Electric Power Material Logistics Distribution Based on Improved Multi-Population Particle Swarms

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Abstract. In view of the problem that the information requirements of electric power supplies logistics distribution are increasingly high, this study proposes the research of electric power supplies logistics distribution based on improved multi-population particle swarm. Firstly, the simulated annealing algorithm is introduced in detail, and then the particle swarm optimization (PSO) is improved by using the domain extension method. Then the multi-population particle swarm optimization was carried out through the optimization of coding system, the updating speed formula and the algorithm convergence control. Finally, the optimization effect was verified. Final results show that, this study put forward based on improved particle swarm more population of electricity supplies logistics distribution model has feasibility and suitability, through the optimized parameters and algorithm of the model, to identify the logistics network of electric power supply company the best optimization model, thus reducing power cost of inventory and logistics distribution time, so as to improve the efficiency of logistics distribution.

Keywords: Electric power material logistics distribution; Simulated annealing algorithm; Multi-population cooperative particle swarm optimization

Introduction
With the continuous improvement of China's economic level and scientific and technological level, the power system is constantly optimized and improved. The development of electric power industry is closely related to the survival of the country and people's life. With the advent of the Internet era, there are higher requirements for the management quality of the power industry in many fields. The traditional power system can not meet the needs of the society and the people. However, with the continuous reform of the power system and the opening of the market, the current power material management level is relatively backward. There are some problems, such as high power inventory cost, long logistics distribution time and low logistics distribution efficiency. The above problems greatly affect the economic benefits and core competitiveness of power enterprises, and seriously hinder the normal operation and effective development of power enterprises. It is not conducive to the development of other industries in the society. Therefore, it is an inevitable trend to optimize and upgrade the power material distribution management system. Many scholars have carried out in-depth exploration and Research on the optimization of power system. For example, Chen Guoyong proposed
the construction and Simulation Research of power grid logistics distribution optimization model. On the basis of Internet of things information technology, the power grid material distribution model is designed, and the main parameters of the model are calculated through genetic algorithm and the shortest distance, so as to obtain an optimization path of power grid distribution [1]. Fan Jiangdong et al. Proposed the intelligent procurement and distribution of distribution network materials based on constraint theory, found out the problems and defects in the process of power system material distribution through the method of TOC theory, and put forward the corresponding solutions and schemes, so as to further improve the power material distribution system, which provides a reference for future research [2]. Based on this, combined with the experience of the above scholars, combined with big data and Internet technology, this study proposes the research of power material logistics distribution based on improved multi swarm particle swarm optimization, and optimizes the power material logistics distribution, so as to reduce the power inventory cost and logistics distribution time, and improve the efficiency of logistics distribution.

1. Algorithm introduction

The Simulated Annealing (SA) consists of three parts: the solution space, the objective function and the initial solution. This algorithm is calculated in the form of general probability, which is embodied in the optimal solution of searching proposition in a certain search area [4]. The algorithm steps are described in detail below:

An initial solution is generated randomly, and then a new solution is generated by perturbation; \( \Delta f = f(\omega^i) - f(\omega) \) can be obtained. If \( \Delta f \leq 0 \), the new solution can be accepted. Otherwise, select according to criterion \( \text{Metropolis} \).

Determine whether the new solution meets the standard condition. If the termination condition is met, the operation is over. If not, it is necessary to re-enter the new solution generated by the disturbance for calculation, and repeat the above steps until the termination condition is met, and the algorithm ends.

Among them, the final solution of the simulation algorithm has no relation with the initial value and the initial solution state. The algorithm has asymptotic convergence and parallelism, and belongs to the global optimization algorithm. The probability of global convergence can be up to 1.

Particle SSararm Optimization (PSO) is an evolutionary algorithm. The algorithm process of this algorithm is roughly the same as that of simulated annealing algorithm, which is from random solution to iteration to calculate the optimal solution [5]. Particle swarm optimization (PSO) can not solve the constrained optimization problem well because of the phenomena of stagnation convergence, local extremum or premature convergence in the algorithm process. Therefore, combined with simulated annealing algorithm, this study uses domain extension method to improve particle swarm optimization algorithm, namely multiple group cooperative particle swarm algorithms (mcps). This algorithm greatly reduces the probability of the optimization results turning into local extremum. Combined with the characteristics of simulated annealing algorithm, it makes the convergence speed of multi swarm collaborative particle swarm optimization faster, so as to further improve the accuracy of multi swarm collaborative particle swarm optimization. The specific algorithm flow of the algorithm is shown in Figure 1,
Figure 1. Flow chart of multi swarm cooperative particle swarm optimization algorithm

2. Multi swarm particle swarm optimization based on simulated annealing algorithm

2.1 Algorithm optimization

2.1.1 Optimization of coding system

The algorithm can be realized by optimizing the coding system. In the process of coding optimization, the solution of the model, that is, the storage location problem, is mapped to particles to realize the optimal location of the power logistics network [6]. In this study, we set up a vector of F-G dimension by constructing the basic principle of the model. F represents whether to leave the preselected transfer area library, G represents whether to leave the preselected material turnover library, and the relationship between the material turnover library and the transfer area library. The expression is as follows (1)

\[
\begin{align*}
\text{Mindex} & = \frac{M_1, M_2, M_3, \ldots, M_n}{M(0,1)} \times \frac{X_1, X_2, X_3, \ldots, X_n}{Mindex} \\
\text{Mindex} & \text{ represents the relationship between the material turnover warehouse and the transfer area warehouse.}
\end{align*}
\]

In formula (1), \( \frac{M_1, M_2, M_3, \ldots, M_n}{M(0,1)} \) represents the optimal data selected after iterative updating of the transfer area warehouse, and \( \frac{X_1, X_2, X_3, \ldots, X_n}{Mindex} \) represents the relationship between the material turnover warehouse and the transfer area warehouse.
2.2.2 Update speed formula

Based on the above algorithm model, according to the principle of mutual communication and cooperation between the main group and the sub group in the biological population, this study can control the evolution speed of the population, so as to better control the local and global convergence, and avoid the data becoming local extremum.

There is only one main group and several sub groups in the algorithm. The relationship between the two is that the sub group gives the optimal coordinate information of the main group itself, the main group searches the target according to the optimal coordinate information provided by the sub group, and the optimization process of the sub group through the particle swarm optimization algorithm is as follows (7) [7].

\[ x_j = \{x_{j1}, x_{j2}, x_{j3}, \ldots, x_{jF}\} \]  
(2)

The initial velocity is expressed as equation (3)

\[ v_j = (v_{j1}, v_{j2}, v_{j3}, \ldots, v_{jF}) \]
(3)

From Equations (4) and (5), the velocity update formula of the main group can be obtained, as shown in Equations (4) and (5):

\[ v_{Mf}^j = wv_{Mf}^j + c_1r_1(p_{Mf}^j - x_{Mf}^j) + c_2r_2(p_{g}^j - x_{Mf}^j) + \varphi c_3r_3(p_{O}^j - x_{Mf}^j) \]  
(4)

\[ x_{Mf}(t+1) = x_{Mf}(t) + v_{Mf}^j(t) \]  
(5)

In Equation (4), M represents the master group; Q is a subgroup; c is the learning factor; r represents uniform random number; Ø represents the migration factor.

Then, the subgroups were divided into N1, N2, and N3, and N1, N2, and N3 were optimized by F-dimensional and G-dimensional micro quantities and crossover methods respectively [8]. Thus, the velocity update formula of N1 subgroup can be obtained as shown in Equation (6):

\[ v_{N1f}^j = wv_{N1f}^j + c_1r_1(p_{N1f}^j - x_{N1f}^j) + c_2r_2(p_{g}^j - x_{N1f}^j) + \varphi c_3r_3(p_{O}^j - x_{N1f}^j) \]  
(6)

The velocity update formula of N2 subgroup is shown in Equation (7):

\[ v_{N2f}^j = wv_{N2f}^j + c_1r_1(p_{N2f}^j - x_{N2f}^j) + c_2r_2(p_{g}^j - x_{N2f}^j) + \varphi c_3r_3(p_{O}^j - x_{N2f}^j) \]  
(7)

Among them, N3 sub group randomly selects a pair of particles \((x_i, y_j)\) as the parent particle in the particle swarm. Then, the new particle \((x_i', y_j')\) is calculated by formula (7). Let \(\lambda\) be a random number of uniform distribution, and then formula (8) ~ (9) is obtained

\[ x_i' = \lambda x_i + (1 - \lambda) y_j \]  
(8)

\[ x_j' = \lambda x_j + (1 - \lambda) y_j \]  
(9)

It can be seen that the velocity update formula of new particles is as follows (10) (11)

\[ v_i' = \frac{v_i + v_j}{|v_i + v_j|} v_i \]  
(10)

\[ v_j' = \frac{v_i + v_j}{|v_i + v_j|} v_j \]  
(11)

2.2.3 Algorithm convergence control

The main purpose of algorithmic convergence control is to minimize the calculation error, so as to get the most accurate and optimal results. In this study, particle swarm optimization is improved on the basis of simulated annealing algorithm to achieve global convergence. In the process of simulated
annealing algorithm, \( x_i(k) \) represents the particle before updating, \( x_i(k+1) \) represents the updated sub swarm particle, \( f(k) \) represents the fitness value of \( f(k) \), and \( f(k+1) \) represents the fitness value of \( x_i(k+1) \) [9]. The calculation formula is as follows (12)
\[
\Delta k = f(k+1) - f(k)
\] (12)

If the calculation results meet the following formula:
\[
\min \left\{ 1, \exp\left( -\frac{\Delta k}{U} \right) \right\} > r
\] (13)

In equation (13), \( R \) is a random value. If the calculated result is greater than \( R \) value, the particle needs to be updated. If the calculated result is less than \( R \) value, the original particle value is kept. If the number of evolutions is smaller than the value of the maximum number of evolutions previously set, the next iteration can be started [10].

Repeat the above steps to achieve convergence control.

3. Verification of optimization effect

3.1 Source of samples
In this study, the logistics network optimization model is implemented by a provincial power grid company. Among them, there are 45 storage and distribution points in the power material storage network samples of the provincial power grid company. The 45 storage and distribution points are numbered s-01, S-02,..., s-45. According to the front-end qualitative access standard, 28 samples are selected from 45 storage and distribution points for the next step timing calculation, which are s-01 to s-27 respectively.

3.2 Algorithm verification
The realization of power network optimization model needs to set the following three parameters

3.2.1 Parameter setting of logistics network model
According to the own conditions of a provincial power company, this study sets the parameters of the logistics network model of the power company. Firstly, the service range parameter of the transfer regional warehouse is set to 40km, and the service range parameter of the material turnover warehouse is set to 30km; The warehouse turnover rate is set to 6; The inventory amount per unit area is 1754.5 yuan / year; The cost of new warehouse is 825.67 yuan / m²; 95 yuan / m² and 300.58 yuan / m² respectively; The warehouse labor cost is set at 267.34 yuan / m²; The time satisfaction index \( \beta \) was set to 0.01.

3.2.2 The parameters of network model algorithm are set
The default value of the algorithm parameters of the network model is set to 4 for the number of subgroups; The particle swarm size is 30; The inertia factor is 1.05; The migration factor was 0.75; The learning factors C1 and C2 were 1494; The learning factor C3 was 0.8; The initial temperature is 10000; The cooling coefficient is 0.3.

3.2.3 Optimization result export
After setting the default values of the above network model algorithm and other parameters, the running system will automatically give the optimization results, and then export the optimization results to the local computer documents.

Through computer calculation and analysis, the total logistics cost of scheme a is 216.9765.74 million yuan, which is the lowest compared with scheme B and scheme C; The total logistics cost of scheme B is 240.153.575 million yuan; The total logistics cost of scheme C is 289.9542.97 million yuan, which is the highest.
### Table 1. Middle end quantitative analysis scheme

|                | Transfer area library | Material turnover warehouse | Total logistics cost (ten thousand yuan) |
|----------------|-----------------------|----------------------------|------------------------------------------|
| **Plan A**     | S26, S03, S04, S05   | S29, S32, S24, S06, S10, S07, S12, S14, S28, S09, S18, S31, S19, S20 | 21697.6574                              |
| **Plan B**     | S26, S03, S04, S05, S27 | S10, S12, S28, S29, S06, S08, S15, S18, S14, S30, S07, S31 | 24015.3575                              |
| **Plan C**     | S02, S03, S04, S01, S05, S09 | S14, S29, S15, S24, S06, S10, S07, S12, S28, S08, S16, S18, S21 | 28995.4297                              |

### 3.3 Comparison of optimization schemes

This study is classified according to various factors affecting the optimization scheme, which mainly includes nine factors and is divided into three levels. The nine factors mainly include social factors, national policies, economic conditions, natural factors, traffic conditions and surrounding conditions. The three levels mainly divide the impact degree of the scheme through various factors, among which, the first level means the scheme is most affected, the second level means the scheme is medium, and the third level means the scheme is the least affected. Then, the scores of the nine factors at three levels on the same program are added together, and the weight of the three factors is compared to finally get the scores of the three programs A, B and C. Finally, the final scores are compared to get the best program. The judgment and comparison results of each influencing factor on the optimization scheme are shown in Table 2.

#### Table 2. Table of the judgment results of influencing factors on the scheme

|                      | Plan A | Plan B | Plan C |
|----------------------|--------|--------|--------|
| **Grade 1 Impact Score** | 16     | 23     | 20     |
| **Secondary Impact Score** | 13     | 16     | 16     |
| **Three-level influence score** | 4      | 3      | 6      |

| The weight size | First-level influencing factors | Secondary Influencing Factors | Three-level influencing factors |
|----------------|---------------------------------|------------------------------|--------------------------------|
|                | 0.678546                        | 0.135789                     | 0.068715                      |

| Final score | 14.69728                  | 20.59753                  | 18.54267                  |

As can be seen from Table 2, the final score of Plan B is 20.59753, which has the highest impact score compared with Plan A and C. The final score of Plan C is 18.54267, ranking the second. The
The final score of Plan A is 14.69728, which is the lowest compared with the other two plans. It can be seen that among the three schemes, scheme A has the lowest score in terms of overall influence factors, indicating the least influence degree. Combined with the comprehensive analysis of the above logistics cost and other factors, this study chooses Plan A as the best plan for the power logistics warehousing system.

4. Conclusion

To sum up, the improved multi-population particle swarm based electric power material logistics distribution model proposed in this study is feasible and practical. Particle swarm optimization algorithm can be controlled by simulated annealing algorithm to accelerate convergence, and the structural model of multi-population cooperative particle swarm optimization algorithm can be obtained. The multi-population particle swarm optimization algorithm based on simulated annealing algorithm can solve many defects of the single algorithm of the optimization model, and obtain the optimal solution. The final results show that this study can determine the optimal logistics network optimization model of the power supply company by setting the model parameters and optimizing the algorithm. Reduce the cost of power inventory and logistics delivery time, so as to improve the efficiency of logistics distribution. This study can provide reference for the realization of optimization of power logistics network and is conducive to the long-term development of power logistics material distribution optimization system.

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