J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 3201--3218

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

Research on Calculation Model and Decision-Making Mechanism of Response Efficiency of the Whole Material Chain under Dynamic Multi-Objective Optimization

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ABSTRACT
Based on the material demand forecasting model using BP neural network and particle swarm algorithm, the study builds the material whole chain response efficiency calculation model under dynamic multi-objective optimization by comprehensively considering the demand level weights of the affected area, and adopts genetic algorithm to assist the model solution in finding the optimal and decision-making. Taking an earthquake as a case for example analysis, the model in this paper can give the Pareto frontier, and combined with the weight coefficients after the transformation of the model solving results are more scientific and feasible, the demand satisfaction rate of the original model and the transformed model are 73.43% and 74.28% respectively, and the demand satisfaction rate of the affected points is improved by 4.24%, and this paper introduces the material allocation model of the demand level weights to be able to obtain better response efficiency of the whole chain of materials, which can provide important theoretical and practical guidance for the whole chain distribution of materials.

Keywords: BP neural network, particle swarm algorithm, demand forecasting, whole-chain response efficiency, dynamic multi-objective optimization

1. Introduction

With the continuous intensification of market competition, the sales model centered on means of production is gradually replaced by the sales model centered on consumer demand, and enterprises must accelerate the response speed to changes in user demand and establish a rapid response supply chain management system [1-2]. This requires that enterprises should formulate supply chain management programs in a targeted manner according to their own product warehousing capacity, product sales in various regions and product after-sales situation [3]. While improving the economy,

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Received 15 April 2024; Revised 05 July 2024; Accepted 25 November 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-179

effectiveness and timeliness of supply chain management, simplifying the enterprise supply chain management process and reducing management costs, enhancing the synergistic benefits of the enterprise in supply chain management, so that the enterprise supply chain management can be based on the consumer's consumption behavior, and strengthening the conversion of production resources [4-5]. In view of this, the introduction of dynamic multi-objective optimization strategy for dynamic analysis of consumer behavior, aimed at improving the response speed of the enterprise supply chain. The establishment of material whole chain response efficiency calculation model and decision-making mechanism, so that it becomes the internal support to strengthen the competitiveness of enterprise development, brand competitiveness, for enterprises to better enhance the economic efficiency of supply chain management and control the cost of product sales time to create favorable conditions [6-7].

Zhang, D. et al. proposed a multi-objective optimization model for energy system considering demand response and dynamic pricing, which is able to analyze the characteristics of joint pricing of multiple subjects and develop dynamic price control strategies with more preferences of different stakeholders in order to improve the economy and reliability of energy system operation [8]. Hasani, A. et al. developed a robust multi-objective optimization model to configure a resilient supply chain network for a global medical device manufacturing system, which is able to respond to global customer demands in an agile and green way, and provide some reference for enterprises to formulate production and manufacturing strategies [9]. Fazli Besheli, S. et al. developed a fuzzy hybrid multi-objective planning model including cost, time, risk, and customer satisfaction for the multi-item multi-cycle problem in a multi-level supply chain and used a non-dominated sequential genetic algorithm to solve the optimal supply chain management strategy [10]. Paterakis, N. G. et al. investigated a power system reserve procurement mechanism incorporating demand-side resources and proposed a joint energy and reserve day-ahead market structure based on two-phase stochastic planning, with a multi-objective optimization model using conditional risk as a value metric to maximize environmental and economic benefits [11]. Mahmoodi, M. considered the production and supply of different stakeholders in the supply chain under stochastic demand in a competitive market and used this to establish a tri-objective model of supply chain network with cost, risk minimization and consideration of fluctuations in market demand and the constructed supply chain network exhibits the flexibility effect of market uncertainty [12]. Nooraie, V. et al. established a multi-objective and multi-cycle supply chain system design and operation scheme based on the conceptual model of SC responsiveness and used heuristic algorithms to solve a specific objective function to provide managers with a reference for decision making that is response oriented and has a low-risk and low-cost [13].

This paper adopts indirect prediction to design PSO-BP based material demand prediction model after selecting material demand prediction indexes by taking earthquake disaster relief as an example, and using PSO algorithm to optimize BP neural network. Based on this, the response efficiency of the whole chain of materials is measured by the minimum transportation time turnover of the distribution center and the maximum demand satisfaction rate of the disaster-stricken point, and the calculation model of the response efficiency of the whole chain of materials based on dynamic multi-objective optimization is constructed by taking into account the weights of the material demand levels. An example analysis is carried out in an earthquake context to predict the demand for the three kinds of materials set, solve the material distribution schemes of the original model and the weighted conversion model, and compare the distribution time and the demand satisfaction rate of each disaster-stricken point of the two schemes. The results of material distribution under different parameters and weighting coefficients are explored, and model validity verification and sensitivity analysis are carried out.

2. Material chain-wide response model under dynamic multi-objective optimization

In this paper, for the large amount of material demand generated in the disaster-stricken areas in the early post-disaster period, based on the disaster situation derived from the demand prediction model, we propose a material chain response efficiency calculation model and decision-making mechanism that takes into account the timeliness of material delivery and the rate of satisfaction of the demand of the disaster victims.

2.1. Materiel Requirements Forecasting Model

In this paper, the algorithm combining particle swarm algorithm and BP neural network is used to predict the casualty rate of the people in the disaster area, and then estimate the demand of various emergency supplies according to the quantitative relationship between the number of injured people, the number of survivors and the demand of different emergency supplies.

2.1.1. Predictors and sample set. Taking the whole chain response of materials in the early stage of a large earthquake as an example, based on the availability of data, a total of eight variables were selected as indicators affecting the demand for emergency materials, namely, the time of the earthquake, the magnitude of the earthquake, the intensity of the earthquake damage, the seismic intensity of the buildings, the collapse of housing, the affected population, the density of the population, and the level of the earthquake prediction.

By checking some official websites and information, a total of 25 sets of data were collected as the sample set for the study, which were all from earthquakes of magnitude 6 or higher.

2.1.2. Network structure of the model:

1) Determine the layers of the network. A three-layer BP neural network is used, i.e., it consists of an input layer, a hidden layer and an output layer, and the transfer function between the input layer and the hidden layer is an S-type function, and the transfer function between the hidden layer and the output layer is a linear function.The number of nodes in the input layer of the BP neural network is 8, the number of nodes in the output layer is 2, and the number of nodes in the hidden layer is set to 8.

2) Setting network parameters. Transfer function: In the problem of predicting the demand for materials, the transfer function between the input layer and the implied layer is the Tan-sigmoid function in the S-type function, and the transfer function between the implied layer and the output layer is the Purelin-type transfer function in the linear function.

Learning rate: After several training sessions, the final learning rate selected is 0.2.

Training function: traingdx function.

Expected error: 0.002.

2.1.3. Predictive modeling:

1) Parameter setting. The PSO algorithm is used to optimize its weights and thresholds in the error back propagation of BP neural network. In this paper, the mean square error (MSE) is used as the fitness function of the PSO algorithm in the following form:

$$MSE=\sum_{i=1}^{N}\sum_{j=1}^{M}\left(y_{ji}^{d}-y_{ji}\right)^{2}/N \tag{1}$$

where, N denotes the number of samples trained, y_{ji}^{d} denotes the desired output value of the j th network output node for the i rd sample, y_{ji} denotes the actual output value of the i th sample at the j th network output node, and m denotes the number of nodes in the output layer of the BP neural network.

The number of particles $N=50$ is selected and the dimension D of the solution space is: $D=(n+m)*h+h+m$, i.e., $D=101$, where n is the number of neuron input nodes, m is the number of output nodes, and h is the number of nodes in the hidden layer. The maximum number of iterations $T_{max}=1000$, the learning factors c_1 and c_2 are 1.0, and the inertia weight w is calculated as follows according to the linear decreasing weight strategy:

$$w = w_{\max} - (w_{\max} - w_{\min}) * t / T_{\max} \tag{2}$$

where $w_{\max}=0.9, w_{\min}=0.4$, t are the current number of iterations and the maximum limiting speed $V_{\max}=1$.

2) Optimization steps. Step 1: Initialize the PSO algorithm and BP neural network. The dimension of the whole search space in the particle swarm is the sum of all the weights and thresholds in the BP neural network. The position of the i th particle is shown in the following equation:

$$X_i = [x_{i1}, x_{i2}, ..., x_{iD}]^T = \begin{bmatrix} \omega_{11} & \dots & \omega_{nl} \\ \omega_{1m} & \dots & \omega_{lm} \\ \theta_1^1 & \dots & \theta_n^1 \\ \theta_1^2 & \dots & \theta_n^2 \end{bmatrix}^T \tag{3}$$

where, $\omega_{11},...,\omega_{nl}$ is the element of the weight matrix between the input layer node and the implied layer node. $\omega_{lm},...,\omega_{lm}$ is the element of the weight matrix between the implied layer node and the output layer node. $\theta_1^1,...,\theta_n^1$ is the element of the threshold matrix between the input layer node and the implied layer node. $\theta_1^2,...,\theta_n^2$ is the element of the threshold matrix between the implied layer node and the output layer node. The position x_{id}^{o} and velocity v_{id}^{o} of the particles are initialized according to Eq. A series of parameters such as the number of particles N, the maximum number of iterations T_{max}, the inertia weights w, the learning factors c_1 and c_2 are set up in the setup parameter stage.

Step 2: Calculate the fitness of the particle at this time, and record its position to find the individual and global optimal values of the current particle.

Step 3: Compare the fitness of the particle with the individual optimum and the global optimum. If the fitness of the particle is less than the individual optimum, then take the current value as the individual optimum. If the current global optimal value is greater than the individual optimal value of the particle swarm, then the global optimal value of the particle swarm is the individual optimal value.

Step 4: The optimal individual obtained by the PSO algorithm through updating the position and speed is taken as the initial weights and thresholds of the BP neural network to train the BP neural network, and when the network training reaches the maximum number of iterations or the mean squared error is lower than the desired error, the training is ended and the results are output, otherwise, it is forwarded to Step 2, and iterations are continued until the algorithm converges.

Step 5: Perform network testing and compare and analyze the results.

2.2. *Materiel chain-wide response efficiency calculation model*

2.2.1. Basic assumptions. The assumptions established for the model of calculating the response efficiency of the whole chain of supplies are as follows:

1) The amount of material reserve of each territorial distribution center, the transportation time from each territorial distribution center to each disaster site, and the situation of transportation vehicles are known.
2) The supply quantity of each distribution center is smaller than the demand quantity, and only all the supplies that the territory would have had are considered, without considering the sinking in of external resources.
3) Only the nearest distribution center is available for distribution at each disaster site, and the distribution distance is the shortest, but there are roads that have been damaged and cannot be distributed.
4) The demand for supplies at each disaster site can be derived from the prediction method described in 2.1.
5) Vehicles can return to the distribution center after transporting the supplies to receive the distribution task again, therefore, it is assumed that the number of vehicles is sufficient, each transport vehicle has the same capacity and load, and the transported supplies are packaged according to the standard unit, allowing for mixing.
6) The distribution of supplies does not consider the distribution cost and has a weak economy. And the transportation vehicles are only considered for one distribution, without considering the return empty truck transportation.
7) The minimum fulfillment rate can be derived from rescue experience and must be satisfied.
8) There is no flow of materials between the affected points and between distribution centers.

2.2.2. Description of symbols. The notation, parameters, and decision variables for modeling are described below:

$A=\{A_m \mid m=1,2,3\cdots M\}$ denotes the set of territorial material distribution centers.

$B=\{B_n \mid n=1,2,3\cdots N\}$ denotes the set of affected points.

$K=\{k \mid k=1,2,3\cdots k\}$ denotes the set of material types.

Y_{mnk} denotes the kth material transportation volume from the distribution center m to the disaster-stricken point n.

U_{mn} is a 0-1 variable indicating the road accessibility from distribution center m to the affected point n.

S_{mk} denotes the Kth supply of emergency supplies from distribution center m.

Q_{nk} denotes the demand of the Kth emergency material at the disaster site n.

λ_k indicates the minimum fulfillment rate of the Kth type of emergency supplies.

T_{mn} is the transportation time from distribution center m to disaster point n.

2.2.3. Model construction. The material whole chain response efficiency calculation model established in this paper is mainly allocated from the territorial distribution center, globally considering the time of distribution and transportation focusing on the rapid response of the territorial material and the maximization of the demand satisfaction of the disaster-stricken points. In the case of meeting the minimum material satisfaction rate of each disaster-stricken point, the timeliness and fairness of rescue are taken into account.

1) Objective function analysis. Minimum transportation time turnover of the distribution center. In the process of material distribution, by transporting a larger amount of materials in a shorter

transportation time, the distribution is more efficient and the time turnover is smaller. Based on the above analysis, the distribution center transportation time turnover minimum expression:

$$minZ_1 = \sum\sum\sum Y_{mnk} \cdot T_{mn} \cdot U_{mn} \tag{4}$$

Maximizing the rate of satisfaction of needs at the point of disaster. In addition to the time factor, the response efficiency of the whole chain of supplies must take into account the maximization of the rate of satisfaction of the emergency needs of the disaster-stricken points. The formula for maximizing the demand satisfaction rate at the disaster point:

$$maxZ_2 = \sum\sum\sum Y_{mnk} / \sum\sum Q_{nk} \tag{5}$$

2) Analysis of constraints. Distribution center material supply and demand conditions constraints. Distribution center to the affected point of transportation is less than the supply of the distribution center, the supply of the distribution center is less than the demand of the affected point, the constraints of supply and demand equation:

$$\sum_{n=1}^{N} Y_{mnk} \le S_{mk} \tag{6}$$

$$\sum_{m=1}^{M} S_{mk} \le \sum_{n=1}^{N} Q_{nk} \tag{7}$$

Constraints on the amount of material required at the disaster site. In order to avoid wasting resources and to rationalize the distribution, the constraints on the amount of material required at the disaster site are formulated:

$$\sum_{m-1}^{M} Y_{mk} \le Q_{nk} \tag{8}$$

Minimum Demand Satisfaction Rate Constraint. In order to balance the distributional equity and the effect of the whole chain response of materials, this paper sets the minimum demand satisfaction rate constraint formula:

$$\sum_{n=1}^{N} Y_{mnk} \ge \lambda_k Q_{nk} \tag{9}$$

Variable Constraints. Since the quantity of emergency supplies is non-negative, the k rd quantity of supplies to be transported from distribution center m to disaster point n is greater than or equal to zero, i.e., $Y_{mnk} \ge 0$. When it is equal to zero, it means that no supplies are distributed. Meanwhile, the damage of public infrastructure during the transportation of supplies can affect the distribution situation. Therefore, this paper defines U_{mn} as a 0-1 variable, when $U_{mn} = 0$ indicates that the road from distribution center m to disaster point n is open, and when $U_{mn} = 1$ indicates that the road from distribution center m to disaster point n is interrupted.

3) Modeling. Objective function:

$$minZ_1 = \sum\sum\sum Y_{mnk} \cdot T_{mn} \cdot U_{mn} \tag{10}$$

$$maxZ_2 = \sum\sum\sum Y_{mnk} / \sum\sum Q_{nk} \tag{11}$$

Constraints:

$$\sum_{n=1}^{N} Y_{mnk} \le S_{mk} (m = 1, 2, \cdots, M; k = 1, 2, \cdots, k) \tag{12}$$

$$\sum_{m=1}^{M} S_{mk} \leq \sum_{n=1}^{N} Q_{nk} (k=1,2,\cdots,k) \tag{13}$$

$$\sum_{m\text{-}1}^{M} Y_{mak} \leq Q_{nk} (n=1,2,\cdots,k; k=1,2,\cdots,k) \tag{14}$$

$$\sum_{n=1}^{N} Y_{mnk} \geq \lambda_k Q_{nk} (m=1,2,\cdots,M; k=1,2,\cdots,k) \tag{15}$$

$$Y_{mnk} \geq 0 \tag{16}$$

$$U_{mn} = 0 \text{ or } 1 \tag{17}$$

$$\forall m \in A, \forall n \in B, k \in K \tag{18}$$

Equation (10) indicates that the distribution center transportation time turnover is minimum.

Equation (11) indicates that the demand satisfaction rate at the affected point is maximum.

Equation (12) indicates that the actual transportation volume from the distribution center to the affected point is less than the supply volume of the distribution center.

Equation (13) indicates that the supply quantity of the distribution center is less than the demand quantity of the affected point.

Equation (14) indicates that the actual transportation volume from the distribution center to the affected point is less than the demand volume of the affected point.

Eq. (15) indicates that the emergency supplies that can be distributed to each disaster-stricken point are not less than the minimum demand of that place.

Equation (16) indicates that the number of decision variables Y_{mnk} is non-negative.

Equation (17) indicates that U_{mn} is 0-1 variable.

Eq. (18) indicates the set of local distribution centers, affected points, and types of emergency supplies.

2.2.4. Model conversion. In the aftermath of a disaster, the degree of urgency of material distribution varies from one disaster site to another, as the severity of the damage varies from one disaster site to another. For the disaster site with large personnel damage, it should be prioritized higher in the distribution of materials. This paper analyzes the factors affecting the disaster and derives the corresponding weight coefficients of each factor. Through the evaluation of the weight of the demand at the disaster-stricken point and the combination of satisfaction in order to optimize the distribution model, the converted model is as follows:

Objective function:

$$minZ_1 = \sum\sum\sum Y_{mnk} \cdot T_{mn} \cdot U_{mn} \tag{19}$$

$$\max Z_2 = \sum_{n=1}^{N} W_n \left(\sum_{m=1}^{M}\sum_{k=1}^{K} Y_{mnk} / \sum_{k=1}^{K} Q_{nk} \right), \text{among} \sum_{n=1}^{N} W_n = 1 \tag{20}$$

Constraints:

$$\sum_{n=1}^{N} Y_{mnk} \leq S_{mk} \tag{21}$$

$$\sum_{m=1}^{M} S_{mk} \leq \sum_{n=1}^{N} Q_{nk} \tag{22}$$

$$\sum_{m-1}^{M} Y_{\text{mak}} \leq Q_{nk} \tag{23}$$

$$\sum_{n=1}^{N} Y_{mnk} \geq \lambda_k Q_{nk} \tag{24}$$

$$Y_{mnk} \geq 0 \tag{25}$$

$$U_{mn} = 0 \text{ or } 1 \tag{26}$$

$$\forall m \in A, \forall n \in B, k \in K \tag{27}$$

2.3. Model decision-making methods

A genetic algorithm is a probabilistic heuristic algorithm that applies the natural laws of biological evolution to the solution process. In this section, genetic algorithms are applied to solve a model for calculating the response efficiency of a full chain of materials as an aid in decision making for selecting the ideal solution from a set of non-dominated solutions.

The basic principle of the genetic algorithm can be stated as follows: store the potential solutions of the problem into a chromosome in an encoding such as binary or decimal, each chromosome is a solution, and calculate the fitness of each chromosome, which is usually related to the objective function. Then a certain number of chromosomes will form a population, and within the population, selection, crossover and other operations will be carried out in a certain way and with a certain probability to generate new chromosomes, and calculate their fitness. According to the fitness value, the "survival of the fittest" elimination mechanism is carried out, and a new population is formed. The cycle repeats until a certain termination condition is reached, and the best individual in the optimal population is the "optimal chromosome". The chromosome is decoded and the resulting solution is the "optimal solution".

In this paper's model for calculating the response efficiency of the whole chain of supplies, the main task is to make a relatively fair allocation of supplies based on the demand at the disaster site d_j, the quantity of supplies in reserve a_i, the degree of disaster r, the minimum fulfillment rate e, and the degree of dependence on the supplies w_j, etc., and the variable that needs to be used for decision-making is the actual allocation quantity c_i.

2.3.1. Coding. Real-valued coding operations are used in this section. Chromosome $X = [x(1)x(2)\dots x(n)]$, where n is the number of affected points, $x(i)$ denotes the distribution of supplies, which is a positive integer with a range of values determined by the joint determination of the demand d_j of the affected points, the stock of supplies a_i, the minimum guarantee rate e, and the length of the chromosome $V = n$.

2.3.2. Initial population generation. The populations are initialized using a random generation method where the number of chromosomes in each population is determined by the population size $sizepop$. The generation of initial populations can be roughly divided into two steps:

Step 1: Generate the material allocation $X_i = [x(1)x(2)\dots x(n)]$ for each affected point according to the pre-designed allocation amount calculation program.

Step 2: Determine whether the allocation amount of each affected point conforms to the maximum-minimum value constraint. If it meets, retain the chromosome and proceed to the next iteration until it reaches $sizepop$. Otherwise, return to Step 1 and continue the initial allocation operation until a new feasible solution is generated.

2.3.3. Adaptation function. In the algorithm, the evaluation index of the chromosome is the fitness. The criterion for designing the fitness function is that it is sufficient to be suitable for the problem under study on the basis of satisfying the basic conditions of the fitness function. The fitness is usually determined by the optimization objective and constraints.

$$fitness = Z_1 = \sum (f_j - \min_{j \in J}(f_j)) \tag{28}$$

Smaller values indicate better quality of feasible solutions obtained.

2.3.4. Genetic manipulation:

1) Selection. Use the roulette method method for selection operations. Notice that a small value of $fitness$, the better the quality of the chromosome, cannot be directly applied to roulette. Therefore, let $fitnessl = 1/(1+fitness)$ be the fitness of the individual in the selection operator.

2) Crossover. Chromosome $X_i = [x(1)x(2)...x(n)]$ is encoded with real values. In order to make some information of the parent chromosome conserved, simulated binary crossover (SBX) is used. The formula is shown below:

$$X_1^k = 0.5*[(1-\alpha_j)*X_1^{'} + (1+\alpha_j)X_2^{'}] \tag{29}$$

$$X_2^k = 0.5*[(1+\alpha_j)*X_1^{'} + (1-\alpha_j)X_2^{'}] \tag{30}$$

where X_1^k, X_2^k denotes cross newly generated individuals, $X_1^{'}, X_2^{'}$ denotes randomly selected individuals, and α_j is given by Equation (31):

$$\alpha_j = \begin{cases} (2*u(j))^{\frac{1}{(m+1)}} & 0 \le u(j) \le 0.5 \\ \{2*(1-u(j))\}^{\frac{-1}{(m+1)}} & 0.5 \le u(j) \le 1 \end{cases} \tag{31}$$

where $u(j)$ denotes the generated random number between [0, 1]. mu is the distribution index, which is taken as $mu = 5$ in this section.

3) Variation. In order to avoid falling into local optimization, real-valued variance is chosen, and the formula is calculated as:

$$X_j = X_j^{'} + \partial_j \tag{32}$$

The solution rule for ∂_j is shown in Eq. (33):

$$\partial_j = \begin{cases} (2*r(j))^{\frac{1}{(m+1)}} - 1 & 0 \le r(j) < 0.5 \\ 1 - \{2*(1-r(j))\}^{\frac{1}{(m+1)}} & 0.5 \le r(j) \le 1 \end{cases} \tag{33}$$

where r_i is a random number between [0, 1].

2.3.5. Law of termination. Each iteration produces a new population, so the optimal individual may also change. In this paper, the optimal individual $bestchrom$ is recorded. When a new population is generated, the fitness of $newbestchrom$ and $bestchrom$ in the contemporary population is compared, and the individual with the smallest value is taken as $bestchrom$ in the current iteration, and so on until the termination law is met, and $bestchrom$ is output.

The termination rule for the upper model is the maximum number of iterations rule. The algorithm terminates when the set number of iterations is reached.

3. Example solution results and analysis

3.1. Scene description

This study takes an earthquake as a case background, obtains relevant data by finding relevant news reports, literature and other information, and simulates the arithmetic example in combination with the actual situation, which does not affect the validity and practical significance of the model.

This example takes the distribution of three kinds of emergency supplies as an example, and designs the information on the reserve quantity of the three kinds of emergency supplies stored in the five territorial supply points, the actual transportation distance to the five disaster-affected points, the number of vehicles owned, and the capacity and load of each vehicle, as well as the information on the unit loading and unloading and handling time, the volume and weight of each unit, and the minimum demand fulfillment rate of the three kinds of supplies, respectively. Based on the projected demand at the disaster-stricken points and the amount of materials in reserve at the supply points, a scientific and reasonable distribution plan is formulated to realize the full-chain response of materials and minimize the losses in the disaster-stricken areas.

3.2. Model solving

3.2.1. Forecast of material requirements. The trained PSO-BP neural network is applied to predict the injured population and estimate the emergency material demand based on the number of injured. The results of injury population prediction and material demand prediction at the affected sites are shown in Fig. 1. The number of injured people in the affected points 1~5 is 156~1795, and the total demand of emergency supplies A, B, and C is 6357, 5413, and 9061 units, respectively.

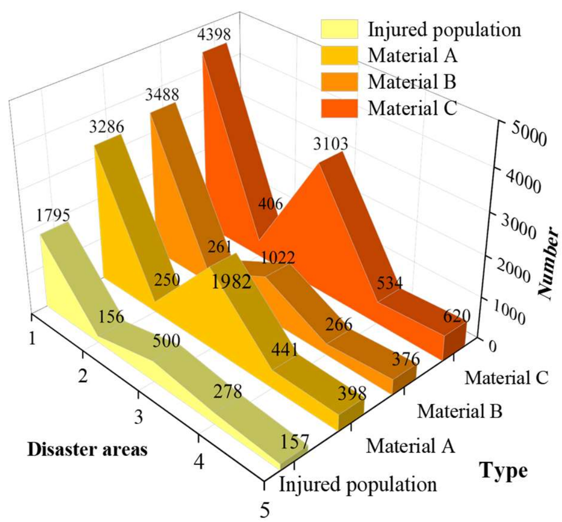


Fig. 1. Forecast results of injured population and materials in disaster areas

3.2.2. Materiel chain-wide response program:

1) Material allocation model solving. The genetic algorithm is used to solve the model, and the code is written in MATLAB b2021a to solve the Pareto frontier of the territorial emergency material allocation model (noted as Model 1) with the objective of maximizing the response efficiency of the whole chain of materials as shown in Fig. 2. According to the fuzzy compromise method to select the compromise optimal solution from the Pareto frontier, the solution result of Model 1 is obtained. Figures 3-Figure 5 show the distribution schemes of the three kinds of emergency supplies solved. A total of 2,568, 183, 1,542, 284 and 319 units of material A are obtained from the disaster-stricken point 1 to disaster-stricken point 5, and it can be obtained that the demand fulfillment rate of

material A at each disaster-stricken point is 78.15%, 73.20%, 77.30%, 71.20% and 75.13%, respectively, which are in line with the minimum demand fulfillment rate of 50%. Similarly, the demand fulfillment rate of Material B at each disaster site is 89.91%, 91.19%, 91.59%, 92.86%, and 90.16%, respectively, which meets the minimum demand fulfillment rate of 60%. The demand fulfillment rates for Material C are 54.43%, 53.45%, 53.24%, 54.49%, and 55.16%, respectively, all of which meet the 40% minimum demand fulfillment rate. Model 1 solves for a distribution scenario with a total material delivery time of 48.52 hours and an average material demand response rate of 73.43% across the five affected sites.

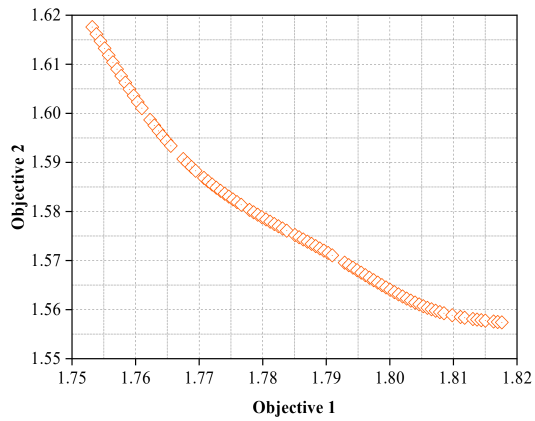


Fig. 2. Pareto solution set of model 1

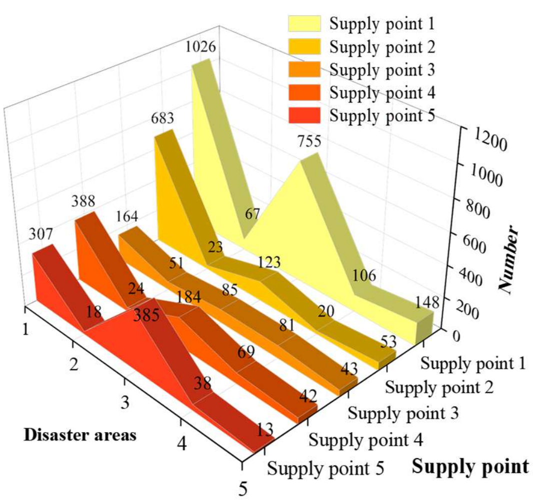


Fig. 3. Results of model 1(material A)

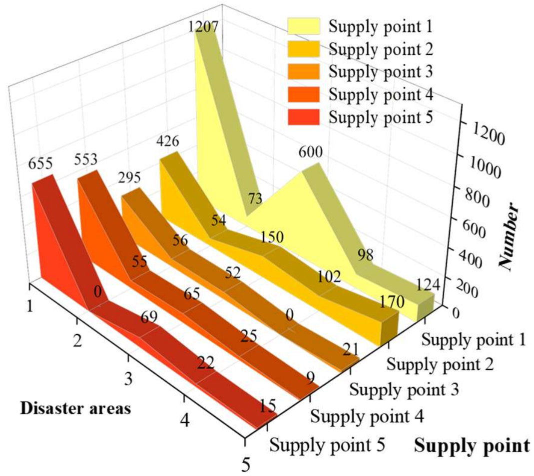


Fig. 4. Results of model 1(material B)

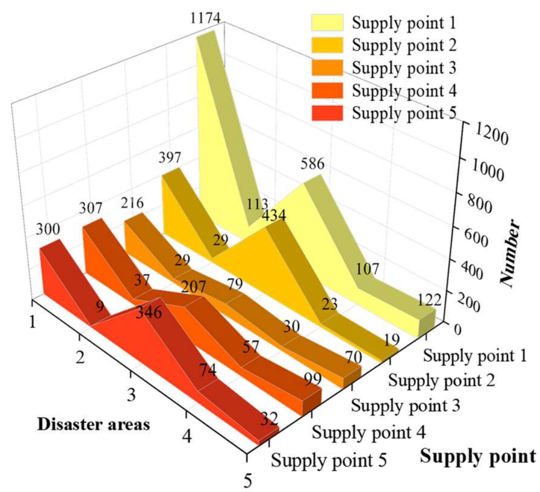


Fig. 5. Results of model 1(material C)

2) Transformed material allocation model solving. The Pareto frontier of the territorial emergency material allocation model (denoted as Model 2), which is solved to maximize the response efficiency of the whole chain of weighted materials at the disaster site, is shown in Figure 6. Selecting the compromise optimal solution from the Pareto frontier, the solution results of Model 2 are shown in Fig. 7-Fig. 9. The demand fulfillment rate of material A at each disaster site is 77.24%, 74.80%, 78.00%, 72.11% and 77.14%, respectively, and the demand fulfillment rate of material B at each disaster site is 88.93%, 92.34%, 92.37%, 93.61% and 92.82%, respectively. The demand fulfillment rate of material C at each disaster site is 53.52%, 61.33%, 54.14%, 50.19% and 55.65%, respectively. In addition, the distribution plan solved by Model 2 has a total delivery time of 47.88 hours and an average demand satisfaction rate of 74.28% for the five affected sites.

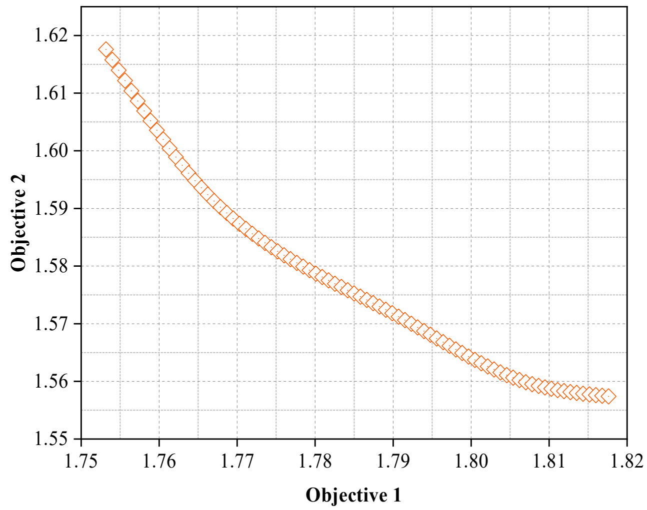


Fig. 6. Pareto solution set of model 2

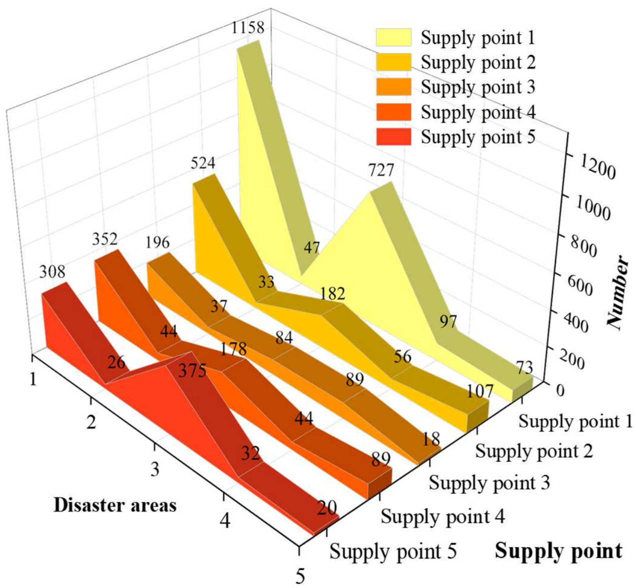


Fig. 7. Results of model 2(material A)

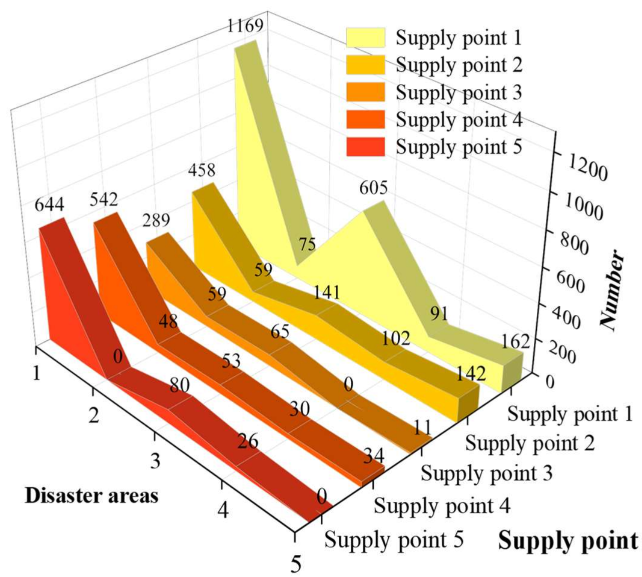


Fig. 8. Results of model 3(material B)

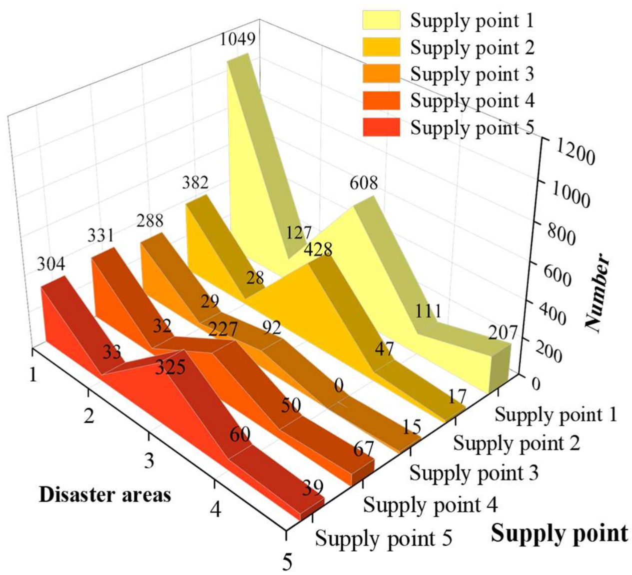


Fig. 9. Results of model 4(material C)

3.2.3. Comparative analysis of program results. Comparison of the demand satisfaction rate at each disaster site between Model 1 and Model 2 solution is shown in Table 1. Comparing the results of the above two allocation schemes, it can be seen that for the allocation scheme solved by Model 1, the total time for material distribution is 48.52 hours, and the average demand satisfaction rate is 73.43%, and for the allocation scheme solved by Model 2, the total time for material distribution is 47.88 hours, and the weighted demand satisfaction rate is 74.28%, and the total time of Model 2 is 0.64 hours less than that of Model 1, and the overall demand satisfaction rate of materials at the disaster sites can be seen that Model 2 has a better effect on improving the efficiency of the whole chain response of materials. The total time of model 2 is 0.64 hours less than that of model 1, and the material demand satisfaction rate of the disaster-stricken points is increased by 4.24%. It can be seen that model 2 has a better optimization effect on improving the response efficiency of the whole chain of materials, which indicates that the material distribution scheme considering the weight of each disaster-stricken point's demand level is more scientific and reasonable, and it takes into account the timeliness and at the same time improves the utility of the emergency materials.

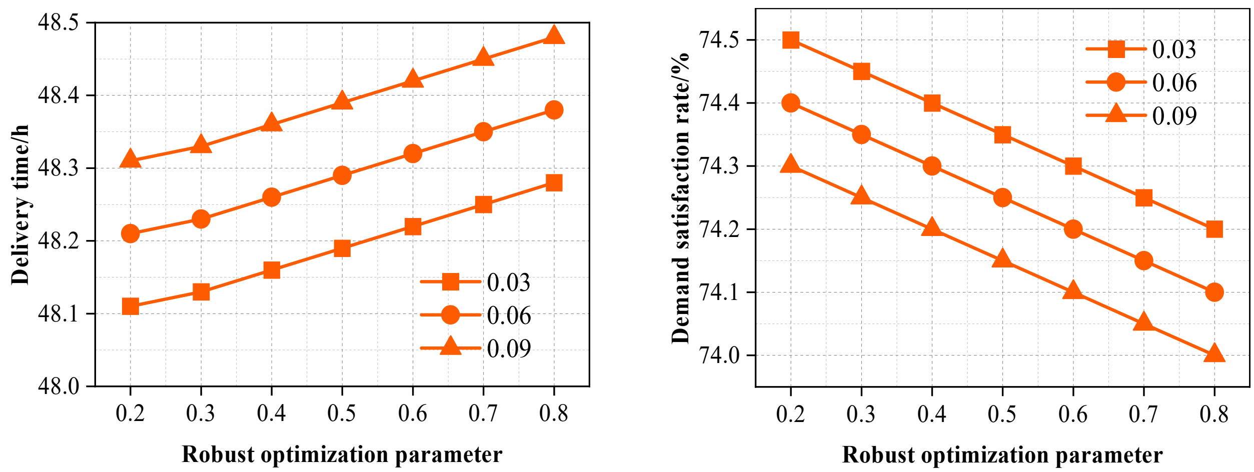
Table 1. The comparison of demand satisfaction rate in model 1 and model 2

Disaster areas	1	2	3	4	5
Demand grade weight	0.227	0.350	0.120	0.138	0.165
Ranking of weights	2	1	5	4	3
Model 1	74.16%	72.61%	74.04%	72.85%	73.48%
Model 2	73.23%	76.16%	74.84%	71.97%	75.20%
Change	-0.93%	3.54%	0.80%	-0.88%	1.72%

3.3. Model validity analysis

The model is solved under different robust optimization parameters, the perturbation proportion coefficients are taken as 0.03, 0.06 and 0.09, and the robust optimization parameters are taken as 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8. The results of the whole-chain response of the materials under different optimization parameters are shown in Fig. 10, and Fig. (a) and Fig. (b) are the distribution time and the demand satisfaction rate, respectively, which are obtained by the model. The larger the perturbation ratio coefficient is, the larger the total distribution time is, and the lower the demand satisfaction rate is. When the perturbation coefficient is 0.09, the demand satisfaction rate decreases from 74.3% to 74.0% with the increase of parameters. This indicates that the greater the demand in the disaster area, the greater the shortage of relief materials, and the longer the required distribution time. As the robust optimization parameters increase, the total distribution time increases and the demand satisfaction rate decreases, but the overall deviation is not large, and the distribution time range remains between 48.0h and 48.5h. This indicates that when the degree of information about the disaster situation is higher, the optimality of the whole chain distribution scheme of materials is higher. On the contrary, when the degree of mastery of disaster information is lower, the formulation of the whole-chain material distribution plan will be more conservative, and the optimality will be reduced. Therefore, the optimality and robustness of the model should be coordinated by weighing the degree of disaster information.

Through the above analysis, it is proved that the model can well realize the set objective function, i.e., to ensure the satisfaction of the material demand while minimizing the distribution time. The model can realize fast and accurate emergency response, and can get scientific and reasonable emergency material distribution scheme in the actual emergency rescue, improve the response efficiency of the whole chain of emergency materials, and achieve the rescue effect.



(a)Delivery time (b)Demand satisfaction rate

Fig. 10. The whole chain response of the different optimization parameters

3.4. Sensitivity analysis

In addition, the importance that the decision maker attaches to each objective function can be evaluated by calculating its corresponding weight coefficient. For example, in the pre-dispatch period, the demand satisfaction rate is the most important, and a certain time delay is acceptable, in which case the value of the weighting coefficient can be set to a smaller value. In this section, the corresponding values of the weight coefficients are changed to re-solve the emergency material distribution optimization scheme based on the multi-objective function. The values of each objective function under different weight coefficients are shown in Fig. 11, and there is a big gap between the final objective values of the emergency material distribution scheme with different values of weight coefficients. When the value of the weight coefficient is small, the solution result of the demand satisfaction rate of the disaster site is better, and the demand satisfaction rate is 0.744 when the weight coefficient is 0.1, and when the value of the weight coefficient is large, the solution result of the total time turnover of the material transportation is better, and the time turnover of the transportation time is 48.05 h when the weight coefficient is 0.9. In summary, the solution of the emergency material distribution program should be combined with the real situation of the disaster area, and the weight coefficient is 0.9. The weighting coefficients of all objective functions are clarified to ensure that the solved emergency material distribution program is consistent with the purpose of the actual emergency rescue operation.

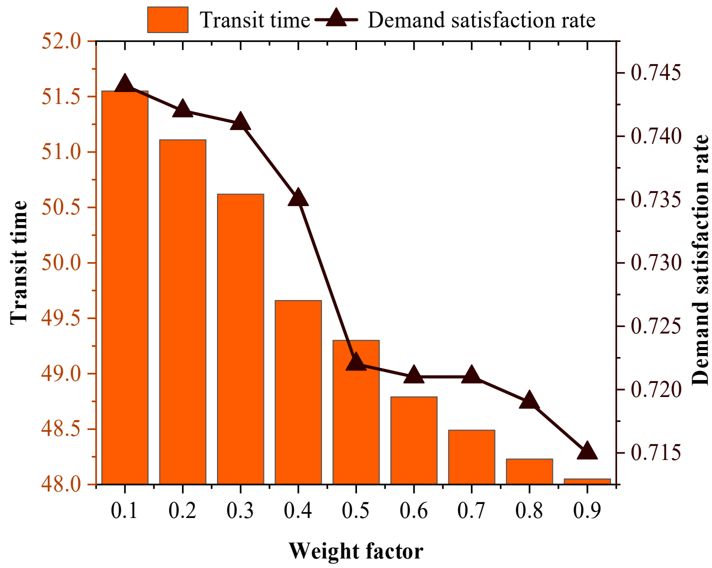


Fig. 11. The values of each target function under different weights

4. Conclusion

In this paper, we start from the distribution of materials for disaster emergency assistance, establish PSO-BP model to predict the demand for materials, construct a dynamic multi-objective optimization-based model for calculating the response efficiency of the whole chain of materials, and use genetic algorithm to solve the model. An example analysis is carried out with an earthquake as the background to analyze the constructed multi-objective optimization model. Comparing the results of the original model and the transformed model, the total material distribution time of the former and the latter are 48.52h and 47.88h, and the demand satisfaction rate is 73.43% and 74.28%, respectively, and the demand satisfaction rate of each affected point is increased by 4.24% after the transformation, which indicates that the computational model of this paper, which takes into consideration of the weight of the demand of the affected point, can improve the response efficiency of the whole chain of materials more effectively. Efficiency. The results of emergency supplies distribution under different robust optimization parameters are analyzed to verify the feasibility and effectiveness of the model. The weight coefficients of the model are proportional to the efficiency of material transportation and inversely proportional to the demand satisfaction rate, and the weight coefficients can be adjusted according to the actual situation. In order to better simulate the actual material full-chain distribution problem, future research can be further improved and perfected in the following aspects: (1) Consider the transportation cost problem. (2) Consider the material attributes and capacity constraint problem. (3) Explore the problem of multiple round trips for material distribution under the premise of meeting the timeliness requirements.

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