportation time of materials required for firefighting. t_{dr} signifies the time cost required to transport materials from the rescue point R to the accident point D, while t_{dk} entails the time cost for transporting materials from the command center K to the accident point D.

F_2 indicates the total cost of emergency resource allocation, where C_K represents the cost of rescue materials for trapped individuals and C_S denotes the cost of materials required to firefight. C_{cdr} signifies the unit cost of transporting material c from R to D, and number (C_{cdr}) represents the quantity of material c needed from R to D. C_{cdk} indicates the unit cost of transporting material c from K to D, with number (C_{cdk}) representing the quantity of material c needed from K to D.

3.2. Allocation Weights for Emergency Resources

3.2.1. Emergency Weighting of Trapped Individuals

In an urban fire, in order to quickly and effectively allocate rescue resources to ensure the safety of trapped individuals, it is first necessary to calculate the emergency weights of the trapped individuals. After the fire occurs, the rescue command center will immediately collect and confirm the number of trapped individuals at incident point D (the location of the fire), denoted as $D(P)$. At the same time, based on past experiences and actual capability assessments, the expected number of trapped individuals that each rescue team can successfully save under ideal conditions will be determined, denoted as P. The value of $W_D(P)$ reflects the professional level and equipment effectiveness of the rescue teams and is an important indicator for assessing rescue capabilities. This weight can be used in the calculation of emergency resources required at rescue points; certain emergency resources related to the number of trapped individuals can be allocated based on the percentage of the total emergency resources corresponding to the weights of different rescue points.

$$W_D(P) = \left\lceil \frac{D(P)}{P} \right\rceil \tag{3}$$

where $W_D(P)$ represents the required number of rescue teams at incident point D and $\left\lceil \frac{D(P)}{P} \right\rceil$ means rounding up, meaning that even if the calculation results in a non-integer, it should be rounded up to the nearest integer. This approach ensures that there are sufficient rescue teams to respond to all trapped individuals, avoiding a shortage of rescue personnel due to minor discrepancies in the calculation results.

3.2.2. Emergency Weights for Hazardous Chemicals

In urban fire incident sites, the emergency response to and management of hazardous chemical leaks are crucial. The classification of their hazard levels directly affects the formulation of rescue strategies and the effectiveness of resource allocation. According to relevant regulations such as the "Regulations on the Safety Management of Hazardous Chemicals" (revised in 2011), the "Safety Supervision and Management Measures for Hazardous Chemical Construction Projects", and the "Production Safety Law of the People's Republic of China", combined with the leak area of the hazardous chemical and its volatility characteristics, it is possible to systematically determine the hazard levels of various chemicals and quantify their emergency risk weight accordingly.

Firstly, when it is confirmed that there are no hazardous chemical leaks at the fire scene, there is obviously no additional risk, so the emergency risk weight is directly assigned a value of 0, indicating that the current situation is relatively safe and no specific emergency measures are required for chemical leakage.

Secondly, if there is a hazardous chemical leakage, a comprehensive assessment must be conducted based on the leak area and its volatility. For cases where the leak area is less than 80 m^2 and the chemicals are non-volatile, it is considered low risk, with an emergency risk weight assigned a value of 1. When the leak area expands to greater than 80 m^2 but less than 160 m^2, if the chemicals remain non-volatile, the emergency risk weight is assigned a value of 2. If the leak area is less than 80 m^2 but the chemicals are volatile, it is regarded as a higher risk, and the emergency risk weight is also assigned a value of 2, because volatile substances may quickly disperse, increasing the risk of fire, explosion, and poisoning. Finally, for leak areas exceeding 160 m^2, particularly those accompanied by high volatility, as well as other leaks that pose significant risks but are difficult to assess quickly, the emergency risk weight is assigned a value of 3. This weight can also be used in the calculation of emergency resources required at rescue points where hazardous material leaks occur. Emergency resources for hazardous material handling can be allocated based on the percentage of the total emergency resources, according to the weights of different rescue points.

$$W_D(C) = \begin{cases} 0,\ S(C) = 0 \\ 1,\ S(C) \le 80\ \text{m}^2 \text{ and non-volatile} \\ 2,\ 80\ \text{m}^2 < S(C) < 160\ \text{m}^2 \text{ and non-volatile or } S(C) < 80\ \text{m}^2 \text{ and volatile}' \\ 3,\ S(C) \ge 160\ \text{m}^2 \text{ and volatile} \end{cases} \tag{4}$$

where $W_D(C)$ represents the emergency weights for hazardous chemical leaks at accident point D, while $S(C)$ denotes the leakage area of the hazardous chemicals.

3.3. Pre-Allocation Model Based on Swarm Algorithm

This paper employs the bee swarm algorithm (BSA), genetic algorithm, and particle swarm algorithm to solve multi-objective functions for comparative experiments. The BSA algorithm is an optimization method based on swarm intelligence, simulating the behavior of bees in search of nectar [30]. The BSA algorithm can be used to search for optimal resource allocation plans aimed at minimizing response time and maximizing rescue efficiency. The algorithm can handle the interactions and coupling relationships between different disasters, ensuring optimal resource allocation under limited resources. The flowchart of the BSA algorithm is shown in Figure 3.

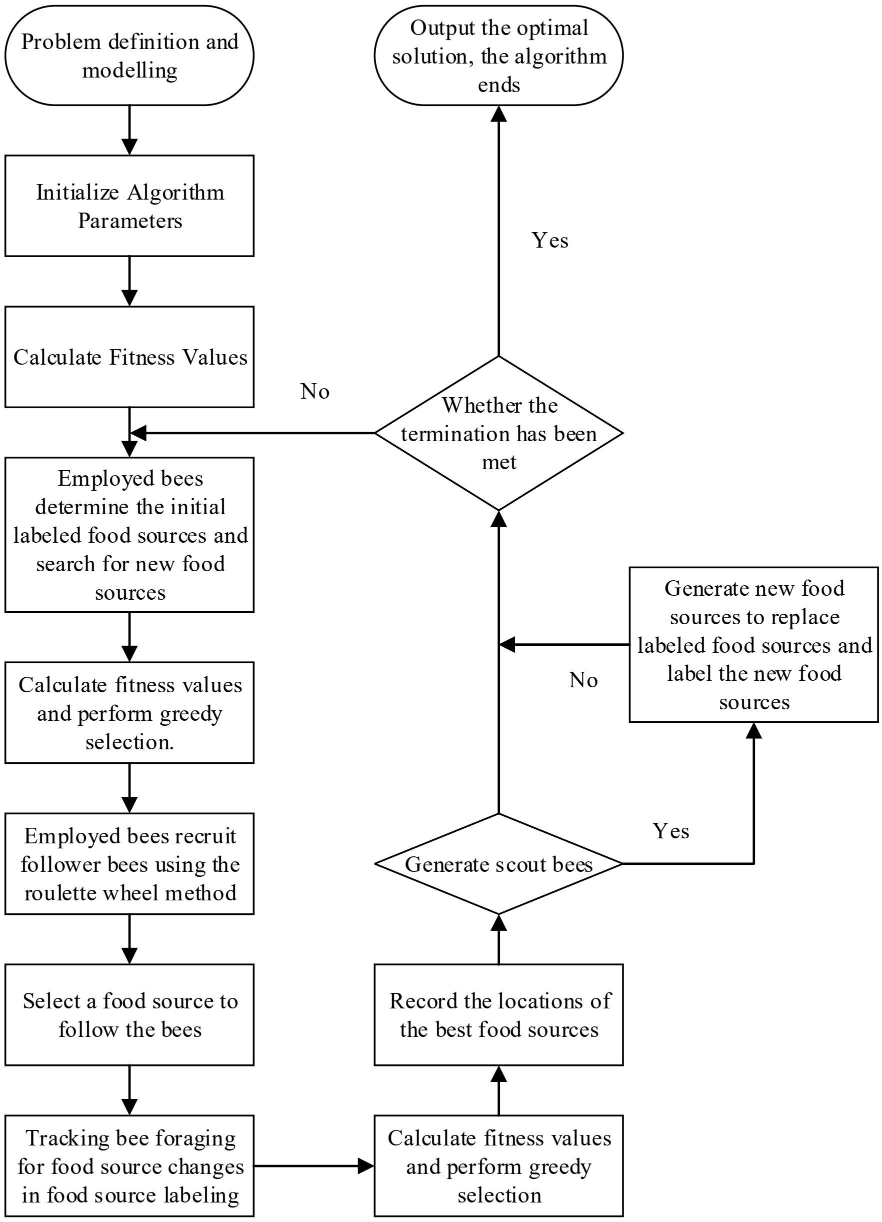


Figure 3. Flowchart of the BSA algorithm.

In the BSA algorithm, the design goal of the fitness function is to optimize the cost and time of delivering rescue supplies, thereby achieving the shortest delivery time and the lowest cost. There are various methods for handling multi-objective functions, including the weighted sum method, constraint method, and Pareto optimization method, each with its own unique applicable scenarios, advantages, and disadvantages. Based on Pareto optimization theory, this paper seeks a set of non-dominated solutions (such as the Pareto optimal solution set) that cannot be compared to each other, achieving a certain balance between different objectives that cannot be further improved through simple trade-offs [31]. The Pareto optimization method can find a set of solutions rather than a single solution, providing decision-makers with more options. In multi-objective optimization problems, if there are two or more solutions and one solution is no worse than another in all objectives while being better in at least one objective, the former is said to dominate the latter. The

Pareto optimal solution set is the collection of all solutions that are not dominated by any other solutions [32]. Therefore, this paper constructs a set of non-dominated solutions and adds offspring solutions that can optimize at least one objective function to the non-dominated solution set during each iteration [33]. Simultaneously, through a greedy strategy, poorer solutions are filtered out from the dominated solution set. Since the various objective functions in this paper are not completely conflicting, it is sufficient to select the solution with the shortest time from the non-dominated solution set, which is usually also the solution with the lowest cost.

The procedure of the pre-allocation model based on swarm algorithm is as follows:

1. Problem definition and modeling: First, the decision variables are defined, including the selection of types of supplies, vehicles, and the allocation number of supplies; then, the objective functions are defined: Objective 1 (minimization): arrival time of rescue supplies F_1. Objective 2 (minimization): transportation cost of rescue supplies F_2.
2. Initialization of algorithm parameters: A certain number of initial solutions (sources of nectar) are randomly generated, with each solution representing a possible rescue plan. The number of bees (including employed bees, onlooker bees, and scout bees), the number of iterations, search limits, and other parameters are set.
3. Fitness assessment stage: Based on the actual conditions of the disaster area (such as fire intensity, number of trapped individuals, and the presence of hazardous chemical leaks), the fitness values of each resource allocation plan are calculated. The fitness value can be measured by the emergency response time and the emergency response cost.
4. Employed bee phase: Each employed bee corresponds to a nectar source (solution) and performs neighborhood searches around it to find better solutions, evaluating the values of the two objective functions F_1 and F_2 for the new solutions [34]. If the new solution is superior to the current solution in any one objective, or is better in a multi-objective sense (such as using Pareto dominance), the current solution is replaced (greedy selection).
5. Perspective bee phase: The onlooker bees select a portion of nectar sources for further searching based on the information (such as fitness) provided by the employed bees. Following a bee search in the vicinity of the selected nectar sources to find new resource allocation plans, the fitness value of the new plan is calculated and compared with that of the original plan. If the fitness value of the new plan is superior, the nectar source location is updated (similar to the employed bee phase).
6. Scout bee phase: If a certain nectar source (solution) has not been updated after multiple iterations (i.e., it has become trapped in a local optimum), that nectar source is abandoned, and a new nectar source is randomly generated by a scout bee. The fitness value of the new plan is calculated and compared with that of the original plan. If the fitness value of the new plan is superior, the nectar source location is updated.
7. Iterative optimization phase: Step 4 (Employed Bee Search), Step 5 (Onlooker Bee Selection), and Step 6 (Scout Bee Search) are repeated, conducting multiple iterations to find better emergency resource allocation plans. In each iteration, update the bee population based on the fitness values, retaining superior solutions while eliminating inferior ones.
8. Termination condition assessment phase: The preset termination conditions, such as reaching the maximum number of iterations or finding a satisfactory solution, are checked. If the termination conditions are met, stop the iteration and output the current optimal emergency resource allocation plan; otherwise, return to Step 7 to continue the iterative optimization.

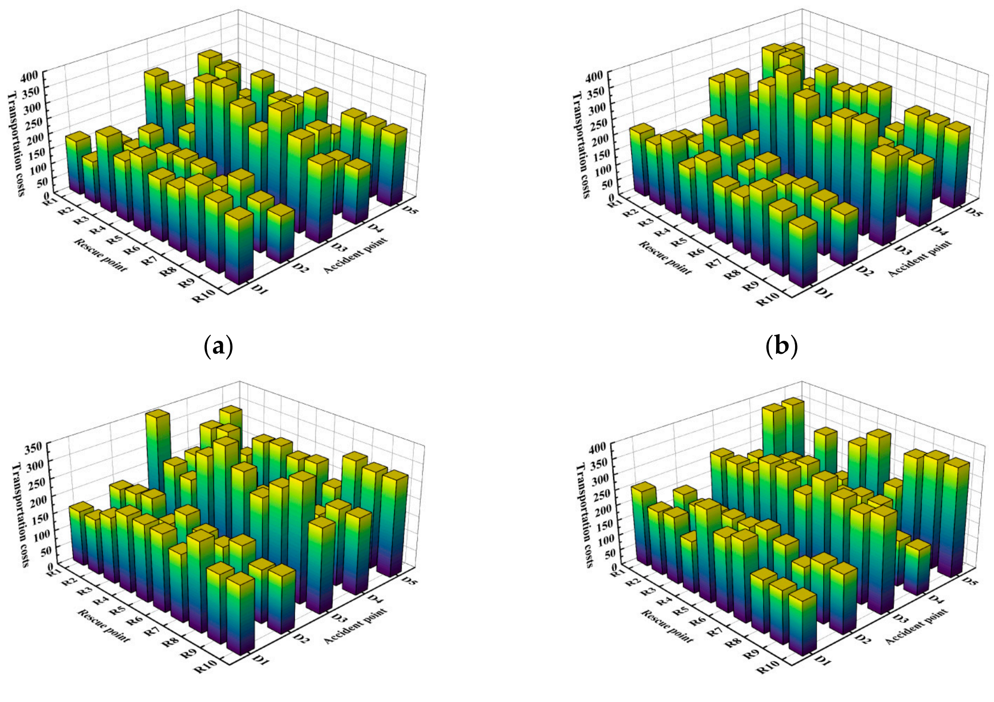
9. Result analysis phase: The output optimal emergency resource allocation plan is analyzed, and its actual effectiveness in urban fire rescue scenarios is assessed. Based on the analysis results, the algorithm is improved or parameters to further enhance the emergency resource allocation are adjusted.

4. Results and Discussion

4.1. Transporting and Time Costs Analysis

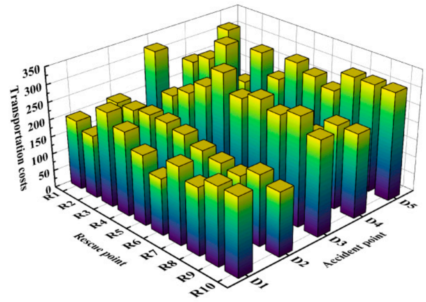
The costs associated with transporting different types of supplies (Material 1 to Material 7) from various rescue points (R_1 to R_{10}) to different accident sites (D_1 to D_5) are shown in Figure 4. The height of each rectangular bar indicates the cost of transporting specific supplies from a particular rescue point (R_i, i = 1–10) to a specific accident site (D_j, j = 1–5). Transportation costs include fuel expenses, vehicle maintenance fees, personnel wages, and more. The cost variations reflect various factors that may be encountered during transportation, such as distance, road conditions, and the choice of transportation vehicle. This figure provides a clear understanding of the transportation costs of supplies between rescue points and affected areas, offering a basis for developing efficient allocation plans for rescue materials.

Figure 5 provides a detailed representation of the time costs required to transport different types of supplies (Material 1 to Material 7) from various rescue points (R_1 to R_{10}) to different accident sites (D_1 to D_5). The height of each rectangular bar indicates the time required to transport specific supplies from a particular rescue point (R_i, i = 1–10) to a specific accident site (D_j, j = 1–10). Road conditions, distances, and potential traffic jams are considered in the time costs. This time cost encompasses all time expenditures related to the transportation process, including loading, transportation, and unloading. The impact of various factors such as road conditions, the speed of transportation vehicles, and the efficiency of loading and unloading materials are reflected as well.



(**a**) (**b**) (**c**) (**d**)

Figure 4. *Cont.*



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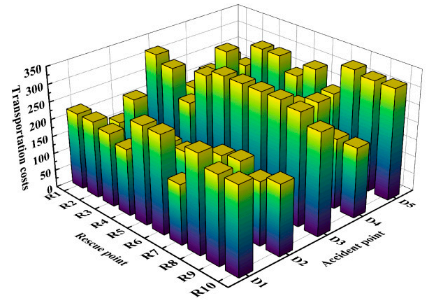

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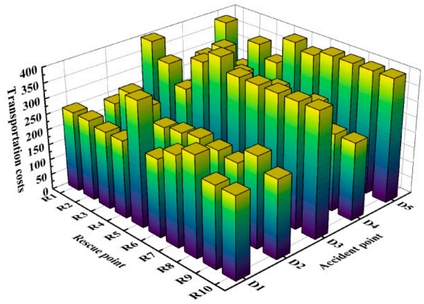
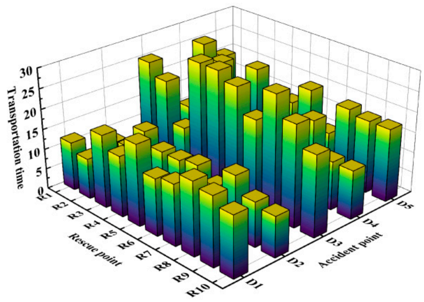


(**g**)

Figure 4. Transportation costs of various supplies from rescue points to accident sites. (**a**) Material 1; (**b**) Material 2; (**c**) Material 3; (**d**) Material 4; (**e**) Material 5; (**f**) Material 6; (**g**) Material 7.



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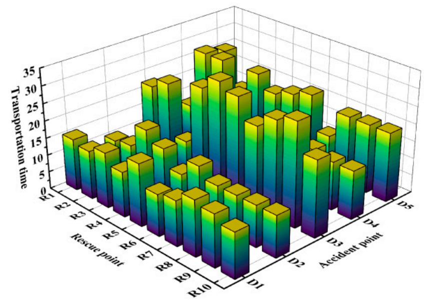

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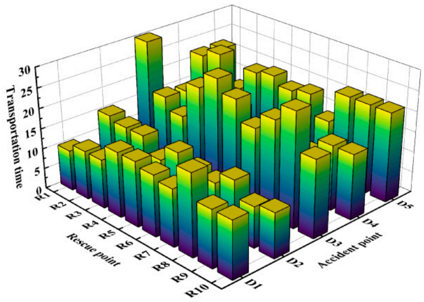

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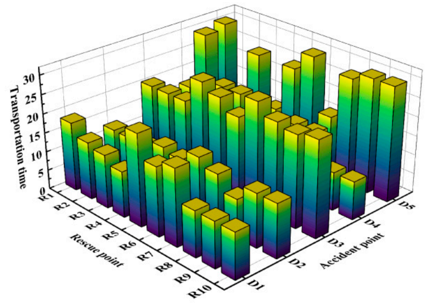
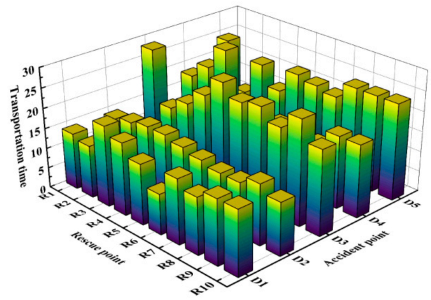


(**d**)

Figure 5. *Cont.*



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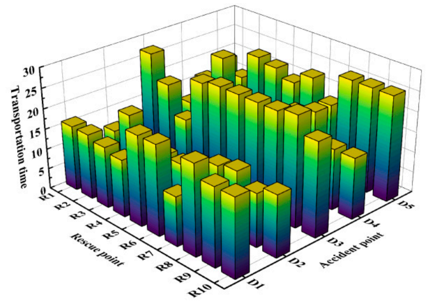

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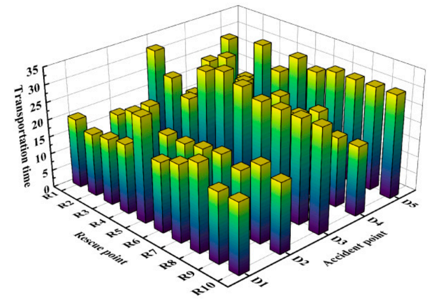


(**g**)

Figure 5. Time costs of transporting various supplies from rescue points to accident site. (**a**) Material 1; (**b**) Material 2; (**c**) Material 3; (**d**) Material 4; (**e**) Material 5; (**f**) Material 6; (**g**) Material 7.

A list of the key information regarding the accident sites, including the number of trapped individuals and the severity of hazardous chemical leaks, are listed in Table 1. These data are of significant reference value for accurately assessing rescue needs.

Table 1. Fire situation initiation at the accident sites.

Fire Situation at the Accident Sites	D_1	D_2	D_3	D_4	D_5
Trapped individuals	10	5	15	8	12
Chemical leaks conditions	Yes	No	Yes	No	Yes
Leak area (m^2)	60	0	120	0	75

Using the weighting calculation method described in Section 3.2, the required number of rescue teams to be dispatched from each rescue point has been determined (please see Table 2). The dispatched rescue teams include rescue teams and hazardous material cleanup teams, aiming to provide a rapid response at the scene and effectively manage various complex situations that may arise during the disaster.

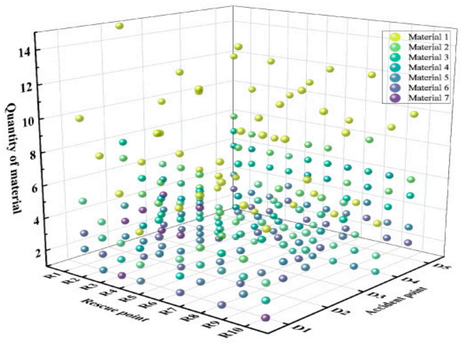
Table 2. Quantity of various rescue teams required at the accident sites.

The Number of Rescue Teams	D_1	D_2	D_3	D_4	D_5
Rescue teams	3	2	4	2	3
Cleanup teams	1	0	2	0	1
Total of rescue teams	4	2	6	2	4

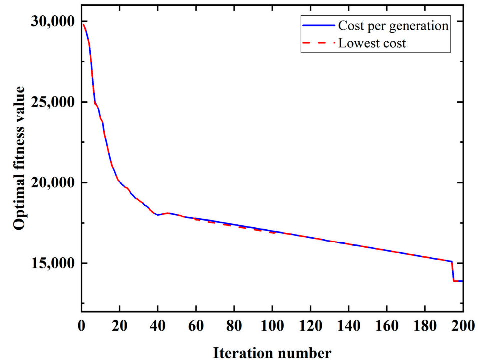
4.2. Comparison of Resource Allocation Schemes Using Three Algorithms

Based on the types and quantities of supplies available at each rescue point, along with the emergency weights of trapped individuals and hazardous chemicals at each accident site, the following three resource allocation schemes can be derived using the multi-objective function solving method proposed in Section 3.1.

According to the operational steps of the bee swarm algorithm, corresponding resource allocation schemes can be generated, as shown in Figure 6a. Each point represents the quantity of supplies allocated from the rescue points to the target accident sites. Figure 6b illustrates the algorithm iterative process, demonstrating how the algorithm gradually approaches the optimal solution through step-by-step adjustments to the resource allocation strategy. The results of this resource allocation scheme for command center K_1 are shown in Table 3.



(a)



(b)

Figure 6. Results of the BSA (**a**) and the algorithm's iteration process diagram (**b**).

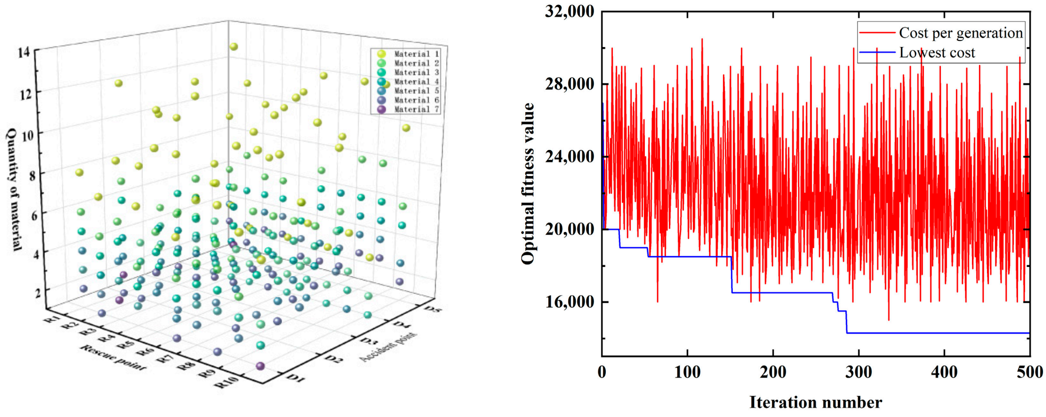
Table 3. Results of resource allocation for command center K_1 using BSA.

	R_1	R_2	R_3	R_4	R_5	R_6	R_7
D_1	20	15	10	5	3	4	2
D_2	15	10	5	3	2	2	1
D_3	25	20	10	8	5	6	3
D_4	10	8	5	4	3	2	2
D_5	18	15	10	6	4	3	2

The genetic algorithm is an optimization algorithm based on the principles of evolution, simulating the biological evolution process in nature. Through operations such as competition, selection, crossover, and mutation among individuals in a population, it gradually optimizes the search for the optimal solution to a problem [35,36]. According to the genetic algorithm procedure, corresponding resource allocation schemes can be generated; please refer to Figure 7a where the quantity of supplies allocated from each rescue point to the accident sites are shown. Meanwhile, the iterative process of the genetic algorithm is shown in Figure 7b, depicting how the algorithm gradually optimizes and evolves in the search space to seek the optimal solution. The results of this resource allocation for command center K_1 are shown in Table 4.

Table 4. Results of resource allocation for command center K_1 using GA.

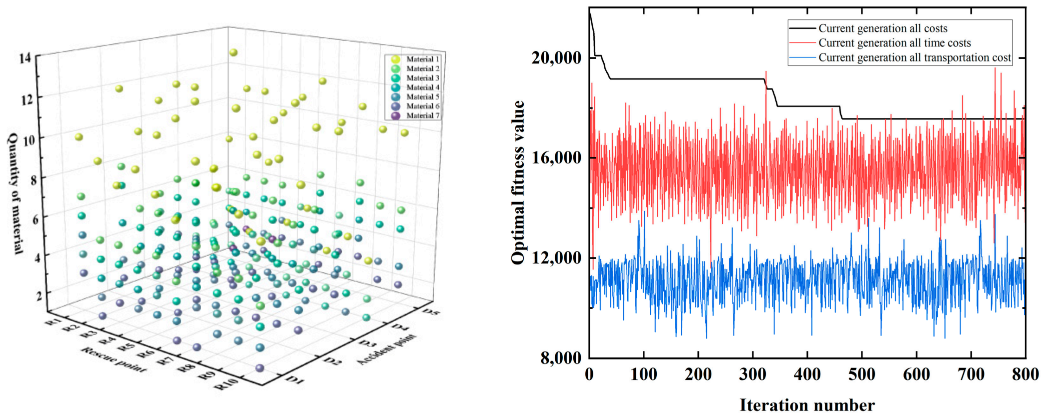
	R_1	R_2	R_3	R_4	R_5	R_6	R_7
D_1	20	15	10	5	3	4	2
D_2	15	10	5	3	2	2	1
D_3	25	20	10	8	5	6	3
D_4	10	8	5	4	3	2	2
D_5	18	15	10	6	4	3	2



(**a**) (**b**)

Figure 7. Resource allocation scheme using GA (**a**) and algorithm iteration process diagram (**b**).

Particle swarm optimization is a meta-heuristic algorithm used to solve optimization problems, with its fundamental idea derived from the study results of modeling and simulating the behavior of bird flocks [37,38]. Based on the particle swarm algorithm procedure, corresponding resource allocation schemes and their iterative processes can be generated. The resource allocation results obtained through the particle swarm algorithm are displayed in Figure 8a, where each point represents the quantity of supplies allocated from different rescue points to the accident sites. Figure 8b depicts the dynamic process of particles continuously adjusting their positions in the search space during the iterative process in order to find the optimal solution. The results of this resource allocation scheme for command center K_1 is shown in Table 5.



(**a**) (**b**)

Figure 8. Resource allocation scheme using PSO (**a**) and algorithm iteration process diagram (**b**).

Table 5. Results of resource allocation scheme for command center K_1 using PSO.

	R_1	R_2	R_3	R_4	R_5	R_6	R_7
D_1	20	15	10	5	3	4	2
D_2	15	10	5	3	2	2	1
D_3	25	20	10	8	5	6	3
D_4	10	8	5	4	3	2	2
D_5	18	15	10	6	4	3	2

4.3. Comparison of Three Algorithms

Through the application of three heuristic algorithms (GA, PSO, and BSA), different resource allocation schemes have been derived, and the transportation and time cost expenditures of each scheme in material transportation have been further calculated. The Table 6. below presents the comparative results of the cost analysis.

Table 6. Results of cost and speed of the three algorithms.

	GA	PSO	BSA
Transportation cost	22,000	27,000	15,000
Time cost	300	400	200
Convergence speed	500	800	200

The bee swarm algorithm significantly outperforms the genetic algorithm and particle swarm optimization in terms of both transportation and time cost efficiency, and it also has a faster overall convergence speed. The result indicates that the bee swarm algorithm, based on the pre-allocation strategy, is not only more efficient than the traditional genetic algorithm and particle swarm optimization in solving emergency rescue resource allocation problems, but also consumes fewer resources, demonstrating a clear advantage.

5. Conclusions

This article focuses on urban fire disaster rescue scenarios, which are characterized by a wide impact range. In response to these scenarios, a plan that includes multiple disaster points and multiple rescue points is designed, and a method for calculating the emergency weights of rescue teams based on the needs of rescue points is proposed. At the same time, to optimize the emergency response efficiency and reduce costs, the transportation and time costs of emergency rescue operations were quantified through simulation experiments. A multi-objective optimization model is constructed to achieve the shortest response time for emergency rescue teams and the lowest cost for emergency material transportation.

A solution method based on a pre-allocated bee swarm algorithm model is proposed. Through comparative analyses with genetic algorithms and particle swarm optimization algorithms, conduct a comparative analysis of the implementation of the plan and the speed of iteration, optimizing the algorithm. This method can effectively select the optimal emergency resource allocation plan, ensuring the rapid and accurate mobilization of resources in emergencies, thus improving rescue efficiency.

Through the verification of the arithmetic cases, it has been found that both heuristic algorithms can effectively complete tasks under the given conditions. In terms of resource allocation effectiveness, the bee swarm algorithm demonstrates a significant advantage over traditional genetic algorithms and particle swarm optimization. This rescue plan holds important significance for addressing emergency situations involving multiple coupled disasters, since rescue teams could complete the emergency rescue tasks in the shortest time at the lowest cost.

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