RESEARCH ON DYNAMIC OPTIMIZATION ALGORITHM OF WAREHOUSING LOCATION LAYOUT BASED ON NONLINEAR OPTIMIZATION

GUANG CHEN,* ZHIWEI TU,† SHENG ZHANG,‡ JING FANG§ AND FAN SHE¶

Abstract. The paper aims to improve the turnover rate and operation efficiency of goods that are shipped out and replenished in the warehouses of electric power enterprises through big data analysis and optimization algorithms.The data is distributed in diverse locations and data nonlinear optimization algorithms certainly helps to understand the patterns for effective management of warehouses.This article focuses on reducing the delay in the operational processes.A multi-objective optimization (MOO) has been proposed which is aiming at improving the efficiency of transition process of commodities, storage, and overall warehouse operations.The study helps in the optimization of the allocation of cargo spaces with the aid of big data analysis optimization technology which collects and manages data in a distributed environment. A multi-objective cargo space optimization algorithm is proposed along with consideration of dynamic constraints.The algorithm is based on the coefficient of variation adaptive differential evolution algorithm.Individual decoding is performed according to the real-time cargo space availability.The simulation results show that the convergence speed of the algorithm is greatly improved.Meanwhile, the efficiency of warehouse transition process, shelf stability and the classification of commodities are remarkably improved.In nutshell, the multi-objective decision-making with the integration of big data analysis optimization technology assists in the effective organization of warehouse allocation system by considering multiple factors and constraints.

Key words: big data analysis; cargo location optimization; dynamic constraints; multi-objective; non-linear optimization

1. Introduction. With the increase in the scale and quantity of power projects, the warehousing management of power materials has become more and more complicated, which is easy to cause problems such as untimely supply of materials and inability to deliver, which affects the smooth development of power projects and the operation of power grids security and stability. In view of the large quantity and variety of power supplies, reasonable storage space allocation can provide higher picking efficiency for the warehouse in operation, reduce the loss of goods in the process of loading, unloading, handling, storage and picking, and effectively reduce the storage in the warehouse. Operating cost.

The optimization of the cargo location layout refers to the process of dynamic adjustment and reconfiguration of the company's inventory settings and the placement of goods according to the characteristics of materials, demand response and changing factors. The optimization of the cargo space requires the cooperation between different equipment, tools and labor. According to the shelf type, the characteristics and classification of the goods, the planning of the cargo space, the artificial factors, etc., the optimal cargo space allocation is jointly realized. Warehouse location optimization can provide higher picking efficiency for operating warehouses, reduce the loss of goods in the process of loading, unloading, handling and storage picking, and effectively reduce operating costs in warehousing. Therefore, there is huge room for improvement in the storage space. The requirements of modern warehouse management systems are complex, and the optimization problem of cargo location decision considering dynamic resource constraints and various objectives has more practical application value.

In this paper, combined with the actual needs of a power company, an improved nonlinear multi-objective adaptive differential evolution algorithm (ADEA) is proposed. By adding secondary optimization links, the

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*State Grid Corporation of China, Beijing, China

†State Grid Electric Power Research Institute, Nanjing, China; Wuhan Nari Limited Liability Company of State Grid Electric Power Research Institute, Wuhan, China

‡State Grid Jiangsu Electric Power Co.,Ltd., Nanjing, China

§State Grid Electric Power Research Institute, Nanjing, China; Wuhan Nari Limited Liability Company of State Grid Electric Power Research Institute, Wuhan, China (Corresponding author, `fjkite@163.com`)

¶State Grid Fujian Electric Power Co.,Ltd., Fuzhou, China

convergence speed of the algorithm is improved. To meet the three requirements of stability and cargo placement correlation, a comprehensive and feasible solution for cargo location optimization was obtained by building a multi-objective optimization model, improving algorithms, and simulation verification, thereby realizing online dynamic cargo location allocation of random inventory.

2. Related Work. The main objectives of the optimization of the cargo location layout are the frequency of storage and exit, shelf stability, commodity relevance, and space utilization. Yang et al. [1] optimize the picking location of the roadway stacker when exiting the warehouse, a mathematical function model was established by analyzing the picking strategy of the warehouse delivery operation, which was established with the shelf stability and access efficiency as the goal according to the principle of storage space allocation. Wang et al. [2] designed an optimized target model based on the vertical stability of the shelf, which meets the maximum load capacity and maximum limit of the shelf, and minimizes the center of gravity of the goods. And designed a hierarchical genetic algorithm, the calculation result reduces the center of gravity of the shelf. Zhang et al. [3] introduced the concept of the demand correlation pattern to describe the correlation among items, based on which a new model is constructed to address the SLAP. The model is subsequently reduced using the S-shape routing strategy, and a method for determining DCPs from historical data is proposed. Zhou et al. [4] established an optimization model by establishing the relationship between storage products, combining the current distribution strategy, and simulating through software. Quintaniua et al. [5] studied the establishment of an optimization model with the goal of maximizing storage space utilization. Solving this method not only greatly improves the warehouse utilization rate, but also shortens the picking time.

When calculating optimization models with diverse objectives and complex constraints, a reasonable calculation method will make the calculation process faster and the calculation results more accurate. Therefore, how to choose an efficient solution algorithm is also the focus of research in the cargo location optimization problem. Lin et al. [6] established a multi-objective optimization model that considers the determination of retrieval time and retrieval frequency based on genetic algorithm, which effectively improves the search ability under the constraints of frequent entry and exit of different goods. Seval et al. [7] improved the performance of the genetic algorithm, which solved the problem of location allocation based on clustering storage strategy and minimizing picking costs as the goal, and effectively optimized the warehouse layout in the automotive industry. Muppani et al. [8] proposed a linear optimization model of cargo location allocation based on simulated annealing algorithm to improve control space utilization and reduce picking costs. This model is better than traditional dynamic programming algorithms in accuracy. For the storage location allocation problem with grouping constraints, Xie et al. [9] established a two-layer grouping optimization model, and solved it by a multi-stage random search method and a tabu search algorithm. Aiming at the problem of product demand fluctuations over time, Patrick et al. [10] proposed an iterative heuristic method that solves the problems jointly and that takes account of future dynamics in customer demand and their influence on the three planning problems.

However, the above research only solves the optimization of cargo location decision under single-batch operation, and does not further discuss the variation law of the optimization target value of multi-batch operations and whether the continuous optimization capability of cargo location is stable. When constructing constraints, Augustyn et al. [11] considered the influence of environmental factors such as warehouse size on the optimization of storage location decisions, but did not consider the dynamics of factors such as inventory and allocable storage locations. In terms of model algorithm implementation, in recent years, research on cargo space optimization using genetic algorithm [12] and machine learning [13] has been emerging, and differential evolution algorithm (DE) has attracted much attention due to its excellent optimization performance [14] , and also has certain applications in warehouse optimization [15]. There are relatively few researches on the optimization of cargo location decision based on differential evolution and Pareto optimal [16].

The above-mentioned various studies mainly limited the consideration of a certain part in the allocation of goods, leading to some deficiencies in the model, such as insufficient model factors and slow algorithm convergence. This paper uses different principles of cargo location allocation to establish a cargo location allocation optimization model, uses the weight coefficient method to convert it into a single objective function, and solves the model through a nonlinear multi-objective adaptive differential evolution algorithm. Considering constraint conditions such as dynamic inventory and allocable cargo locations, and based on adaptive differential

evolution of mutation parameters, a multi-objective cargo location optimization algorithm that responds to dynamic constraints is proposed. The Pareto solution set is further evaluated based on the analytic hierarchy process, and the influence of multi-objective weights on the continuous optimization of multi-batch operations is studied. The optimization algorithm in this paper can jump out of the local minimum extremal region, so as to find the global optimal solution faster, thereby ensuring the convergence of the algorithm. In the establishment of the objective function, this paper takes into account the nearest storage of the goods, the lowest center of gravity, and the correlation criteria of the goods, which is more comprehensive than the previous research.

3. Model. Improper distribution of goods is the primary problem that restricts the efficiency of warehouse inbound and outbound. At present, most power material warehouses use random storage strategies, which not only greatly increase the time for goods in and out of the warehouse, but also increase the difficulty of picking goods accordingly. In addition, the quality of different types of goods and the frequency of their storage will also affect the shelf life and the efficiency of goods storage. Therefore, it is necessary to set an appropriate storage strategy for warehouse space optimization and re-plan it using the distribution principle of the storage space; then use different principles to establish multiple models for optimization, and the final distribution of the storage space can reach the ideal state. The traditional optimization method of cargo location is only optimized according to the frequency of its storage and exit, but this optimization method considers few aspects and is not comprehensive enough.

General scheduling optimization uses Petri nets, expert systems, temporal logic, simulated annealing, neural networks, genetic algorithms, etc. [12][13][14]. The genetic algorithm is the most efficient way to achieve global search, but its coding method will become difficult as its model becomes more complicated. In this paper, the nonlinear algorithm based on multi-objective adaptive differential evolution is used to solve the problem, so that the evolutionary algorithm jumps out of the local extreme value region, finds the global optimal solution, and ensures the convergence of the algorithm.

3.1. Problem assumption. Different power material warehouses have different characteristics. Combining the characteristics of multiple power material warehouses, some special circumstances are not considered for the time being. The following assumptions and explanations are made for the warehouse warehousing operation process[17]: (1) The volume of each cargo space in the warehouse is equal (2) The goods are placed side by side in a single layer in the cargo space; (3) The warehouse adopts a storage strategy of random storage; (4) The warehouse operations are completed by manual handling equipment, and the handling equipment is in the shelf area The walking route is arbitrary; (5) During the warehousing process, forklifts are used as handling equipment, and each forklift has the same load capacity and can carry different types of goods at the same time; (6) The warehouse has enough space to meet all waiting Demand for incoming goods.

3.2. Model establishment. The symbols used in the model are explained as follows: There are a row of shelves in the warehouse, and each row of shelves has column b and layer C. The coordinates (0, 0, 0) indicate the location of the inbound and outbound platform, and the position coordinates of a certain cargo k are (x_k, y_k, z_k) (The value range of x_k is 1 to a, the value range of y_k is 1 to b, and the value range of z_k is 1 to c); v_x represents the transmission speed of the stacker in the x-axis direction; v_y is the transfer speed of the stacker in the y-axis direction; v_z is the transfer speed of the stacker in the z-axis direction; L is the length of the shelf cell; L_0 is the distance between the shelves; r_k is the turnover of the k-th product Rate (frequency of in and out of storage); w_k is the unit mass of the k-th product.

3.3. Analysis of optimization goals. The principle of cargo space allocation mainly includes the principle of nearby storage and exit, the principle of the lowest center of gravity, the principle of relevance of goods, and so on. A good distribution principle can not only reduce the distance between goods in and out of the warehouse and shorten the time required for operations, but also make full use of its storage space while meeting the requirements of shelf stability and reduce storage costs. The optimization objectives of the three types of allocation principles are as follows:

(1) The principle of nearby storage. In order to improve the efficiency of warehousing and warehousing, materials with high turnover rate should be closer to the entrance and exit so that the overall warehousing time is shorter. Assuming that the stacker pick-up time is negligible, for a cargo located on the z-layer of the x row, y column, and z layer, its in-out time can be simplified as the total operation time of the stacker.

The running time of the stacker in the x direction is $\sum_{x=1}^{a} \frac{x_k \times (L+L_0)}{v_x}$, and the running time in the y direction is $\sum_{y=1}^{b} \frac{y_k \times L}{v_y}$, the running time in the x direction is $\sum_{z=1}^{c} \frac{z_k \times (L+L_0)}{v_z}$ respectively. The shortest distance that the goods move in and out of the warehouse in a single time is: $2\sqrt{[x_k \times (L+L_0)]^2 + (y_k \times L)^2 + [z_k \times (L+L_0)]^2}$, so the optimization objective function of the nearby storage principle is as follows:

$$\min f_1(x,y,z) = \sum_{x=1}^{a} \sum_{y=1}^{b} \sum_{z=1}^{c} \left(\frac{x_k \times (L+L_0)}{v_x} + \frac{y_k \times L}{v_y} + \frac{z_k \times (L+L_0)}{v_z} \right)$$
$$\times 2\sqrt{[x_k \times (L+L_0)]^2 + (y_k \times L)^2 + [z_k \times (L+L_0)]^2} \times r_k \tag{3.1}$$

The goal of this optimization function is the sum of the moving distances of goods k.

(2) The principle of the lowest center of gravity. In order to maintain the stability of the warehouse shelves, according to the principle of light up and down and lower center of gravity, the total center of gravity of the warehouse or warehouse should be as low as possible. Its optimization function can be expressed as:

$$\min f_2(x,y,z) = \frac{\sum_{x=1}^{a} \sum_{y=1}^{b} \sum_{z=1}^{c} w_k n_{xyzk} z_k (L+L_0)}{\sum_{x=1}^{a} \sum_{y=1}^{b} \sum_{z=1}^{c} w_k n_{xyzk}} \tag{3.2}$$

where n_{xyzk} represents the number of k-th goods on the shelf (x, y, z). The objective function represents the position of the center of gravity of the k-th cargo. Therefore, Goal 2 represents the principle of lightness on the shelf and heavy weight. The function value f_2 of Goal 2 reflects the degree of center, so the optimization goal is to make it as smallest as possible.

(3) Cargo-related principles. If there is a certain correlation between the goods, put the goods that need to be out of the warehouse at the same time and put them in the close or adjacent cargo space. Considering the nature of the cargo itself, the cargo location should be carefully arranged. For example, special types of cargo should be placed in a special location and placed together as much as possible. Its optimization function can be expressed as:

$$\min f_3(x,y,z) = \sum_{x=1}^{a} \sum_{y=1}^{b} \sum_{z=1}^{c} \sqrt{(x_k - \bar{x}_k)^2 + (y_k - \bar{y}_k)^2 + (z_k - \bar{z}_k)^2} \tag{3.3}$$

where $(\bar{x}_k, \bar{y}_k, \bar{z}_k)$ the center coordinate of the k-th category of goods, and its value is calculated based on the weighted average of all such goods. It can be seen that the target 3 represents the distance between the center position coordinates of a certain type of goods and the position coordinates, so the distance between adjacent goods in the entire warehouse is obtained.

According to the analysis of different principles, three objective functions are established. Combining these three objective functions into a whole can form the mathematical model of the main research problem. This is a multi-objective optimization problem. The mathematical model can be expressed as follows:

$$\begin{cases} \min f_1(x,y,z) \\ \min f_2(x,y,z) \\ \min f_3(x,y,z) \\ \text{s.t} \begin{cases} 1 \le x \le a \\ 1 \le y \le b \\ 1 \le z \le c \end{cases} \end{cases} \tag{3.4}$$

For multi-objective optimization problems, in order to comprehensively consider the factors of multiple objectives, this paper studies how to set weights for different objectives to obtain weighted single-objective problems. Starting from the practical application of warehousing, a reasonable single solution needs to be selected from the Pareto solution set. Therefore, the weight is calculated by the commonly used AHP method, and the weight is used to solve the multi-objective weighting, and the individual with the smallest comprehensive

objective function value is obtained, and the relationship between the multi-objective weight and the continuous optimization ability of the cargo space is observed. Construct the judgment matrix $B = (b_{ij})_{n \times n}$ according to the importance scale, normalize it by column to get the matrix $C = (c_{ij})_{n \times n}$, divide the sum of the row elements of the C matrix by the sum of the elements The weight of each target can be obtained.

$$c_{ij} = \frac{b_{ij}}{\sum_{k=1}^{n} b_{kj}} \tag{3.5}$$

$$\varepsilon_i = \frac{\sum_{k=1}^{n} c_{ik}}{\sum_{j=1}^{n} \sum_{i=1}^{n} c_{ij}} \tag{3.6}$$

Determine the weight of the principle of the nearest in and out warehouse, the principle of the lowest center of gravity, and the principle of the correlation of goods through the AHP. After solving ADEA to obtain the Pareto solution set, calculate the comprehensive objective function value F of all individuals in the Pareto solution set according to formula (3.7), and select the individual with the smallest F as the optimal individual. The multi-objective optimization objective translates into the following formula:

$$\min f(x,y,z) = \varepsilon_1 \min f_1(x,y,z) + \varepsilon_2 \min f_2(x,y,z) + \varepsilon_3 \min f_3(x,y,z)$$
$$\text{s.t} \begin{cases} \varepsilon_1 + \varepsilon_2 + \varepsilon_3 = 1 \\ 1 \le x \le a \\ 1 \le y \le b \\ 1 \le z \le c \end{cases} \tag{3.7}$$

4. Optimization algorithm.

4.1. The cargo location optimization algorithm based on adaptive differential evolution. According to the analysis of the problem, solving the optimal cargo location for cargo distribution is essentially a multi-objective optimization process. The optimization function is shown in the above formula. In this paper, a multi-objective adaptive differential evolution algorithm (ADEA) is used to calculate the optimization process, and the evolutionary parameters and evolutionary operators are adjusted through the adaptive process, which can effectively improve the convergence performance of the algorithm. Through adaptive adjustment of mutation parameters, the individual decodes according to the real-time feasible domain response dynamic constraint conditions of the cargo location, and the comprehensive evaluation of the multi-objective Pareto solution set to obtain the optimal operating cargo location. The algorithm flow is as follows:

(1) Initialization and coding. The individual uses the floating point code in the range of [0,1], the length is equal to the job number D, and the individual gene index number is the job number. Initialize the Pareto solution set R_p as an empty set, and randomly generate NP initial individuals with dimension D. (x_k, y_k, z_k) corresponding to each gene is the rank, column, and layer of the goods.

(2) Individual decoding in response to dynamic constraints. Through the gene value xik corresponding to job k and the real-time feasible domain $D_k(x_1, y_1, z_1), (x_2, y_2, z_2), ...(x_n, y_n, z_n)$, the corresponding target location (x_k, y_k, z_k). Calculate the objective function value through the set of cargo locations.

(3) Mutation operation. Assuming that the size of the population is NP and the dimension of the solution is N, then the population $X \subset R^N$, the G-th generation individual i can represent the vector $P_i^G = \left(P_{i1}^G, P_{i2}^G, \ldots, P_{iN}^G\right)$, randomly select 3 individuals from the contemporary population as parent individuals for compilation, and generate mutant individuals u_i^G:

$$u_{ij}^G = P_{r1j}^G + F \times \left(P_{r2j}^G - P_{r3j}^G\right) \tag{4.1}$$

where formula (4.1) is the individual variation formula, and u_{ij}^G is the j-th dimension element of the variation individual u_i^G.

The variation scaling factor F is adaptively generated according to formulas (4.2)-(4.4):

$$F_{i1} = F_u e^{\frac{In(F_1/F_u)t}{G-1}} \tag{4.2}$$

$$F_{i2} = \frac{f_i - f_{\min}}{f_{\max} - f_{\min}} \tag{4.3}$$

$$\mathrm{F} = \frac{F_{i1} - F_{i2}}{2} \tag{4.4}$$

where F consists of two parts, F_{i1} and F_{i2}. Among them, F_{i1} exhibits nonlinear adaptive decay according to time, which can ensure that the algorithm can efficiently perform global search in the early process of evolution, and can obtain a stronger ability to locally seek the optimal solution in the later process of evolution; F_{i2} The optimization parameters are dynamically and adaptively adjusted according to the difference between the objective function value of each individual and the optimal individual in the population; r_1, r_2, and r_3 are 3 integers that are completely different from each other, and are not equal to i. The value is a random selection from the set of 1,2,…,NP; F_l is the lower limit of F_i; F_u is the upper limit of F_i; G is the maximum upper limit of the iteration; $g \in [0, G-1]$ is The current number of iterations; f_i is the real-time target value calculated by a single individual; f_{min} is the smallest target value among all individuals in the current population; f_{max} is the largest target value among all individuals in the current population.

(4) Cross operation. The diversity of the population is the best way to improve the efficiency of finding the optimal solution, the experiment vector $v_i^g = \left[v_{1,i}^g, v_{2,i}^g, \ldots, v_{D,i}^g \right]$ is obtained by using the binomial crossover operation , As shown in formula (4.5), $\mathrm{R}_{i,\,\mathrm{rand}} \in (1, 2, \ldots, D)$, which can ensure that at least one parameter of $v_{j,i}^g$ comes from U; the crossover operator $\mathrm{CR} \in [0, 1]$.

$$v_{ij}^g = \begin{cases} u_{ij}^g, & \text{if } \mathrm{rand}(0,1) \leq CR \text{ and } j = \mathrm{rnbr}(i) \\ P_{ij}^G, & \text{otherwise} \end{cases} \tag{4.5}$$

where rand(i,j) represents the estimated value of a random number between i and j, and rnbr() represents a randomly selected sequence. CR is the crossover operator.

(5) Select operation. Based on the dominant relationship in the multi-objective algorithm, the selection operator is shown in formula (4.6), $\mathrm{LC}\left(P_i^{g+1}, v_i^g\right)$ represents the congestion entropy in P_i^{g+1} and v_i^g Smaller individuals.

$$\mathrm{LC}\left(U_i^{g+1}, X_i^g\right) = \begin{cases} P_i^{g+1}, & \text{if } f\left(P_i^{g+1}\right) \gtrsim f\left(v_i^g\right) \\ v_i^g, & \text{if } f\left(P_i^{g+1}\right) \lessapprox f\left(v_i^g\right) \\ \mathrm{LC}\left(v_i^{g+1}, P_i^g\right), & \text{otherwise} \end{cases} \tag{4.6}$$

(6) Obtain the Pareto solution set. $\mathrm{x}^* \in \Omega$ is the Pareto optimal solution, which means $\nexists x \in \Omega$ such that $f(x) < f(x^*)$, Ω is the feasible domain of the variable x, and the Pareto optimal solution set X_k refers to all P-optimal solutions collection. The P-optimal solution set of the t generation and the population of the t+1 generation are merged to solve the Pareto solution set of the t+1 generation to obtain an optimal solution set that is sufficiently diverse and distributed throughout the Pareto front.

4.2. Algorithm flow. The basic flow of the algorithm is shown in Fig. 4.1.

The specific steps are described as follows:

1. Set the population size NP, the maximum number of iterations G, the termination condition, and the crossover operator CR; initialize the population, the individual vector dimension D is equal to the number of jobs n, encode the individuals with random numbers, and initialize the Pareto solution set as an empty set.
2. Determine whether the maximum number of iterations G is reached, if so, select the individual with the smallest comprehensive objective function value from the Pareto solution; if not, proceed to the next step.
3. Perform mutation crossover operation and calculate the objective function value.
4. Determine the dominant relationship between P_i^{g+1} and v_i^g, and select the individual v_{i+1}^g.
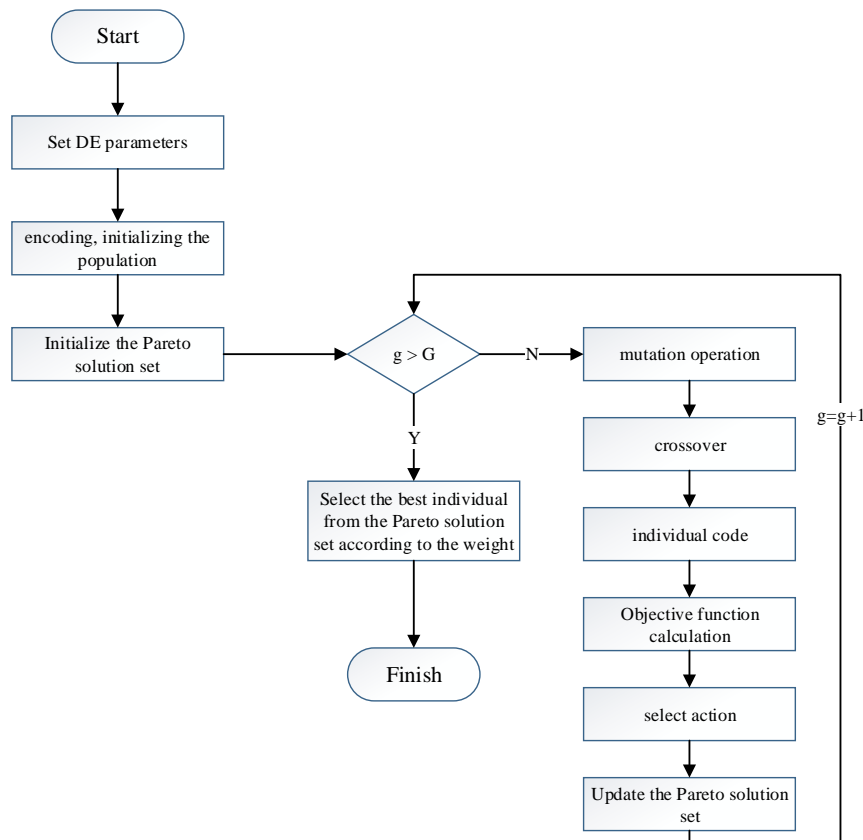
Fig. 4.1: Flowchart of ADEA

5. Compare the target vector v_i^g with all vectors in the Pareto solution set v_P, and update the Pareto solution set.

6. The number of iterations g=g+1, merge the Pareto solution obtained in the g-th generation in the population, and go to step 2.

5. Experiment.

5.1. Setting. A simulation experiment has been developed to verify the effectiveness of this algorithm, the experiment taked a warehouse of a power company as a prototype,builded a simulated automated three-dimensional warehouse.there are 100 random storage positions, the warehouse has 10 rows, 10 rows and 4 floors, and the center position coordinates of various types of goods. Set as (2,2,2), (3,2,2), (2,3,2) respectively. The experimental data set in this paper comes from randomly generated simulation data. The warehouse uses conveyor belts in the horizontal direction and tunnel stackers in the vertical direction. The relevant parameters of the warehouse and cargo space are shown in Table 5.1. The simulation experiment platform was windows 10 system, the computer configuration was Intel CPU 2.90 GHz, memory 16G, GPU was GeForce GTX 1650, programming language was Python 3.1, and the integrated open environment was Anaconda 3. The neural network is implemented using the Pytorch open source framework.

5.2. Iterative performance analysis. Fig. 5.1 shows the change curve obtained from the experiment, which represents the optimal fitness function value in the solution process of the multi-objective adaptive differential evolution algorithm and the traditional genetic algorithm. The process of iterating with the population. According to the curve in Fig. 5.1 , we find that the convergence speed of the multi-objective adaptive dif-

Table 5.1: Optimize simulation parameters

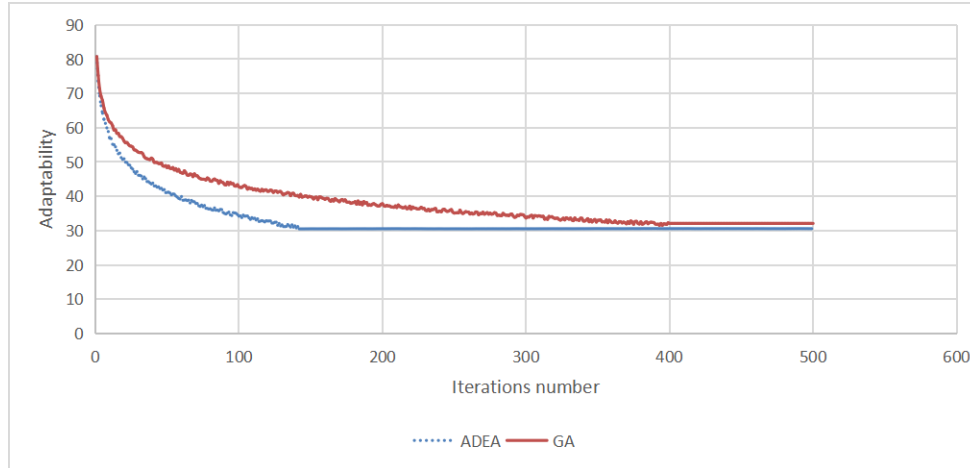| Movement speed in X and Y directions	1 m/s	Algorithm iteration times	400
Movement speed in Z direction	0.5 m/s	initial population	100
warehouse slot length	1 m	Number of shelves	10
Number of shelves	10	Shelf layers	4

Fig. 5.1: Adaptability curve

ferential evolution algorithm is very fast in the early stage of the iteration; when the population is iterated to 150 times, the result tends to be stable, which reflects that the calculation time and error are better; and Correspondingly, the traditional genetic algorithm needs about 400 iterations to obtain the same result; from this, it can be found that the convergence speed of the multi-objective adaptive differential evolution algorithm is about 2.7 times faster than that of the traditional algorithm.

5.3. Optimization effect analysis. In order to analyze the function of the optimization algorithm in this paper more intuitively, the function values of the three objective functions before and after optimization are solved separately. Table 5.2 shows the comparison of the three objective functions before and after optimization. The three objective functions respectively represent the optimized target value of the nearest storage principle, the optimized target value of the lowest center of gravity principle, and the optimized target value of the cargo-related principle. The smaller the value, the better the effect. The results show that the values of the three objective functions are reduced by 47%, 55%, and 72% respectively compared with before optimization, and the optimization effects are different. Among them, the optimization effect of goods-related storage is the best.

It can be seen from Table 5.2: According to the comprehensive analysis of multi-objective decision-making, the average objective function has dropped by 58%, and the optimization effect is significant. Comparing the distribution status of the cargo space before and after optimization, we can find that the cargo space distribution before optimization is chaotic and the layout is chaotic; the optimized cargo space is mostly concentrated near the exit position, and most of the goods are located on the bottom floor, and the overall layout is reasonable and orderly. Comprehensive analysis of warehouse entry and exit efficiency, rationality of goods classification and storage, and overall stability of shelves have been significantly improved compared with the optimization before.

The experimental results show that the method proposed in this paper can meet the needs of multi-project and multi-material, combined with the cost, time and efficiency of different project locations, as well as the balance problem of multiple types of materials in a single project in different storage locations, and solve the ambiguity of multiple optimization objectives. The matching problem can intelligently determine the optimal

Table 5.2: Object values compare

Objective function	Before optimization	After optimization	Decrease rate
f_1	168	89	47%
f_2	77	34	55%
f_3	298	81	72%

allocation plan based on the global perspective, which can effectively improve the utilization efficiency of materials in the warehouse and the utilization efficiency of materials.

6. Conclusion. Warehouse management includes various processes that make the in-out process of goods convenient and easy by enhancing the efficiency of operations. This paper focuses on the optimization of three factors namely- nearby storage, the CoG, and correlation among the goods for optimization enabled warehousing locations. To optimize these processes and to ascertain the values of optimization functions, a multi-objective ADEA method is proposed. The evolutionary parameters and evolutionary operators in the algorithm are adjusted through the adaptive process. This effectively improves the convergence performance of the algorithm. The results show that the values of the three FFs are reduced by 47%, 55%, and 72% respectively as compared to the values before optimization. It can be concluded that the proposed optimization algorithm can respond to dynamic constraints such as allocating the feasible region of the cargo space optimally. When compared with the simple weighted differential evolution algorithm, the proposed algorithm shows better performance. The proposed methods are suggested to minimize the time of storage operations and to minimize the time for transition of goods. The weight of the optimization target affects the continuous optimization ability of the cargo space. To sum up, the proposed algorithm can effectively solve the optimization problem of dynamic cargo location allocation for power generation inventory. In future, we will enhance the algorithm to consider complex situations such as inbound and outbound mixed batches and consider a case of diverse commodities.

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