Multi-objective emergency supplies allocation technology based on an improved simulated annealing algorithm

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Abstract—**In emergency response, the administration of emergency supplies constitutes a critical facet. On the one hand, it ensures a more comprehensive preparation of emergency supplies, thereby facilitating the rescue of a larger number of individuals; on the other hand, it can improve the efficiency of emergency response and guide emergency response. This study introduces a simulated annealing algorithm to address the issue of an excessively large initial solution space in the simulated annealing method. The algorithm initially adjusts according to the demand ratio to expedite the iteration speed and augment computational efficiency. Concurrently, it performs distinct calculations for various allocation schemes, considering the actual circumstances and the weighting factors of different damage levels. Wenchuan earthquake as a case study, this paper conducts an initial validation of the weight allocation calculation method and the supplies allocation technique under various scenarios, thereby demonstrating the feasibility of the proposed method.**

Keywords—simulated annealing algorithm, resource allocation, algorithm for weighting factors

Introduction (*Heading 1*)

I. Introduction and Background

Managing emergency supplies is an integral part of the emergency response process. On the one hand, research into emergency supplies can ensure better preparedness and enable more individuals to receive aid. On the other hand, such research holds significant value in enhancing the efficiency of emergency response and offering guidance for emergency operations.

Emergency supplies studies can be specifically segregated into three distinct categories based on the objective functions they encompass. The first category pertains to the scheduling problem of emergency supplies, intending to minimize the total transportation time. The second category addresses the scheduling problem of emergency supplies, with the goal of minimizing the total transportation cost. Lastly, it involves the scheduling problem of emergency supplies.

It emphasized that the scheduling problem of emergency supplies in disaster scenarios should strive for the shortest transportation time, aiming to deliver various emergency supplies to the corresponding disaster site as quickly as possible. Haghani and Oh [1] proposed a large-scale, multi-commodity, and multi-mode emergency supplies scheduling network flow model with time window constraints, marking an early research endeavor in the field of multi-mode scheduling of emergency supplies. Yao [2] considered the actual situation of post-disaster road network damage and incorporated both transportation time and road network repair time into the model construction, aiming to minimise total time and analyse the optimization problem of disaster emergency supplies transportation path. Aharon et al. [3] examined the time dependence of emergency logistics in disaster situations and proposed a scientifically robust optimized path planning model for emergency transportation. Mete and Zabinsky [4], in constructing a two-stage emergency rescue supplies transportation optimization model for earthquake disasters, aimed to minimize transportation costs, delivery time, and supplies shortages as the optimization objectives for the first and second stages, respectively. Chi et al. [5] constructed an emergency supplies scheduling time measurement function based on scheduling time and supplies scheduling satisfaction and analyzed the impact of specific factors, such as supplies demand quantity and delivery time, on the measurement function, to minimize emergency supplies scheduling time. Additionally, several scholars have also studied corresponding emergency supplies scheduling problems with the goal of minimizing total transportation time (such as Afshar et al. [6], Berkoune et al. [7], Widener et al. [8], Vitoriano et al. [9], Rika et al. [10], Camacho Vallejo et al.[11], Vanajakumari[12], etc.).

Knott [13] aims to minimize the total transportation cost and maximize the total transportation volume, and constructs a planning model for the transportation of emergency rescue supplies after disasters, and analyzed the corresponding emergency vehicle selection problem. Kannan takes minimizing total transportation costs and maximizing disaster coverage as optimization objectives, and constructs a critical path identification and selection model for post disaster emergency rescue supplies transportation for multiple types of emergency supplies.

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The goal is to minimize the total transportation cost based on constraints such as capacity constraints, road network capacity constraints, and available resource constraints. This has been explored in depth by researchers such as Equi et al.[14] and Wael[15].

Moreover, scholars have also considered the minimum total transportation cost, minimum total transportation time, and shortest path in the study of emergency supplies scheduling problems for various transportation modes, and have conducted relevant analyses. Thengvall et al. [16] and Yu et al. [17] analyzed the advantages of air transportation in emergency rescue when the disaster impact range is large and the road network is severely damaged in response to the large-scale destructive impact of sudden disasters. It, based on the constraint of the emergency restriction period, constructed an emergency vehicle path model with multiple emergency rescue points and disaster-affected points by analyzing modes such as air transportation, road transportation, and railway transportation, as well as post-disaster traffic network damage. It proposed an optimization model for scheduling and allocating emergency rescue supplies based on the combination of road and helicopter transportation in response to the reality of short disaster relief time and heavy tasks after an earthquake. It proposed an optimization model for earthquake disaster emergency rescue supplies scheduling and allocation based on a three-level emergency supplies allocation system to solve the problems of limited emergency supplies supply, dispersed supply points, and constrained allocation time. Their research objective was to minimize the system loss of rescue supplies allocation. It extended the analysis of transportation networks in their research and proposed a single-start-stop multimodal transportation shortest scheduling path optimization model based on time-varying scheduling networks. With the gradual advancement of research, scholars have continuously introduced genetic algorithms, soft computing, neural networks and other methods into the design of emergency rescue supplies scheduling systems, providing certain methodological support for multimodal transportation scheduling of emergency rescue supplies.

The characteristics of insufficient supply and dynamic changes in demand for emergency supplies in existing research batches. This model aims to maximize the minimum demand satisfaction rate of disaster-affected points as a measure of fairness while minimizing the latest delivery time of emergency supplies as an efficiency goal. Based on this, decisions are made regarding allocating emergency supplies across multiple disaster-affected and rescue points.

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II. EMERGENCY SUPPLIES ALLOCATION AND SIMULATED ANNEALING ALGORITHM

The allocation of emergency supplies is a special type of resource allocation problem. Resource allocation problem mainly refers to the process of optimally allocating certain limited resources to competing objects or entities. The allocation of emergency supplies, as a key link in the entire emergency response and rescue work, is an important guarantee of the emergency supplies required for earthquake disaster emergency rescue. Long pointed out that efficient and reasonable allocation of emergency rescue supplies can be achieved by constructing a scientific supplies allocation assistance decision support system. Its core idea is to develop a scientific and reasonable optimization plan for allocation of emergency supplies based on various information collected from disaster-stricken areas, such as needs.

In recent years, domestic and foreign scholars have mostly used operations research optimization and combinatorial mathematics methods to study the optimization of emergency supplies allocation. With the continuous deepening of research, some scholars have also conducted research based on game theory and control theory.

A. Emergency Supplies Allocation Problem Based on Operations

Research Optimization Method

Existing literature on emergency supplies allocation based on operational research optimization methods mostly studies the problem by setting optimization objectives and constructing mathematical planning models.

Linet et al. [18] proposed a multi-cycle resource allocation optimization model to maximise resource allocation satisfaction and solved the model using the Lagrangian relaxation algorithm. Fiedrich et al.[19] emphasized that the main task in the early stage after an earthquake is to reduce casualties. On this basis, an emergency resource allocation model was constructed to minimize the number of deaths, and factors such as the geographical location of the disaster area, the number of casualties, and available supplies were considered. Sheu [20] used mathematical programming methods such as fuzzy clustering and data fusion to group multiple disaster areas by analyzing the supply needs and the changing trends of different disaster areas after the disaster, serving as a decision-making basis for emergency supplies allocation in quantity and urgency. Zhang Guofu et al.[21] proposed an optimization model for emergency supplies scheduling and allocation based on multiple demand points, multiple supply points, multiple supplies, and multiple objectives. Wang Haijun et al. [22] proposed to construct an optimization model to minimize the cost of rescue supplies allocation and emergency time based on the fuzzy and uncertain characteristics of the actual demand for supplies and allocation time at each disaster-affected point after the disaster. Shen Xiaobing et al. [23] proposed a multimodal emergency supplies allocation model with the optimization objective of minimizing supplies delivery time and shortage based on mixed integer nonlinear programming method. The feasibility of the constructed model and solution algorithm was verified using data related to the Wenchuan earthquake. Liu Changshi et al.[24] constructed an optimization model for disaster emergency rescue supplies allocation to minimize the time and cost of rescue supplies allocation in their research. Chen Gang and Fu Jiangyue [25] constructed the first batch of emergency supplies allocation models for post disaster rescue to minimize the total logistics cost and the total weighted jealousy value of the affected point. However, they only studied the problem of emergency supplies allocation for a single variety.

Oloruntoba and Gray [26] pointed out in their study that in emergency supply allocation, it is necessary to consider the impact of various realistic constraints or uncertain factors on supply allocation activities in disaster situations. On this basis, relevant literature has appropriately considered the constraints that different disaster rescues may face in the research to make the constructed model and research analysis more in line with the actual disaster situation. Generally, research on emergency supplies allocation is focused on considering cost constraints, transportation capacity constraints, restriction period constraints, fairness constraints, satisfaction constraints, road network damage constraints, complex networks with multiple rescue points and demand points, multiple types of emergency supplies, and different scenarios.

B. Emergency Supplies Allocation Problem Based on Combinatorial Mathematics Method

The combinatorial mathematical method is mainly used to study the selection of rescue points in emergency rescue supplies allocation. The selection of emergency rescue points refers to the process of scientifically selecting emergency rescue points by setting relevant optimization objectives to achieve the optimal distribution of supplies, considering constraints such as supplies supply, demand, transportation capacity, and time when multiple emergency rescue supplies supply points exist simultaneously during the disaster emergency rescue process.

At the same time, when the emergency response time after a disaster is a fuzzy and uncertain interval number, a rescue supplies allocation plan is proposed with the optimization decision objective of maximizing the possibility of rescue starting time within the constraint period range. Based on this research, He Jianmin et al. introduced the concept of "shortest time" in their research, taking into account the fact that the strong timeliness of emergency rescue may conflict with the number of rescue points, and proposed using a fuzzy optimization algorithm to analyze the combination optimization problem of multiple rescue points in emergency rescue with limited period constraints. Liu Chunlin et al. proposed an emergency rescue supplies allocation model that minimizes the number of rescue points based on the premise of the earliest emergency response time, based on the scheduling and allocation problem of emergency rescue supplies with multiple rescue points under demand constraints. Liu Chunlin proposed an emergency supplies allocation model under fuzzy rescue supplies demand and rescue response time constraints by analyzing a one-time consumption system; Liu Chunlin et al. proposed to construct an allocation optimization model based on the strong timeliness of emergency rescue and the stability of the rescue system, with the earliest emergency response time and the least number of emergency rescue points. Wang Yu and He Jian constructed an optimization model for the allocation of multiple types of emergency rescue supplies for multiple rescue points to minimize the number of rescue points and the start time of rescue.

C. The Problem of Emergency Supplies Allocation Based on Game Theory

With the integration of intelligent algorithms into emergency resource management research, game theory has gradually been introduced to analyze the allocation of emergency supplies for sudden disasters. The optimization plan for allocating emergency rescue supplies is typically determined by decision-makers who scientifically evaluate various strategies (rescue allocation plans) in the context of multi-objective conflicts during emergency decision-making. The ultimate goal is to develop an optimization plan that maximizes benefits or minimizes costs.

Shetty and Gupta conducted a comprehensive analysis of emergency supply allocation by utilizing a game model that considers the availability of supplies and the severity of disasters. They proposed a rescue supplies allocation and optimization strategy based on Nash equilibrium in a static game process involving multiple demand points. Zhao Shuhong focused on real-time disaster information updates and analyzed the relationship between subjects, objects, and game dynamics in emergency management. They proposed an optimization plan for emergency supplies allocation based on this analysis. A closed-loop emergency supplies allocation model that considers the dynamic nature of emergency management was developed. Their model includes a cooperative game module that allows individual disaster points to select cooperative strategies, leading to equilibrium independently. They introduced an improved core method to obtain a collaborative game-based supplies allocation plan among disaster points. In their research, Zhang Jing et al. formulated the emergency supplies allocation problem in the presence of multiple concurrent disaster events as a non-cooperative finite strategy game under complete information. They proposed an optimized decision-making scheme for allocating emergency rescue supplies in multiple accidents. Considering the limited supply of emergency resources in the early stages of post-disaster emergency rescue, Yang Jijun et al. studied optimization allocation models and plans by incorporating cooperative, non-cooperative, and dynamic games in the competition for supplies allocation among multiple disaster-affected areas. Pang et al. treated the disaster area as a game player and the optimization results of emergency rescue supplies allocation as a set of game strategies. An incomplete extinction method for disaster emergency rescue was proposed and the particle swarm optimization algorithm was utilized to solve the Nash equilibrium solution of the proposed model.

III. Simulated Annealing (SA) Algorithm

A. Simulated Annealing (SA) Algorithm

The Simulated Annealing (SA) algorithm was initially proposed in 1983. They discovered a profound relationship between the behavior of systems with numerous degrees of freedom in thermal equilibrium at a finite temperature and multivariate or combinatorial optimization. By leveraging this connection, they developed the algorithm. The Simulated Annealing Algorithm draws inspiration from the annealing process of solid materials. In the initial stages, when solid supplies are subjected to high temperatures, the molecules exhibit higher mobility and tend to stabilize as the temperature decreases. The algorithm incorporates this annealing process and establishes a criterion to determine whether state changes should be accepted or rejected, which allows the algorithm to escape local optima and approach global optima.

The simulated annealing algorithm is commonly employed for tackling intricate optimization problems due to its inherent ability to escape local optima and consider suboptimal solutions. It applies to both continuous and discrete optimization problems. This algorithm has garnered extensive usage in diverse problem domains, including clustering, multi-objective optimization, and deep learning.

However, the SA algorithm is too slow and unsuitable to solve complex optimization problems like scheduling. Ram Sreenivas has applied parallel computing techniques to speed up the SA algorithm. Except for a slow convergence rate, the SA algorithm also needs an initial temperature and a proper cooling strategy to achieve better performance, which is a methodology to improve the SA algorithm. Moreover, the SA algorithm cannot guarantee the finding of global optima every time, which requires more running times and iterations to increase the search space. In the next part, the article will detail how the simulated annealing algorithm works.

However, the simulated annealing algorithm exhibits inadequate computational speed, rendering it unsuitable for addressing complex optimization problems such as scheduling. To mitigate this limitation, Ram, Sreenivas et al. endeavored to employ parallel computing techniques to expedite the SA algorithm. Additionally, apart from its sluggish convergence rate, the SA algorithm necessitates specifying an initial temperature and implementing a sound cooling strategy to enhance its performance. This constitutes a methodological approach aimed at refining the SA algorithm. Furthermore, the SA algorithm does not guarantee the identification of global optima on every occasion, necessitating executing the algorithm multiple times with increased iterations to explore a broader search space. The subsequent section of the article will provide a comprehensive overview of the operational principles underlying the Simulated Annealing Algorithm.

B. Simulated Annealing Algorithm Flow

The Simulated Annealing Algorithm has a few parameters: an initial temperature, the maximum temperature, a final temperature, the minimum temperature, an initial random solution, and the cooling strategy. Formula 1 shows the Metropolis criterion, also called the acceptance criterion, representing the probability of accepting a new solution. (1)

The algorithm incorporates several essential parameters, including the initial temperature (also referred to as the maximum temperature), final temperature (also referred to as the minimum temperature), initial random solution, and the cooling strategy. Formula 1 illustrates the Metropolis criterion, also known as the acceptance criterion. This criterion quantifies the probability of accepting a new solution within the algorithm.

The formula 1 represents the probability of cooling, which means the decrease in temperature. The initial solution will be randomly generated from the problem space. The cooling strategy will decide the decrease of temperature in each iteration, which will normally use exponential or linear cooling strategies, gradually reducing the probability of accepting worse solutions. The represents the internal energy under temperature and the change of internal energy. In the simulated annealing algorithm, the formula of internal energy represents the targeted optimized formula. Figure 3-1 shows how the simulated annealing algorithm iterates, finding the optimal solution for a given formula. Algorithm 1 shows how the SA algorithm works in code.

In Formula 1, "*p*" represents the probability of cooling, which signifies the decrease in temperature. The initial solution is randomly generated from the problem space. The cooling strategy determines the rate at which the temperature decreases during each iteration, typically employing exponential or linear cooling strategies. This gradual reduction in the probability of accepting worse solutions is a characteristic of simulated annealing. "E" represents the internal energy under temperature, while "ΔE" represents the change in internal energy. In the simulated annealing algorithm, the formula for internal energy represents the targeted optimization criterion. Figure 3-1 illustrates the iterative process of the simulated annealing algorithm in searching for the optimal solution for a given formula. Algorithm 1 provides a code representation of how the simulated annealing algorithm operates.

The algorithm consists of two iterations: the outer iteration and the inner iteration. The outer iteration decreases the temperature, while the inner iteration randomly finds the next solution within the neighborhood. When encountering a worse solution, the algorithm may accept it with a probability determined by the current temperature. Higher temperatures lead to a higher probability of accepting worse solutions, whereas cooler temperatures make the algorithm less likely to accept a worse solution. This behavior aligns with the micro procedure of annealing.

Algorithm 1: Simulated Annealing Algorithm

```
Input: x_0: initial solution,
       E: target function,
       t_max: maximum temperature,
       t_min: minimum temperature,
       d: cooling strategy,
       k: inner iteration times,
Output: x: optimal value for E(x);
Initialized Outer Iteration count K
let x_i = x_0, t_K = t_max
while t_K > t_min do
    repeat
        Randomly pick x_j from neighborhood N(x_i)
        Compute E = E(x_j) − E(x_i)
        if ΔE ≤ 0 then
            x_i = x_j
        else
            if exp(−ΔE/t_K) > Random(0,1) then
                x_i = x_j
            else
                Do Nothing!
    until reach given inner iteration times k;
    t_{K+1} = d(t_K)
    K = K + 1
return x_i
```

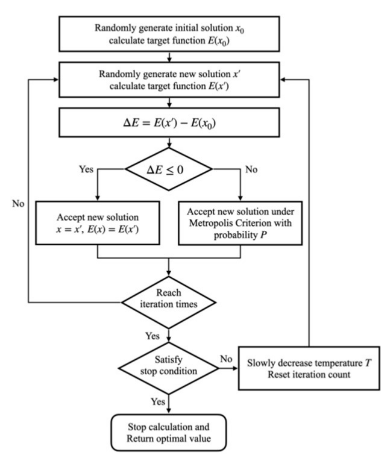

Fig. 1. The procedure of the SA Algorithm optimizing the target formula

IV. VERIFICATION OF IMPROVED SIMULATED ANNEALING SCHEME BASED ON WEIGHT ALLOCATION

A. Traditional calculation methods

There were 8 disaster areas and 2 rescue points for the distribution of emergency supplies tents in the 2008 Wenchuan earthquake. The raw data for supply distribution are shown in Table 1. The number of tents available for distribution in Chengdu and Xi'an rescue points is 710,000 and 30000, respectively.

Using the distribution of emergency supplies, specifically tents, during the 2008 Wenchuan earthquake as an illustration, there were eight disaster areas and two rescue points. Table 1 presents the raw data detailing the distribution of supplies. Specifically, the number of available tents for distribution at the Chengdu and Xi'an rescue points is 70,000 and 30,000, respectively.

Using a simulated annealing algorithm, two effective solutions were obtained. The objective function value of effective solution # 1 is Z10.297%, Z,=3.43h. The specific results are shown in Table 2. It can be seen that the allocation plan is to transport all the supplies from the Xi'an rescue point to the nearest disaster-stricken area, Qingchuan County. In contrast, the other disaster-stricken areas are supplied with emergency supplies from the Chengdu rescue point, and the supplies demand satisfaction rate tends to be at the same level. The objective function values of effective solution # 2 are Z=13668%, Z=3.93h. The specific results are shown in Table 3, which shows that the supply-demand satisfaction rate of each affected point has reached equilibrium.

In the referenced literature [Ref], the simulated annealing algorithm was employed to obtain two effective solutions. The objective function value for effective solution #1 is Z=10.297% and Z'=3.43h. The specific results are presented in Table 2. The allocation plan indicates that all supplies from the Xi'an rescue point are transported to the nearest disaster-stricken area, Qingchuan County. The remaining disaster-stricken areas receive emergency supplies from the Chengdu rescue point, resulting in a relatively balanced satisfaction rate for supply demand. For effective solution #2, the objective function values are Z=13668% and Z'=3.93h. The detailed results are displayed in Table 3, demonstrating that the supply-demand satisfaction rates for each affected location have reached equilibrium.

TABLE 1. RAW DATA FOR SUPPLIES ALLOCATION

Disaster Area	Tent Demand/Item	Total affected people/Number	Total missing people/Number	Delivery Time/h	
				Chengdu	Xian
Wenchuan county	18490	111935	7662	1.90	6.93
Mianzhu City	104940	515830	298	1.35	4.68
Qingchuan county	51810	253416	124	4.23	3.43
Dujiang Weir	128700	621980	429	0.88	5.82
Pengzhou City	160380	770749	676	0.85	5.03
Shifang City	73280	432579	214	1.15	4.83
Jiangyou City	177880	849761	44	2.40	3.93
Li County	14520	43668	29	3.05	10.12

B. Improved simulated annealing algorithm based on practical needs

The traditional simulated annealing algorithm, implemented using the method above, has successfully achieved on-demand allocation of emergency supplies. However, during the actual emergency supply scheduling process, it was observed that if the initial solution dimension of the simulated annealing method is too large, there is a higher probability of getting trapped in a locally optimal solution. The calculation results show that Xi'an has only been allocated to Qingchuan County and Jiangyou City. However, other counties and cities have not been allocated, which indicates an unreasonable outcome in the calculations.

This article introduces several improved simulated annealing algorithms for the given model:

(1) The initial solution can be adjusted dynamically based on the demand proportion, which helps accelerate the iteration speed and improve the overall calculation efficiency.

(2) Tents are allocated to the disaster areas in Chengdu and Xi'an based on the demand proportion relative to the initial solution.

(3) The calculation process considers different allocation factors based on the actual situation and the severity of the disaster, resulting in customized supply-demand configurations.

C. Method Comparison

（1）*Comparative explanation of method results*

Given the higher severity of missing people in Wenchuan County compared to other counties and cities, there is a greater need for tents in that area. Consequently, the weight assigned to Wenchuan County in the initial solution should be increased. Considering the actual situation, it is recommended that we set a weight coefficient of 1.45 for Wenchuan County.

disaster area			Actual allocation/top	Demand satisfaction rate/%	Latest delivery time/h
	Chengdu	Xi'an			
Wenchuan County	2626.26058	1125.54025	3751	0.202866414	1.9
Mianzhu City	9936.89508	4258.66932	14194	0.135258243	1.35
Qingchuan County	4905.95134	2102.55058	7007	0.135244161	4.23
Dujiangyan Irrigation Project	12186.7581	5222.89633	17408	0.135260295	0.88
pengzhou	15186.5755	6508.53235	21694	0.135266243	0.85
Shifang City	6938.97152	2973.84494	9911	0.135248362	1.15
Jiangyou City	16843.6716	7218.71639	24061	0.135265347	2.4
Lixian County	1374.9163	589.249843	1963	0.135192837	3.05
(Sum of integers)	69994	29995	integer	Z_1=0.135267772	Z_2=4.23

The iterative calculations prioritize the allocation of surplus tents to disaster areas with low demand satisfaction rates, and the obtained actual results are as follows.

disaster area	efficient solution#3 /item		Actual allocation/top	Demand satisfaction rate/%	Latest delivery time/h
	Chengdu	XiAn			
Wenchuan County	2626	1125	3751	0.202866414	1.9
Mianzhu City	9937	4258	14195	0.135267772	1.35
Qingchuan County	4906	2103	7009	0.135282764	4.23
Dujiangyan Irrigation Project	12186	5223	17409	0.135268065	0.88
pengzhou	15187	6508	21695	0.135272478	0.85
Shifang	6939	2974	9913	0.135275655	1.15
Jiangyou City	16844	7218	24062	0.135270969	2.4
Lixian County	1375	590	1965	0.135330579	3.05
(Sum of integers)	70000	30000	integer	Z_1=0.135267772	Z_2=4.23

V. CONCLUSION

This article addresses the challenge of allocating emergency supplies during the initial stages of earthquake disasters when resources are limited. It focuses on developing a model and algorithm that balances fairness and efficiency, considering the dynamic changes in emergency supply demand. Through theoretical analysis and numerical examples, the study draws the following conclusion: by constructing a dual objective model and algorithm that considers both fairness and efficiency, it is possible to obtain emergency supply allocation plans that cater to different preferences.

While this project has successfully developed an emergency supplies allocation model, it is imperative to consider the dynamics of road traffic during actual emergency command operations. Furthermore, for future supply scheduling and the subsequent allocation of resources, carefully considering real-time road traffic conditions becomes crucial to ensure an optimal and efficient distribution process.

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REFERENCES

[1] Haghani A, Oh S. Formulation and Solution of a Mufti-commodity, Mufti-modal Network Flow Model for Disaster Relief Operations. Transportation Research A: Policy and Practice, 1996, 30(3): 231-250.

[2] Yao S Y, Shih Y L. Optimal Scheduling of Emergency Roadway Repair and Subsequent Relief Distribution. Computers and Operations Research, 2009(36): 2049-2065.

[3] Ben-Tal A, Chung B D, Mandala S R, et al. Robust Optimization for Emergency Logistics Planning: Risk Mitigation in Humanitarian Relief Supply Chains. Transportation Research Part B: Methodological, 2011(45): 1177-1189.

[4] Mete H O, Zabinsky Z B. Stochastic Optimization of Medical Supply Location and Distribution in Disaster Management. Internarional Journal of Production Economics, 2010, 126(1): 76-84.

[5] Chi H, Li J, Shao X, et al. Timeliness Evaluation of Emergency Resource Scheduling. European Journal of Operational Research, 2017, 258(3): 1022-1032.

[6] Afshar A, Haghani A. Modeling Integrated Supply Chain Logistics in Real-time Large-scale Disaster Relief Operations. Socio-Economic Planning Sciences, 2012, 46(4): 327-338.

[7] Berkoune D, Renaud J, Rekik M, et al. Transportation in Disaster Response Operations. Socio-Economic Planning Sciences, 2012, 46(1): 23-32.

[8] Widener M J, Horner M W. A Hierarchical Approach to Modeling Hurricane Disaster Relief Goods Distribution. Journal of Transport Geography, 2011, 19(4): 821-828.

[9] Vitoriano B, Ortuno M T, Tirado G. A Multi-criteria Optimization Model for humanitarian Aid Distribution. Journal of Global Optimization, 2010, 51(2): 189-208.

[10] Hadiguna R A, Kamil I, Delati A, et al. Implementing a Web-based Decision Support System for Disaster Logistics: A Case Study of an Evacuation Location Assessment for Indonesia. International Journal of Disaster Risk Reduction, 2014(9): 38-47.

[11] José-Fernando Camacho-Vallejo, Edna González-Rodríguez, Almaguer F J, etal. A Bi-level Optimization Model for Aid Distribution after the Occurrence of a Disaster. Journal of Cleaner Production, 2015, 105: 134-145.

[12] Vanajakumari M, Kumar S, Gupta S. An Integrated Logistic Model for Predictable Disaster. Production and Operations Management, 2016, 25(5): 791-811.

[13] Knott R. Vehicle Routing for Emergency Relief Management: A Knowledge-based Approach. Disaster, 1988(12): 285-293.
[14] Equi L, Gallo G, Marziale S, et al. A combined Transportation and Scheduling Problem. European Journal of Operational Research, 1997, 97(1): 94 -104.
[15] Wael M E. Some Development in Transportation Network Analys is and Design with Application to Emergency Management Proble ms. Partial: North Carolina State University, 1998: 93-123.
[16] Thengvall B, Bard J F, Yu G. Balancing User Preferences for Airc raft Recovery during Airline Irregular Operations. IEEE Transacti onson Operations Engineering, 2000, 32(3): 181-193.
[17] Yu G, Arguello M, Song G, et al. A New Era for Crew Recovery a t Continental Airline. Interfaces, 2003, 33(1): 5-22.
[18] Özdamar L, Ekinc E, Küçükyazici B. Emergency Logistics Planni ng in Natural Disasters. Annals of Operations Research, 2004,129(1-4): 217-245.
[19] Fiedrich F, Gehabauer F, Rickers U. Optimized Resource Allocati on for Emergency Response after Earthquake Disasters. Safety Sci ence, 2000, 35 (1): 41-57.
[20] Sheu J B. Dynamic Relief-demand Management for Emergency L ogistics Operations under Large-scale Disasters. Transportation R esearch Part E: Logistics and Transportation Review, 2010, 46(1): 1-17.
[21] Zhang Guofu, Wang Yongqi, Su Zhaopin, et al Modeling and sol ving the multi-objective allocation and scheduling problem of eme rgency rescue supplies Control and Decision Making, 2017 (1): 86 -92
[22] Wang Haijun, Du Lijing, Hu Die, etc Emergency material distribu tion location routing problem under uncertain conditions Journal o f Systems Management, 2015, 24 (6): 828-834
[23] Shen Xiaobing, Yang Baohua Multi objective dynamic optimizati on of post earthquake emergency logistics system based on double layer intermodal transportation System Simulation Technology, 2 017, 13 (1): 28-33
[24] Liu Changshi, Peng Yi, Kou Gang Research on Fuzzy Location an d Path Problem of Emergency Material Distribution after an Earth quake Chinese Management Science, 2016, 24 (5): 111-118
[25] Chen Gang, Fu Jiangyue Research on multi-objective emergency material allocation problem that balances fairness and efficiency J ournal of Management, 2018, 15 (3): 459-466
[26] Oloruntoba R, Gray R. Customer Service in Emergency Relief Ch ains. International Journal of Physical Distribution and Logistics Management, 2009, 39(6): 486-505.