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Research Article

An Improved PSO Algorithm for Optimized Material Scheduling in Emergency Relief

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Efficient emergency material dispatch, amid the aftermath of an emergency event, can help control the spread of the disaster and reduce disaster losses. Herewith, we propose a model with the urgency of material demand as the target coefficient, and the minimum load time and the minimum transportation cost as the total cost. For this model, an improved particle swarm optimization (PSO) algorithm is proposed as the means to optimize the initial positions of particles with good point sets and improve the convergence speed with adaptive dynamic weights to improve the optimization of the emergency material dispatch model. In order to verify the effectiveness of the proposed model and algorithm improvement strategy, the experimental results are verified by means of simulation experiments and algorithm comparison experiments, which show that the proposed emergency material dispatch model and the improved PSO algorithm cannot only solve the post-disaster relief material distribution and dispatching problem but also effectively reduce the total cost of emergency material dispatching.

1. Introduction

In recent years, natural disasters, social security incidents, public health threats, and safety production emergencies have occurred frequently around the world, posing a serious threat to people's lives and property [1]. Events such as the Wenchuan earthquake in China in 2008 [2], the earthquake and tsunami in Japan in 2011 [3], the fires in Australia in 2019 [4], and the global COVID-19 epidemic in 2020 [5] occurred suddenly, and each of these disasters caused huge losses to people and socioeconomics around the world [6]. Therefore, when a disaster occurs, efficient emergency material relief is an important role in controlling the spread of the disaster and reducing disaster losses [7]. Accordingly, the question of how to reasonably dispatch disaster relief materials has become a popular topic of research.

To effectively improve the efficiency of material dispatch, one of the key issues is to find a suitable set of mapping function tasks to achieve specific optimization goals, such as minimum loading time and minimum transportation cost consumption. The material dispatch task in disaster relief refers to the reasonable material dispatch allocation between different distribution centers and relief points, with the aim of reducing the time and cost consumption to achieve an optimal material dispatch solution. However, in reality, it is not enough to consider only the cost of timeliness but also the urgency of the need for supplies at the rescue point, giving priority to rescue points with high urgency so that the disaster can be contained as quickly as possible. Therefore, this requires a balance between the cost of time and the cost of material dispatch according to the urgency of the actual relief point so that the sum of the two costs is minimized. However, the emergency material scheduling problem is considered to be an NP-hard (nondeterministic polynomial hard) problem.

Because material dispatch in disaster relief is an NP-hard problem, it is difficult for existing algorithms to find the most optimal solution [8]. We therefore need a heuristic strategy that can quickly obtain the relative optimal solution. There are many heuristic algorithms for solving emergency material scheduling, and particle swarm optimization (PSO) is a very popular meta-heuristic in solving material scheduling optimization problems [9]. Compared with other heuristics, particle algorithms have clear mathematical methods, few control parameters, and low complexity and can converge to the optimal solution with satisfactory probability in complex environments [10]. We therefore believe that the PSO algorithm is more advantageous for material scheduling optimization problems.

However, the basic PSO algorithm has some drawbacks for material scheduling solutions. On the one hand, PSO is initialized with randomly generated population of particles (initial swarm), and the inadequate distribution of the initial swarms in the search region will not only weaken the global optimal solution identification performance when solving in multidimensional space but will also directly impact the algorithm stability [11]. On the other hand, the PSO algorithm is prone to fall into local optima due to constant inertial weights or random changes when dealing with complex problems such as material scheduling [12]. To overcome the shortcomings of the PSO algorithm, an improved PSO algorithm is proposed, which first optimizes the initial swarm by the good point set technique to improve the robustness of the algorithm. Then, the adaptive function is applied to dynamically set the inertial weights to enhance the convergence of the algorithm.

Since most of the models do not consider the urgency of material demand in the process of emergency material scheduling, the PSO algorithm has the problem of poor stability and easy to fall into the local optimum when solving the emergency material scheduling; therefore, the following contributions are made in this paper:

(1) In order to prioritize the rescue points with high urgency and meet the minimum time cost and transportation cost so as to contain the disaster situation as soon as possible, an emergency material dispatch model that minimizes the time spent and the cost for material transportation by weighting the urgency of material demand is proposed.

(2) Facing the problem of emergency material scheduling, a new improvement strategy is proposed to improve the performance of the PSO algorithm, i.e., optimizing the initial state of particles with the good point set technique and optimizing the local search ability by setting the inertia weights with the adaptive function, so that the PSO algorithm can better handle the problem.

(3) Through the experimental verification of simulation data, the experimental results show that the improved PSO proposed in this paper can significantly improve the convergence speed and accuracy of the algorithm when dealing with emergency material scheduling.

The rest of this paper is organized as follows. Section 2 discusses the related work. Section 3 introduces the material scheduling model, and Section 4 describes the improved PSO algorithm. Section 5 describes the simulation experiments and the analysis of the experimental results. The conclusions are presented in Section 6.

2. Related Work

Most of the current research efforts meant to resolve the problems inherent with emergency resource scheduling employ operation research methods and computer simulation methods to develop models with different objectives and design reasonable algorithms to optimize the solution of the material scheduling model. We will analyze the literature from the aspects of emergency material dispatch model establishment and algorithm design.

2.1. Material Movement Model. Emergency material dispatch should focus first on time and model with the goal of minimum delivery time or minimum transportation time. Hu et al. [13] constructed a dynamic dispatch optimization model for emergency supplies with the goal of shortest dispatch time and lowest cost. Liu and Qian [14] considered a rescue dispatch model for the purpose of shortest time and highest fairness in the case of multiple supply stations, relief stations, commodities, and transportation modes. This enhances the fairness of rescue dispatching, especially for disaster areas with small demand. Sheu and Pan [15] proposed a multiobjective model to establish the shortest path for vehicle travel in order to meet the shortest delivery time and material demand. Wang et al. [16] proposed a cooperative approach to correct the supply-demand imbalance in post-disaster relief by first identifying potential relief suppliers using a clustering mechanism. Then, a stochastic dynamic programming model is developed that minimizes the impact of the imbalance between relief supply and demand. Decision makers can choose from the available relief measures and decide the amount and type of relief to be sent to the disaster area. To reduce the complexity of solving the multiobjective model, Akbari and Salman [17] proposed a multiobjective nonlinear integer programming method in which the decision maker can assign weights to multiple objectives, allowing the multiobjective to be transformed into a single-objective solution.

2.2. Optimization Algorithm. Because emergency material scheduling is an NP-hard problem, scholars have shifted their research on such problems from the past exact algorithm solutions to the present heuristic algorithm solutions [18]. Several modern heuristic algorithms such as genetic algorithm, ant colony optimization (ACO) algorithm, PSO algorithm, and simulated annealing algorithm, [19], have been developed in order to resolve the material scheduling problem. However, compared to other heuristics, PSO algorithms are robust and stable but also simple. They are also better at solving difficult and complex optimization problems [20]. Ghasemi et al. [21] designed the binary particle swarm optimization algorithm and continuous particle swarm optimization algorithm to deal with emergency material deployment plans with different decisions, which is better than genetic algorithm and Pareto evolutionary algorithm (PEA) with higher solution accuracy. Hu et al. [13] designed the MPSO algorithm to solve the model, which not only allows emergency supplies to be delivered to the accident site within the specified time but also avoids unnecessary waste. Pervaiz et al. [22] proposed an uncertain multiobjective planning model, which was applied to a real case study in Tehran and solved using modified multi-objective particle swarm optimization (MMOPSO) algorithm. The results showed that the MMOPSO algorithm has greater superiority over the epsilon constraint method and the non-dominated sequential genetic algorithm (NSGA-II).

2.3. Literature Summary. For emergency material dispatch models, most of the literature has considered modeling with the goal of meeting minimum time, minimum cost, minimum distance, or maximum satisfaction. However, few have considered the urgency of material requirements. Most of the literature on optimization of multiobjective models is using a linear weighting method, which makes the multi-objective model turn into a single-objective model. However, the weighting of the target coefficients is subjectively decided by the decision maker and lacks scientific objectivity. Here, we propose to linearly weight the load time and transportation cost by the urgency of the material demand, which transforms the multiobjective into a single-objective emergency material dispatch model and avoids the subjectivity of the target coefficient assignment.

For emergency material scheduling solution, it can be seen from most of the literature that the PSO algorithm has superiority in solving scheduling optimization problems. However, the PSO algorithm has a low fault tolerance, and the optimization results cannot meet the requirements of each distribution, which easily falls into local optimization [23]. Also, PSO algorithms usually construct initial values randomly, so there is an uneven distribution of initial particles, which may lead to uneven solutions [24]. Here, we propose an improvement to the PSO algorithm by first constructing uniformly distributed initialized particles using the good point set technique and then dynamically setting the inertial weights using an adaptive function, thereby improving the search effect and convergence speed of the algorithm.

3. Emergency Material Dispatch Model Establishment

3.1. Problem Description. When an unexpected event occurs, the disaster area may fall into a shortage of supplies at any time, which requires the support of a material distribution center to provide relief supplies to the disaster area. Let n relief points $D_1, D_2, \ldots, D_n$ have an urgent need for supplies, and there are m material distribution centers to provide emergency supplies: $P_1, P_2, \ldots, P_m$, and each material distribution center can provide z kinds of supplies as $R_1, R_2, \ldots, R_z$. Now, assume that B_{yj} denotes the demand for y materials at relief point j and A_{yi} denotes the storage quantity of the yth material in distribution center i. Thus, the conditions are satisfied: $1 \le i \le m$, , $1 \le j \le n$, , and $1 \le y \le z$ as shown in Figure 1. It is necessary to give an optimal solution to the rescue-material dispatch scheme with the minimum loading time and minimum transportation consumption cost as the optimization objective in disaster rescue.

3.2. Urgency of Material Needs. The entropy weighting method is a relatively objective method for determining weights and has a high degree of confidence in the decision results [25]. We therefore use the entropy weighting method to determine the urgency values of demand for different materials at each demand point. The specific steps are as follows:

Step 1: establish a matrix of indicators based on the need for different materials at different relief points.

If$n$disaster points$D_1, D_2, \ldots, D_n$have different demand for$z$kinds of supplies$R_1, R_2 \ldots, R_z$, there are $p = n * z$kinds of needs. Thus, the set of p demands is $Y = \{y_1, y_2, \cdots y_p\}$, and each demand in the set has q impact factor indicators. Let the b-influencing ($b = 1, 2, \cdots q$) factor indicator for demand a ($a = 1, 2, \cdots p$) be y_{ab}, whereby the indicator data matrix Y is as follows:

$$Y = (y_{ab})_{p\times q} \begin{bmatrix} & y_{11} & y_{12} & \\ & y_{21} & y_{22} & \\ & & \cdots & y_{1q} \\ & & \cdots & y_{2q} \\ \vdots & \vdots & \vdots & \vdots \\ y_{p1} & y_{p2} & \cdots & y_{pq} \end{bmatrix}. \tag{1}$$

Step 2: normalize operations on data.

Because each impact factor indicator has a different scale, data standardization is required, as follows:

$$y^*_{ab} = \frac{y_{ab} - \min\{y_{1b}, \ldots, y_{qb,}\}}{\max\{y_{1b}, \ldots, y_{qb,}\} - \min\{y_{1b}, \ldots, y_{qb,}\}}, \tag{2}$$

where y^*_{ab} is the normalized value of the data.

Step 3: normalize the index matrix.

$$G = \frac{y^*_{ab}}{\sum_a^p y^*_{ab}}, a = 1, 2, \ldots, p; b = 1, 2, \ldots, q, \tag{3}$$

$$G = (g_{ab})_{p\times q} = \begin{bmatrix} & g_{11} & g_{12} & \\ & g_{21} & g_{22} & \\ & & \cdots & g_{1q} \\ & & \cdots & g_{2q} \\ \vdots & \vdots & \vdots & \vdots \\ g_{p1} & g_{p2} & \cdots & g_{pq} \end{bmatrix}. \tag{4}$$

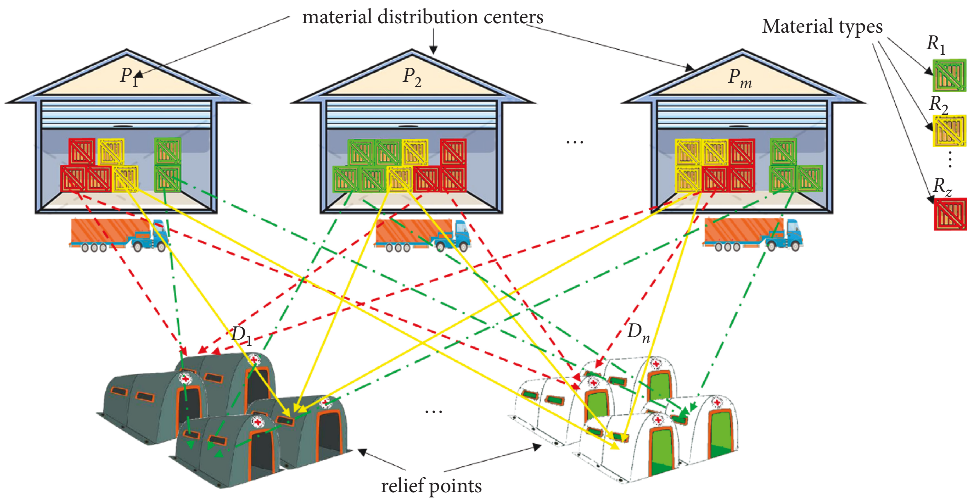

Figure 1: Multidepot dispatch of relief materials network.

Step 4: calculate the entropy value; e_b is the entropy value of the b index.

$$e_b = -\left(\frac{1}{\ln(p)}\right)\sum_{a}^{p} g_{ab}\ln(g_{ab}), b = 1, 2, \ldots, q. \quad (5)$$

Step 5: calculate the weight of each indicator β_b as follows:

$$\beta_b = \frac{1 - e_b}{q - \sum_{a=1}^{q} e_b}, b = 1, 2, \ldots, q. \quad (6)$$

Step 6: determine the urgency of demand for different materials at different relief points.

The weighted summation is applied in order to calculate the demand urgency composite score F_i as follows:

$$F_a = \sum_{b=1}^{q} \alpha_b \times g_{ab}, a = 1, 2, \ldots, p, \quad (7)$$

$$\gamma_a = \frac{F_a}{F_{\min}}, a = 1, 2, \ldots, p, \quad (8)$$

where γ_a is the demand urgency of a.

3.3. Construction of Emergency Material Dispatch Model Based on Demand Urgency. The model is established so as to optimize the material loading time and transportation cost as follows:

$$\min T(x) = \sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{y=1}^{z} x_{yij} t_{yi}, \quad (9)$$

$$\min W(x) = \sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{y=1}^{z} x_{yij} C_{ij}, \quad (10)$$

subject to

$$\sum_{i=1}^{m} A_{yi} \geq \sum_{j=1}^{n} B_{yj}; y = 1, 2, \ldots z; m = 1, 2, \ldots, i; n = 1, 2, \ldots, j, \quad (11)$$

$$\sum_{j=1}^{n} x_{yij} \leq A_{yi}; y = 1, 2, \ldots, z; n = 1, 2, \ldots, j, \quad (12)$$

$$\sum_{i=1}^{m} x_{yij} \leq B_{yj}; y = 1, 2, ; \ldots z; m = 1, 2, \ldots, i, \quad (13)$$

where equations (9) and (10) indicate the cost of loading time and transportation consumption cost, respectively. x_{yij} indicates the amount of y material transported from material distribution center i to the relief point j, t_{yi} indicates the unit amount of time used to load y material from material distribution center i, and C_{ij} indicates the cost consumed to transport the unit amount from material distribution center i to the relief point j. Equation (11) indicates that the sum of the storage of y materials at all material distribution centers is not less than the sum of the demand for y materials at all relief points. A_{yi} denotes the storage of y materials at material distribution center i, and B_{yj} denotes the demand for y materials at j relief points. Equation (12) indicates that the total amount of material y shipped out of distribution center i cannot be greater than the total amount of material y stored in i. Equation (13) indicates that the sum of all y materials shipped to the relief point j is not greater than the demand for y materials at the relief point j.

This paper proposes to transform the above multi-objective function into a single-objective function with the urgency of material demand as the weighting factor. From the practical point of view of emergency supplies, the weight value of loading time should be greater than the weight value of transportation consumption, and the sum of the weight value of loading time and the weight value of transportation consumption should be 1, which leads to the following:

$$\min f(x) = \varphi \sum_{j=1}^{n} \sum_{i=1}^{m} \sum_{y=1}^{z} x_{yij} t_{yi} \left(\gamma_{jy}/2\right) + \sum_{j=1}^{n} \sum_{i=1}^{m} \sum_{y=1}^{z} x_{yij} C_{ij} \left(1 - \gamma_{jy}/2\right). \quad (14)$$

Equation (14) represents the total cost of material loading time and material transportation consumption. φ is the coefficient of material loading time so that time as part of the consumption cost; γ_{jy} is the material-demand urgency value at the relief point j for y.

4. Improved PSO Algorithm

This section focuses on the question of how to improve the PSO algorithm using the good point set technique and adaptive functions so as to more effectively solve the emergency material scheduling problem. First, we introduce the basic theory of the PSO algorithm and the description of solving the emergency material scheduling problem with the PSO algorithm. Second, we introduce the theory of good point set and adaptive function, and on the basis of mathematical model transformation, we explain how to construct uniformly distributed particle swarms in multi-dimensional space by means of the cyclotomic field method in good point set theory as well as how to set inertial weights dynamically using adaptive function. Finally, the process of the improved PSO algorithm is illustrated with pseudo-code.

4.1. PSO Algorithm Based on Emergency Material Scheduling

4.1.1. PSO Algorithm. The PSO algorithm is an intelligent optimization algorithm based on the population activity designed by studying the predatory behavior of a flock of birds [26]. The basic idea of the PSO algorithm is that the population search process is completed by the velocity and direction of motion of the particles, while the position of the optimal particle is continuously updated. The PSO algorithm optimization can be viewed as the process of searching for the optimal position of N particles in D-dimensional space. Thus, the particle i position in D-dimensional space is represented as $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$, the velocity of particle i is denoted as $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$, the best position visited by the particle is called *p-best*, which is denoted as $p\mathrm{best}_i = (\mathrm{pbest}_{i1}, \mathrm{pbest}_{i2}, \ldots, \mathrm{pbest}_{iD})$, and the best position occupied by the particle swarm in the global is called *g-best*, which is denoted as $\mathrm{gbest}_i = (\mathrm{gbest}_{i1}, \mathrm{gbest}_{i2}, \ldots, \mathrm{gbest}_{iD})$. The d-dimensional $(1 \le d \le D)$ velocity and position of particle i at moment $t+1$ are updated by the following equations:

$$v_{id}^{t+1} = \omega v_{id}^{t} + c_1 r_1 \left(\mathrm{pbest}_{id}^{t} - x_{id}^{t}\right) + c_2 r_2 \left(\mathrm{gbest}_{id}^{t} - x_{id}^{kt}\right), \quad (15)$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1}. \quad (16)$$

In Equation (15), c_1 and c_2 are learning factors, usually 2, r_1 and r_2 are random numbers in the range (0, 1), and ω is the inertial weight.

		P_1	P_2	…	P_m
D_1	R_1	21.26	28.72	…	36.85
	…	…	…	…	…
	R_z	22.45	30.74	…	18.32
⋮	⋮	⋮	⋮	⋮	⋮
D_n	R_1	15.89	20.96	…	8.51
	…	…	…	…	…
	R_z	27.92	35.34	…	12.38

FIGURE 2: Solution description.

4.1.2. Solution Description. A solution for emergency material dispatch is a matrix consisting of $n \times z$ rows (n, the affected point; z, the number of species of material) and m columns (m, the number of material support points). The values of each cell are within the corresponding constraints, and the overall matrix represents the solution for dispatching different supplies from existing support points to each demand point. Figure 2 depicts an example of the emergency supplies dispatching solution. PSO-based emergency material dispatch can be described as follows: a particle represents a solution, and each cell in Figure 2 represents the value of the particle in different dimensions. The total cost of emergency material dispatch is the objective function of the particle algorithm, and the ultimate goal is to find the dispatching solution with a minimum of overall cost.

Figure 2 shows that the emergency material dispatching is a multidimensional problem solving. When using the traditional PSO algorithm to resolve the problem, because the initial particles are randomly generated, it will lead to extremely uneven distribution of particles on the multidimensional space, so that it is difficult to discover its own best position and the best position of the swarm. Moreover, because each particle determines its own direction based on its own historical best position and the historical best position of the domain, when the search environment becomes complex and has a large number of local optima, if the particles cannot be adjusted according to their own situation, it is easy to fall into the local optimal solution, which affects the search results and convergence speed.

4.2. Improvement Strategies of PSO Algorithm.

An improved PSO algorithm is proposed for solving the model. The main idea can be described as follows: firstly, the initial distribution of the particle swarm is optimized by the good point set, thus improving the PSO search effect; secondly, adaptive dynamic functions are used to set the inertial weights to optimize the iterative process, which makes the convergence effect to be improved.

4.2.1. Initialization Based on Good Point Set. The principle of good point set is as follows: set G_s is a unit cube in S-dimensional Euclidean space, if $r \in G_s$, whereby the point set in G_s can be expressed as

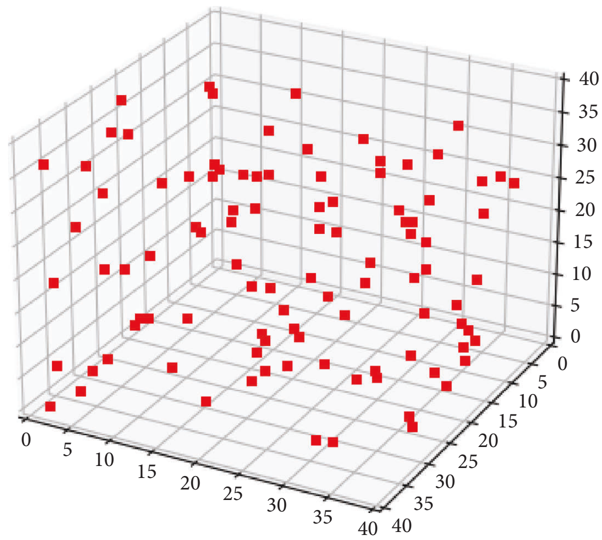

Figure 3: Randomly distributed n data points.

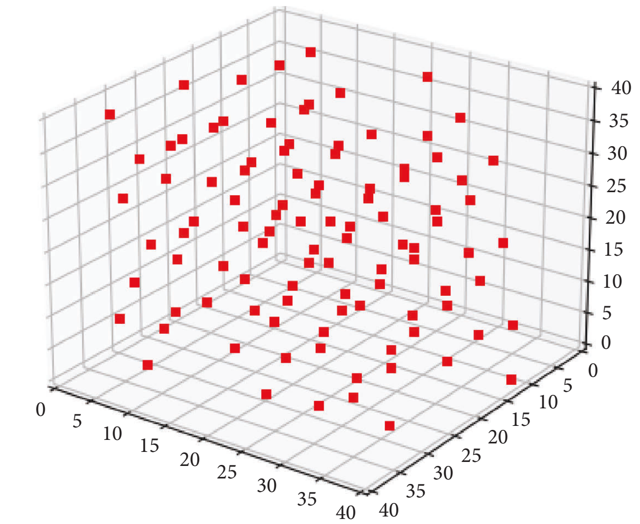

Figure 4: n data points distributed in good-point set cyclotomic field method.

$$p_n(k) = \left\{\left(\left\{r_1^{(n)} \cdot k\right\}, \left\{r_2^{(n)} \cdot k\right\}, \ldots, \left\{r_s^{(n)} \cdot k\right\}\right), 1 \le k \le n\right\}. \tag{17}$$

Suppose the deviation $\varphi(n)$ of $p_n(k)$ satisfies $\varphi(n) = C(r,\varepsilon)n^{-1+\varepsilon}$, then $p_n(k)$ is considered as the good point set, where $C(r,\varepsilon)$ is a constant related to r and ε and $\varepsilon > 0$.

The above theorem proves that for point set objects possessing n unknown distributions, the results obtained using good point sets are significantly better than those obtained by random methods [27]. Moreover, for the deviation, $\varphi(n)$ is only related to n, independent of the spatial dimensionality of the sample so that the good point set can better support the computation of high-dimensional spaces [28]. Due to this feature of the good point set, it can provide a better initial distribution scheme for the PSO algorithm.

The method of good point set PSO is that assume the initial PSO algorithm with the number of n; choose n points in the s-dimensional space as the initial position of the particles. In this paper, we use cyclotomic field method to find r, which is expressed as $r = \{2\cos(2\pi\mu/p), 1 \le \mu \le s\}$, when p satisfies $(p-3)/2 \ge s$ the smallest prime number, then r is the good point. All points in Equation (17) are uniformly distributed in the interval [0, 1], and if these points are distributed in the range $[lb, ub]$, then the expression is

$$x_i(j) = \left(ub_j - lb_j\right) \cdot \left\{r_j^{(i)} \cdot k\right\} + lb_j. \tag{18}$$

In Equation (18), ub_j and lb_j denote the upper and lower bounds of j dimensions.

Let $s = 3$ and $n = 100$ and construct a good set of points in the range (0 to 40) (initial PSO distribution). Figures 3 and 4 show the distribution of data points under random conditions and when applying the circle tangent method, respectively.

The comparison between the above application theorem and Figures 3 and 4 shows that for n particle objects with unknown distribution, the particle points obtained using these particle point deviations $\varphi(n)$ are more uniformly distributed than those obtained by the random method. Therefore, this property of the good point set can provide a better initial allocation scheme for the particle swarm distribution in the PSO algorithm, which will result in better coverage of the solution space in the process of devising a global particle solution. Moreover, the allocation effect of the good point set is invariant when n is constant, and consequently the good point set can provide a more stable initial swarm allocation scheme for the PSO algorithm.

4.2.2. Inertial Weights. Inertial weights are generally used to maintain the balance of local and global search capabilities, which are key factors affecting the search results and convergence speed [29]. In order to overcome the problem of slow convergence and local optimality of the PSO algorithm in complex search environment, the inertial weights in the PSO algorithm are adaptively changed. Therefore, in this paper, the inertial weights are improved with reference to literature [30] by dynamically setting the inertial weights with the objective function values [30], which are expressed as follows:

$$w = w_{\max} - \left(w_{\max} - w_{\min}\right) \times \frac{f - f_{\min}}{f_{avg} - f_{\min}}, if\ f_{avg} \ge f, \tag{19}$$

$$w = w_{\max}, if, f_{avg} < f. \tag{20}$$

In the above equation, $w_{\max}$ is the maximum inertial weight, $w_{\min}$ is the minimum inertial weight, f is the value of the objective function for the current iteration, $f_{\min}$ is the minimum value of the objective function, and f_{avg} is the average value of the objective function.

By applying the theory, it is proved that the inertial weight value is set dynamically for the objective function. Moreover, when the value of the objective function in the

Table 1: The pseudo-code of the GP-APSO algorithm for emergency material scheduling.

Improved PSO emergency material scheduling algorithm
Initialization: the number of particles is N, the dimension is s, $\mathbf{s} = \mathbf{n} \times \mathbf{z} \times \mathbf{m}$, number of demand points n, number of material types z, number of material support points m. initialize particle:
(1) Uniformly distribute n particles in s-dimensional space according to the set of good points
(2) According to equation (18) so that the particles are mapped to the range of equations (11)–(13)
(3) Randomly generated initial particle velocity in a specified range
(4) While termination condition is not satisfied, do
Calculation of adaptation values to determine p-best and g-best:
(5) For each particle
(6) Calculate fitness value
(7) If the fitness is not a feasible solution
(8) Penalize with an extreme value
(9) If the fitness value is better than the best fitness value (p-best) in history
(10) Set the current value as the new p-best
(11) End
(12) Choose the particle with the best fitness of all the particles as the g-best
Update particle weights, positions, and velocities:
(13) For each particle
(14) Calculate particle weight according to
If $f_{avg} \geq f$
$w = w_{\max} - (w_{\max} - w_{\min}) \times (f - f_{\min})/(f_{avg} - f_{\min})$
If $f_{avg} < f$
$\mathbf{w} = \mathbf{w_{max}}$
(15) The particle positions and velocities are updated according to equations (15) and (16)
(16) End
End while

current iteration is larger than the average value of the objective function, the inertial weight value is the maximum value, which increases the global search ability. When the value of the objective function is smaller than the average value of the objective function, the inertial weight value is adjusted downward according to the feedback from the swarm search, which makes the local search ability increase. This dynamic setting of inertial weights for the objective function is more helpful to improve the robustness and convergence of the algorithm when dealing with complex problems that is the constant or random setting of inertial weights.

4.3. Improved PSO Algorithm. We propose an improved PSO algorithm as the means to resolve the problems inherent with emergency material scheduling by initializing the particles with a uniform distribution of good point sets and applying an adaptive function to dynamically set the inertial weights, which we call GP-APSO. The pseudo-code of the GP-APSO algorithm for emergency material scheduling is shown in Table 1.

5. Simulation Experiments and Evaluation

5.1. Description of the Simulation Data Set. In order to validate the models, the data are constructed with reference to Literature [17] to develop many-to-many emergency material dispatch simulation data. Assume that after an unexpected event, there are two relief points D_1 and D_2 and there are three emergency supplies R_1, R_2, and R_3. There are five emergency material distribution centers $P_1, P_2, \ldots, P_5$ which can provide these three emergency supplies, at which the simulation data model dimension is $s = 2 \times 3 \times 5 = 30$. Here, the emergency supplies are in quantity, such as food (unit: ton/quantity) and medicine (unit: ton/quantity). Thus, the quantity of various materials available at emergency material distribution centers and the quantity of emergency materials demanded by relief points are shown Table 2.

Assume the unit transportation volume cost c (unit: 1,000 dollars) and the unit loading time t (unit: minutes) of various materials for material distribution centers to the relief point as shown Table 3.

The urgency of demand γ for different materials at different relief points is calculated according to equations (1–8) as shown Table 4.

5.2. Model Solving. The objective function is established with Equation (14) and simulation data, and the coefficient of material loading time is set to $\varphi = 1$. Under WIN10 environment, the GP-APSO algorithm proposed in this paper is executed in MATLAB2019B to solve the emergency material scheduling. After testing, we finally set the maximum number of iterations to 1000, the number of particles is $N = 50$, $w_{min} = 0.4$, $w_{max} = 0.9$, and $c_1 = c_2 = 2$, and the average value of the objective function is 444.64 after the program is run 30 times. The distribution of the optimal solution is shown in Figure 5. It can be seen that the solution obtained by the algorithm each time is close to the average value and has great stability.

The optimal allocation scheme is obtained by taking a set of optimal solutions close to the mean value, as shown in Table 5 and Figure 6.

Table 2: The number of supplies provided by the emergency supplies distribution center and the number of supplies needed at the relief point.

	P_1	P_2	P_3	P_4	P_5	D_1	D_2
R_1	42	38	26	30	28	48	42
R_2	28	32	0	40	18	26	52
R_3	0	18	36	22	40	36	28

Table 3: Unit transportation cost and the unit loading time of various materials in emergency material distribution center.

	P_1	P_2	P_3	P_4	P_5
D_1	3	5	2	6	7
D_2	4	7	5	3	2
R_1	2	1	1.5	0.5	1.6
R_2	1	1	0.6	2.2	1.5
R_3	1.2	0.8	1.2	1.5	1

Table 4: Information on the demand for different materials at different relief points.

	Material requirements (tons)	Inadequate supply of material life hazard level	Degree of material irreplaceability	Tightness factor γ
D_1R_1	48	3	5	1.0654
D_2R_1	42	3	5	1.0000
D_1R_2	26	5	7	1.1597
D_2R_2	52	5	7	1.4430
D_1R_3	36	7	6	1.5406
D_2R_3	28	7	6	1.4534

*annotation: the range of the degree of life-threatening and non-substitutable levels of undersupply is [0–10].

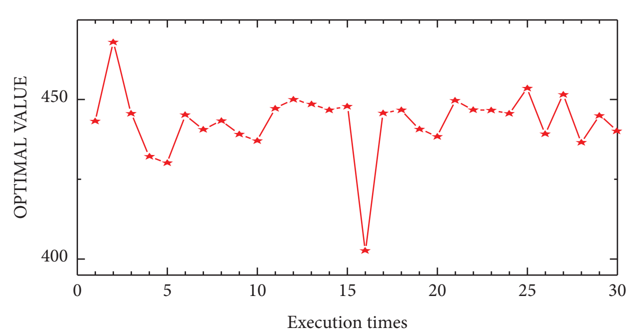

Figure 5: The distribution diagram of optimal solutions.

Table 5: The amount of emergency supplies allocated from material distribution centers to relief points.

		P_1	P_2	P_3	P_4	P_5
D_1	R_1	23.83	0.00	24.21	0.00	0.00
	R_2	0.00	0.00	0.00	12.60	13.54
	R_3	0.00	6.06	30.00	0.00	0.00
D_2	R_1	0.00	0.00	0.00	30.00	12.22
	R_2	26.15	26.06	0.00	0.00	0.00
	R_3	0.00	0.00	0.00	0.00	28.00

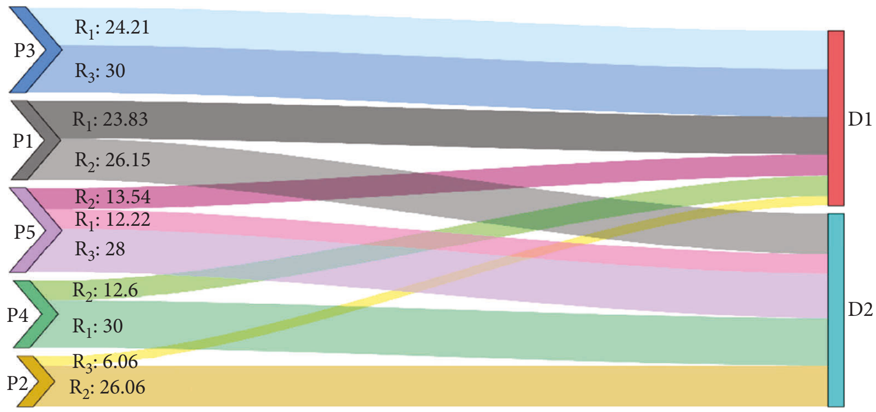

FIGURE 6: Finding the optimal value of emergency material scheduling scheme with GP-APSO algorithm.

As shown in Table 5, the emergency material dispatching scheme for which the GP-APSO solution yields the optimal solution of 399.63, and Figure 6 shows the dispatching of different supplies between the material distribution center and the rescue point under this scheme.

5.3. Performance Analysis of the Improved PSO Algorithm. To investigate the optimization performance of the GP-APSO algorithm herewith proposed in the emergency material dispatch model, the GP-APSO algorithm, the particle swarm optimization (PSO) algorithm, the PSO algorithm based on the good point set (GP-PSO), the PSO algorithm with adaptive dynamic inertial weights (APSO), the differential evolution (DE) algorithm, Literature [31]'s JADE algorithm [31], and genetic algorithm (GA), respectively, were solved 30 times and compared in terms of convergence, robustness, and statistical analysis. The parameters for setting the DE, JADE, and GA algorithms with reference to Literature [31] and [12] are shown in Table 6.

TABLE 6: The parameter setting strategies of the compared algorithms.

Algorithm	Parameter settings
GP-APSO	$N=50,\ w_{\min}=0.4, w_{\max}=0.9,\ c_1=c_2=2$
PSO	$N=50,\ w_{\min}=0.4, w_{\max}=0.9,\ c_1=c_2=2$
GP-PSO	$N=50,\ w_{\min}=0.4,\ w_{\max}=0.9,\ c_1=c_2=2$
APSO	$N=50,\ w_{\min}=0.4,\ w_{\max}=0.9,\ c_1=c_2=2$
DE	$N=50,\ F=0.6,\ \mathrm{Cr}=0.9$
JADE	$N=50,\ P=0.05,\ C=0.1,\ F=0.5,\ Cr=0.9$
GA	$N=50,\ Pc=0.6,\ Pm=0.01$

*annotation: F is the scaling factor, Cr is the crossover probability, P is the degree of greediness that determines the variation strategy, C is the rate of adapting the control parameters, P_c is the crossover probability, and P_m is the variation probability.

5.3.1. Convergence Analysis. As shown in Figure 7, the GP-APSO algorithm significantly outperforms several other algorithms in terms of convergence accuracy. The particle distribution of the good point set optimization covers almost all local optimal solutions of the function. Then, by introducing a dynamic adaptive inertial weight setting strategy, each particle is able to perform a better local search. Because the swarm diversity is improved, the ability to jump out of the local optimum is enhanced and the search process presents a continuous optimization; the algorithm can generally avoid the risk of falling into the local optimum.

In terms of convergence speed, calculate the time complexity of the algorithm with reference to Literature [10].

$$O(t)=\sum_{i=1}^{n} M_i \times T_i, \tag{21}$$

where: the parameter M_i denotes the number of iterations when the particles converge to the optimum, T_i denotes the time required for each particle to iterate once, and n denotes the size of the initial swarm. For different algorithm improvement strategies, the size of the initial swarm is basically an order of magnitude, whereby the difference in the time complexity of these algorithms is generally determined by M_i and T_i.

For the GP-APSO algorithm, it can be seen from Figure 7 and Equation (21) that the state of the initial swarm optimized with the good point set is superior to the PSO algorithm without the good point set. The initial swarm distribution obtained from the good point set covers almost all optimal solutions, and the excellent initial swarm state can reduce the number of redundant iteration steps by direction guidance. Thus, the time complexity can be improved on the basis of the reduction of M_i. The adaptive dynamic inertial weights enable each particle to find a high-quality solution with a faster convergence speed. Thus, the time complexity can be improved on the basis of the reduction of T_i. This shows that the convergence of the GP-APSO algorithm is faster than that of other algorithms.

Additionally, the standard deviation bars are shown in Figure 7. These are the standard deviation values of the adaptation values for each algorithm on the corresponding number of iterations. Furthermore, the shorter standard deviation bars indicate that the standard deviation values are smaller, which also indicates the good stability of the algorithm. As shown in Figure 7, using the good point set as the initial swarm provides better operational stability than the PSO algorithm without the good point set, and the standard deviation of the GP-APSO algorithm still has a

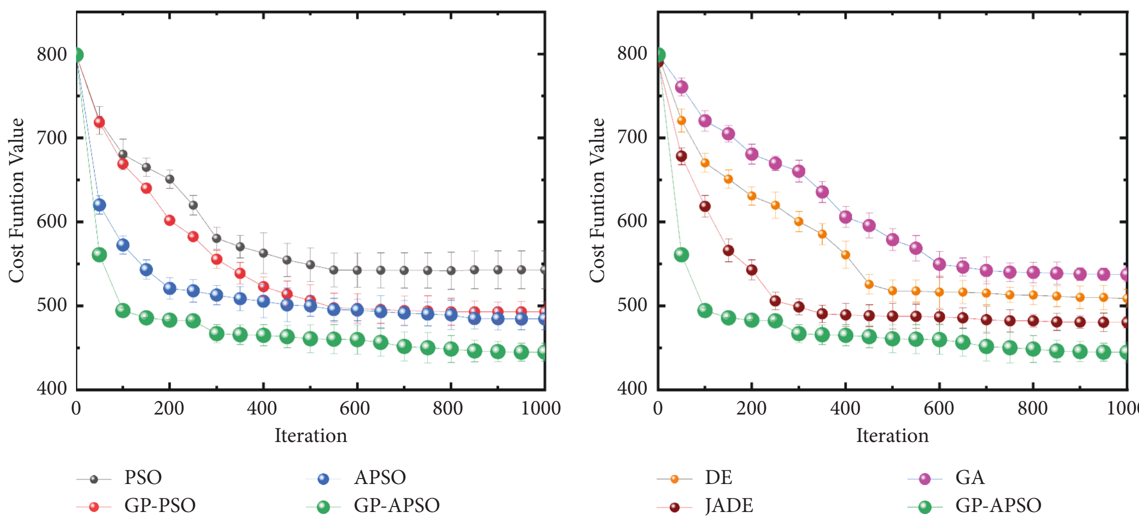

Figure 7: Mean convergence curves of the test.

Table 7: The value of R and the SD of 30 independent experiments.

	GP-APSO	PSO	APSO	GP-PSO	DE	JADE	GA
Mean	444.64	542.76	484.28	492.73	508.63	480.23	537.28
SD	10.24	16.29	14.35	11.56	13.81	11.47	15.29
R (%)	10.12	21.11	16.33	13.21	16.37	12.58	18.34

Table 8: Wilcoxon signed ranks test results.

Algorithm	$\mathbf{R}^+$	$\mathbf{R}^-$	p value	$\alpha = 0.05$	$\alpha = 0.1$
GP-APSO vs. PSO	402	63	0.027627	Yes	Yes
GP-APSO vs. APSO	370	95	0.092663	No	Yes
GP-APSO vs. GP-PSO	386	79	0.079244	No	Yes
GP-APSO vs. DE	392	73	0.036532	Yes	Yes
GP-APSO vs. JADE	408	57	0.001729	Yes	Yes
GP-APSO vs. GA	411	54	0.006782	Yes	Yes

*annotation: the symbol "$R+$" means the sum of ranks for the problems in which the first algorithm outperformed the second, and the "$R-$" means the sum of ranks for the opposite.

significant advantage even in comparison to the DE and JADE algorithms. This demonstrates the good applicability and stability of the GP-APSO algorithm in dealing with the complex optimization problem of emergency material scheduling.

5.3.2. Robustness Analysis. In this paper, the stability of the algorithm is determined by the standard deviation values of multiple experimental results and the proposed R (stability of the optimal solution) in the literature [27], where R is calculated as follows:

$$R = \frac{AC^* - AC'}{AC^*} \times 100\%, \tag{22}$$

where AC' is the minimum optimal solution obtained by operating the algorithm many times and AC^* is the average of the optimal solutions obtained by operating the algorithm many times. The smaller the value is, the higher the robustness of the algorithm will be.

As shown in Table 7, the average value of material-scheduling cost consumption shows that the GP-APSO algorithm saves 18.08%, 9.76%, 8.1%, 12.58%, 7.41%, and 17.24% of the consumption cost than the PSO, APSO, GP-PSO, DE, JADE, and GA algorithms, respectively. Given the complexity of the material scheduling optimization problem, the difficulty of searching the multidimensional space of randomly assigned particles increases, and the increase of local extremes significantly decreases the successful convergence rates of other algorithms. However, although the GP-APSO algorithm also takes more time, the standard deviation values and R-values of its operation results are smaller than those of other algorithms, which demonstrate the robustness and reliability of the GP-APSO algorithm.

5.3.3. Statistical Analysis. In this section, as the means to verify the statistical superiority of the GP-APSO algorithm, the significant differences between the GP-APSO algorithm proposed in this paper and other comparison algorithms are verified through statistical measurements[10, 32]. We ran each algorithm on the emergency material dispatch model 30 times independently, matched the GP-APSO algorithm with other algorithms two by two (set the GP-APSO algorithm as matching object 1 and other comparison algorithms as matching object 2) and then divided them into six groups for statistical tests. Because the sample data of the experimental results does not precisely adhere to the normal distribution, this paper uses the Wilcoxon rank sum test to conduct a nonparametric statistical test on the results.

In Table 8, $\mathbf{R}^{+}$, $\mathbf{R}^{-}$, and p value (calculated with SPSS) are shown for all of the algorithms that were compared in pairs with the GP-APSO algorithm. If the p value of the statistical test is lower than the value of the significance level α, it means there is a significant difference between the experimental results of the two algorithms. If the p value of the statistical test is higher than the significance level, it means there is no significant difference between the experimental results of the two algorithms. As stated in Table 8, GP-APSO shows a significant improvement over PSO, DE, JADE, and GA, with a level of significance $\alpha = 0.05$, over APSO and GP-PSO, with $\alpha = 0.1$. This is consistent with the experiment results in Table 7 and the convergence analysis of Figure 7. That is to say, the GP-APSO algorithm proposed in this paper has obvious advantages in handling emergency material scheduling.

6. Conclusion

This paper proposes an emergency material dispatch model based on the demand urgency, with the objective of minimizing the cost of material loading time and transportation cost. In order to obtain the relative optimal solution of the model quickly, an improved PSO algorithm is designed. The main idea of the algorithm is to provide a state of good initial swarm by optimizing the initial swarm with a good set of points. Then, an adaptive inertial weight setting strategy is introduced to motivate each particle to perform a better local search. Finally, simulation data experiments are conducted with six other commonly used algorithms. The analysis of the experimental results shows that the GP-APSO algorithm proposed in this paper cannot only solve the post-disaster relief material scheduling problem but will also improve the accuracy rate of problem solving and the stability of the algorithm.

Additionally, we note that the GP-APSO algorithm is not computationally more efficient than other algorithms when solving optimally in high dimensions, which may be due to the sharp increase of local optima in the high-dimensional case, and the GP-APSO algorithm needs a better bootstrap strategy in order to avoid local optima. This implies that we will continue to improve the GP-APSO algorithm in high dimensions in the future for better application to the post-disaster relief material scheduling problem.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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