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Research on Optimization Method and Decision Support Model of Allowance Allocation Based on Genetic Algorithm under New Carbon Emission Trading Mechanisms

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Abstract Under the background of “dual-carbon” target, carbon trading mechanism, as the core carrier of market-based emission reduction tools, the scientificity and flexibility of its quota allocation directly affects the efficiency of emission reduction and the fairness of the industry. This study proposes a dynamic allocation framework integrating entropy weight method and multi-objective genetic algorithm (MOGA), aiming at the synergistic optimization of fairness, efficiency and operability of carbon emission quotas. By constructing a two-layer allocation model for carbon trading mechanism, the quota object is firstly divided into two types of equipment: power generation and heat production, and the initial quota is dynamically allocated based on the benchmark value of carbon emission per unit of power. In view of the limitations of the baseline method, the entropy weight method is introduced to construct a three-level index system of “emission reduction responsibility-capacity-potential”, quantify the weights of each link in the coal power supply chain, and solve the complex multi-objective optimization problem by combining with the improved MOGA algorithm. Simulation results show that the improved MOGA converges to the Pareto frontier in the IEEE 30-node system in only 53 iterations, and the optimization efficiency is improved by 36.05%, and the running time is shortened to 34.17 seconds, which is significantly better than that of the traditional genetic algorithm (47.33 seconds) and the ant colony algorithm (53.43 seconds). In the case of industrial carbon emission allocation in province A, the efficiency value of each region is improved to 1.00 after optimization, and the direction of quota adjustment is linked to the potential of emission reduction, e.g., the quota of area G is increased by 1,294,800 tons, and the quota of area K is decreased by 1,435,100 tons, which verifies the model's dynamic synergistic ability in terms of fairness and efficiency.

Index Terms carbon emissions trading, quota allocation, entropy weight method, multi-objective genetic algorithm, multi-objective optimization problem

I. Introduction

Climate change has brought about a series of problems such as glacier melting and sea level rise, affecting human development and species diversity. In order to cope with climate change and mitigate the impacts of large amounts of greenhouse gas emissions on human society, governments have introduced a number of carbon emission reduction policies, which mainly include carbon trading, carbon tax and carbon labeling system [1], [2]. Among them, carbon trading has been widely adopted by countries or organizations such as the United States and the European Union due to its significant effect of market mechanism and better social welfare [3].

Carbon emission allowance, or carbon quota, refers to the carbon emission credits allocated by the competent authorities to key emission units included in the scope of greenhouse gas emission reduction control for a specified period based on the requirements of the national target of controlling greenhouse gas emissions [4]. However, when the issue of climate change was put on the international political agenda, the allocation of carbon allowances was focused from the target to the issue of fairness, and some scholars found that the allocation of fairness was conflicting when they used a number of fairness criteria to allocate the right to emit greenhouse gases [5]-[7]. The Chinese government also attaches great importance to the issue of carbon emissions, and adopts a carbon cap-and-trade policy to encourage enterprises to reduce carbon emissions [8]. Scholars' research on carbon quota allocation issues likewise focuses on the fairness and efficiency of allocation as well as the allocation among some key industries and among provincial regions [9], [10]. In the unified carbon trading market, how to select the trading object, determine the appropriate trading volume, and minimize the trading risk and trading cost while fulfilling the quota are important issues to be solved in the decision-making of carbon emission rights trading [11]-[13]. By introducing incentive and constraint mechanisms to construct a decision-making model of carbon emission quota allocation weights, it can take into account the equity and efficiency of carbon emission, so as to mitigate the inequality of development between regions or provinces and districts, and at the same time, enhance the efficiency of carbon emission right allocation and reduce the cost of emission reduction, which is of great practical significance [14]-[17].

This study focuses on the optimal allocation of quotas under the new carbon trading mechanism, and proposes a dynamic allocation framework integrating entropy weighting method and multi-objective genetic algorithm (MOGA), aiming at synergistic optimization of the fairness, efficiency and operability of carbon emission quotas through the modeling of the mechanism, the optimization of the weights, and the iteration of the intelligent algorithm. The article firstly constructs a two-layer allocation model of carbon trading mechanism, and for the Chinese national situation of initial quota allocation without compensation, the quota objects are divided into two categories of power generation and heat production equipment, and the initial quota is dynamically allocated based on the benchmark value of carbon emission per unit of power, respectively. However, the baseline method has limitations in terms of industry variability and dynamic adaptability. Therefore, the entropy weighting method is introduced to optimize the quota weights, and by constructing a three-level indicator system of “emission reduction responsibility-capacity-potential”, the fairness and efficiency weights of each link in the coal supply chain can be quantified, so as to solve the problem of insufficient horizontal fairness and lack of vertical efficiency in the baseline method. Further, to address the nonlinearity and dynamics of multi-objective optimization under complex constraints, an improved multi-objective genetic algorithm is proposed, which achieves global optimization of carbon quota allocation through the enhancement of the diversity of the initial population, the adaptive adjustment of the boundary of the feasible domain and the fast convergence of the Pareto frontier.

II. Carbon trading mechanism modeling and dynamic optimization of quota allocation based on entropy right-genetic algorithm

II. A. Carbon trading mechanism modeling

II. A. 1) Overview of carbon trading mechanisms

Carbon trading mechanism refers to each country's carbon emission main body through the paid or unpaid way to obtain carbon emission quota if the quota is higher than their actual carbon emissions, the remaining quota can be sold in the carbon trading market to obtain the response revenue. If the amount of allowances is lower than their actual carbon emissions, the lack of allowances need to be purchased in the carbon market, paying the cost of purchasing the first quota in order to obtain the right to respond to the carbon emissions. The carbon trading mechanism is a means for countries to cope with the temperature-solstice effect and climate problems, and is designed to use the market to guide carbon emitters to respond positively to energy-saving and low-carbon production and living styles. By adjusting the allocation of carbon allowances, the carbon trading mechanism can be made more flexible. In this paper, the entropy weight method is used to guide the allocation of carbon quotas, which will make the carbon trading mechanism more adaptable.

II. A. 2) Initial allocation of carbon allowances

At present, the widely used allocation method is the gratuitous allocation of carbon emission allowances, in which each market entity can obtain the initial carbon emission allowances for free, and the other carbon quota method is the paid quota, in which the enterprises need to purchase the first carbon emission allowances according to their own carbon emission level. The development of China's carbon trading market is still in the primary stage, in order to avoid the reduction of the enthusiasm of enterprises to participate in the market, the initial carbon quota allocation method is more in line with China's national conditions.

The objects of initial carbon allowance allocation can be divided into two categories, one is the equipment/sources that generate carbon emissions and output electric power, and the other is the equipment that generates carbon emissions and outputs thermal power.

The first category of equipment/sources includes GT, grid purchased power and CCPP, and the amount of carbon allowances will be initially allocated based on the amount of power generated by GT, the amount of power purchased from the grid and the net output power of CCPP, which are calculated as follows:

$$Q_{cJ} = q_c(P_{GTcJ} + P_{grdJ} + P_{nctJ}) \tag{1}$$

where, $Q_{c,t}$ is the value of the quota for the actual generation power at moment t; q_c is the value of the quota per unit of generation power.

The second category of equipment/sources includes GT and GB, and the amount of carbon quota will be based on the initial quota of GT and GB heat production power, which is calculated as follows:

$$Q_{h,t} = q_h(P_{GTh,t} + P_{GBh,t}) \tag{2}$$

where, $Q_{h,t}$ is the value of the quota for the actual thermal power production at the moment t; q_h is the value of the quota per unit of thermal power production. The average emission level of the industry determines q_h to be 0.3672t/MWh and q_e to be 0.728t/MWh.

II. B.Research on carbon quota allocation of coal power supply chain based on entropy weight method

Although the initial carbon quota allocation provides a basic framework for the carbon trading mechanism, the limitations of the baseline method in terms of industry variability and dynamic adaptability urgently require the introduction of a more scientific weight allocation method. To this end, this section constructs a multi-dimensional carbon quota allocation index system based on the entropy weight method, which realizes the synergistic optimization of vertical equity and horizontal efficiency of the coal and power supply chain by quantifying the emission reduction responsibility, capability and potential.

II. B. 1) Analysis of carbon quota allocation indicators

The advantages and disadvantages of adopting the baseline method for carbon quota allocation are summarized below. The “benchmark method” needs to compare the carbon emission data of each enterprise in the production of the same product, in which there are a large number of enterprises and a large number of similar products, which makes it difficult to implement, and the operationalization is difficult. However, the benchmark method can effectively promote carbon emission reduction of enterprises and encourage enterprises to use advanced technology to realize carbon emission reduction. In the process of carbon quota allocation, the carbon emission accounting standards of new enterprises and old enterprises are the same, so there is a certain fairness and efficiency issue.

Carbon quota allocation mostly follows the above principles, and the principle of fairness ensures equal allocation of quotas for each segment of the coal and power supply chain. The principle of efficiency requires that enterprises with high carbon emission efficiency in each link of the coal and power supply chain have fewer carbon emissions with the same output. Based on the principle of equity, from the perspective of emission reduction responsibility and capacity, emission reduction responsibility is mainly based on the principle of whoever pollutes, whoever manages, to realize the fairness of emission reduction in the industry. Emission reduction capacity is based on the economic and technological level of different industries, and industries with a high level of economic development have greater emission reduction capacity to realize the vertical equity of carbon quota allocation; based on the principle of efficiency, the emission reduction potential is the indicator that best reflects the principle of efficiency, and is assessed according to the development of the industry and energy consumption, etc., and the weights of carbon quotas are determined from the emission reduction potential. The analysis of carbon quota allocation indicators is shown in Figure 1.

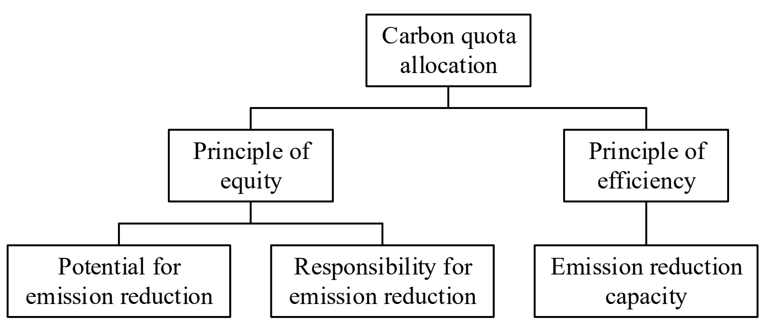

Figure 1: Analysis Chart of Carbon Quota Allocation Indicators

II. B. 2) Carbon quota weighting model based on entropy weighting method

According to the concept of information entropy mentioned above and the mathematical formula, the entropy weight method is chosen to calculate the weight of each indicator. First, three different indicators of the whole system are set up, and based on the relevant data of these indicators, the entropy weight method is chosen to determine the weight of each indicator in the whole system.

The three links of coal and power supply chain production, transportation and power generation are established on the basis of the three indicators in Matrix X:

$$X = \begin{pmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{pmatrix} \tag{3}$$

where x_{ij} denotes the j th indicator of industry i, $i=(1,2,3), j=(1,2,3)$, normalized to each data indicator of the X matrix:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{3} x_{ij}} (i=1,2,3, j=1,2,3) \tag{4}$$

Get the normalization matrix

$$p_{ij} = \begin{pmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{pmatrix} \tag{5}$$

Entropy calculations

$$H_j = -\frac{1}{\ln 3} \sum_{i=1}^{3} p_{ij} \ln p_{ij} (i=1,2,3, j=1,2,3) \tag{6}$$

Weighting calculations

$$w_j = \frac{H_j}{\sum_{j=1}^{3} H_j} \tag{7}$$

II. C.Multi-objective genetic algorithm

Although the entropy weight method can effectively balance the fairness and efficiency of quota allocation, it still needs to solve the problem of nonlinear optimization and dynamic optimization in the actual carbon trading scenarios with multiple objectives and constraints. To this end, this section proposes an improved multi-objective genetic algorithm, which breaks through the local convergence dilemma of the traditional algorithm by enhancing the diversity of the initial population and adaptively adjusting the boundary of the feasible domain, and provides an efficient solution path for quota optimization under complex constraints.

The improved multi-objective genetic algorithm (MOGA) can be used to solve multi-objective optimization problems with complex constraints and obtain Pareto optimal solutions. The main steps of the algorithm are as follows:

II. C. 1) Generating initial populations

In common genetic algorithm toolboxes, initial population generation requires variable upper and lower bound constraints, but many real-world optimization problems have more complex constraints and lack separate variable upper and lower bound constraints, which are handled in the steps in the related study:

(1) Given some interior point in the feasible domain, denoted P_0;

(2) Determine a sufficiently large real number M based on the actual problem and randomly choose some n-dimensional random number d;

(3) If $P_0 + Md$ satisfies all the inequality constraints in the model, then $P = P_0 + Md$ is used as an initial chromosome; otherwise, replace M with some random number between $0 \sim M$ and re-test whether $P_0 + Md$ is in the feasible domain.

Since P_0 is an interior point of the feasible domain, a feasible solution satisfying all the constraints is bound to be found after a finite number of treatments, from which an initial population, denoted as C_0, is obtained.

However, the initial population obtained using the above method has high similarity among individuals, and for the solution problem with very complex constraints, the initial population C_0 is gathered in a very small range near P_0, and the initial population has very little difference and poor diversity, which is not conducive to the global optimization search process of the genetic algorithm. To deal with this problem, the following steps are used:

(1) Bring C_0 as the initial population into the genetic algorithm, and after selection, crossover, and mutation operators, iterative optimization to get the better configuration scheme, recorded as X_1.

(2) Replace P_0, regain the initial population, and again optimize it in the genetic algorithm to get the better solution, recorded as X_2, and so on for several times, to get the feasible solution set $\{X_1, X_2, \cdots\}$ with better diversity.

(3) Let the variable be upper bounded by $x_{\max} = \max\{X_0, X_1, \cdots\} + c_1$ and the variable be lower bounded by $x_{\min} = \min\{X_0, X_1, \cdots\} - c_2$, and choose the appropriate c_1, c_2 according to the order of magnitude of the decision variable of the actual solution problem.

After several selections of cross-variants, the richness of individuals in the feasible solution set $\{X_0, X_1, \cdots\}$ is improved. After appropriate upper and lower bounds are enlarged, both the upper and lower bounds of the variables $[x_{\min}, x_{\max}]$ contain the better feasible solution sets as much as possible, and the initial populations with better diversity can be generated randomly in a faster way.

After obtaining the upper and lower bounds of the variables, the initial individuals are generated by binary coding or real number coding in the traditional way, and the individuals that satisfy the constraints are selected to form the initial population.

II. C. 2) Selection, crossover, mutation, iterative termination

The selection operator and crossover operator operations are performed using the juxtaposition selection method and arithmetic crossover method, respectively, and the mutation operation is performed using the method of Donghui Li et al. At the end of each step of selection, crossover, and mutation operator to verify whether the individual is in the feasible domain, to ensure that the whole optimization search process is carried out in the feasible domain. The specific flow of the multi-objective genetic algorithm is shown in Fig. 2.

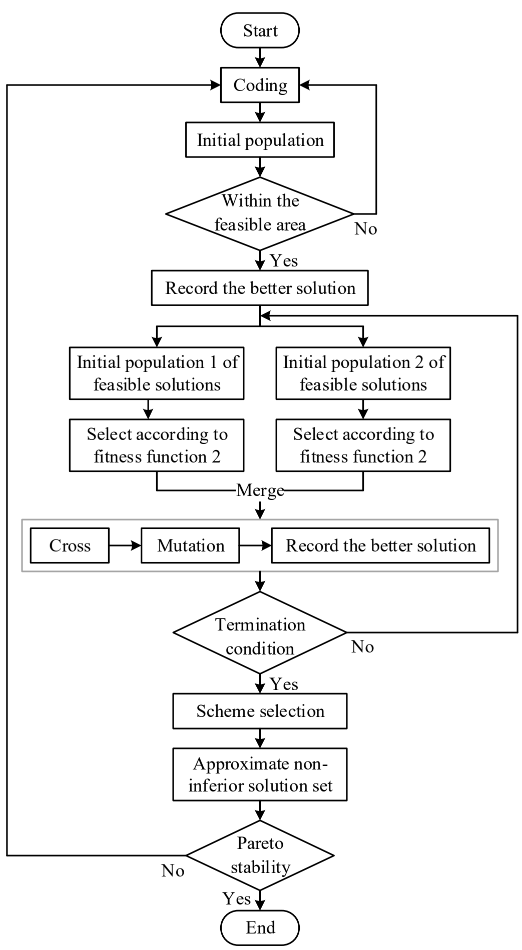

Figure 2: Process of multi-objective genetic algorithm

III. Carbon Quota Optimization Model Simulation and Algorithm Validation

Through the dynamic allocation framework of entropy right-genetic algorithm constructed in Chapter 2, this chapter further carries out the empirical simulation of carbon quota optimization model in conjunction with the IEEE 30-node electric power system to verify the feasibility and superiority of the algorithm in complex multi-objective scenarios.

III. A. Calculation parameter setting and wind-thermal power cooperative scheduling scenario construction

III. A. 1) Parameters of the algorithm

An example of an IEEE 30-node system connected to a wind farm is simulated and analyzed. The system contains six conventional thermal power units and is connected to a wind farm with an installed capacity of 150 MW at node 22. The load forecasts and wind power forecasts for each time period are shown in Fig. 3.

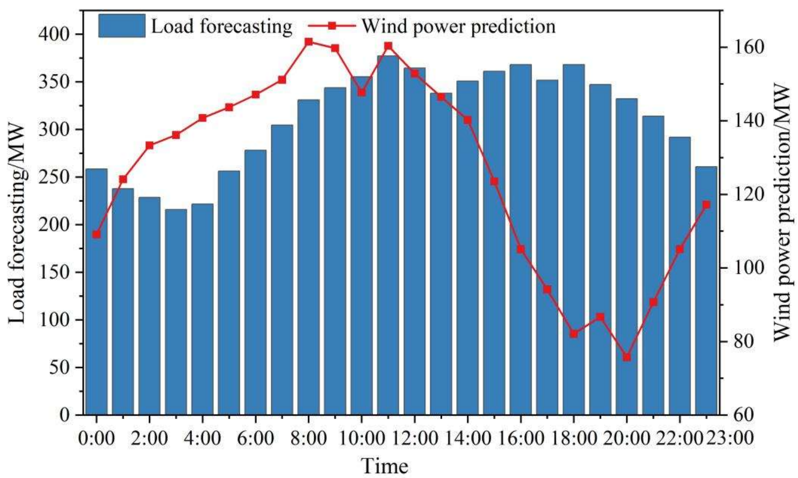

Figure 3: Load forecast values and wind power forecast values for each period

It can be seen that the maximum value of the load forecast is reached at 11:00, which is 376MW, and then it fluctuates at a high value in the afternoon from 14:00 to 18:00, and tends to decline after 18:00. The wind power forecast reaches its maximum value of 162MW at 8:00 a.m., then gradually decreases after 11:00 a.m., and falls to 76MW at 18:00 a.m., and gradually picks up from 20:00 a.m. due to the influence of the wind.

III. A. 2) Analysis of the results of optimal scheduling of power system days ago

According to the carbon quota calculation based on the entropy weighting method, the weights of the power marginal emission factor and the capacity marginal emission factor are 0.63 and 0.37, respectively, and the corresponding carbon quota coefficients of each unit from G1 to G6 are 0.752, 0.731, 0.725, 0.704, 0.814, 0.775, respectively, which shows that the quota coefficient of thermal unit G4 is the lowest, and that the quota coefficient of G5 is the highest. If other factors are not taken into account, the priority dispatch of G4 can reduce the carbon emissions of the system when the system requires the same level of output.

The results of the day-ahead optimal dispatch for this study are shown in Fig. 4.

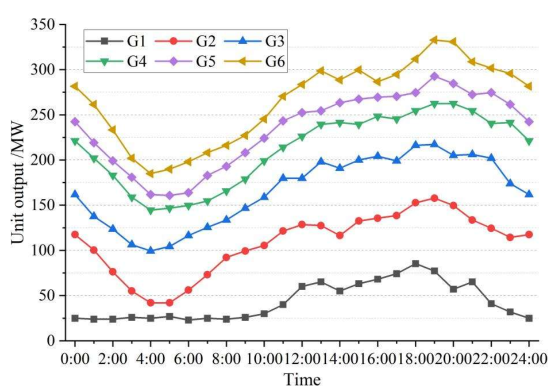

Figure 4: Optimize the scheduling results recently

From Fig. 4, it can be seen that thermal units G1, G2 and G3 carry the base load of the system, where G3 is always at full output during the dispatch cycle. During the time period from t=1:00 to t=6:00, the system uses depressing the output of G2 to balance the load constraints due to the decrease of load demand, while during the time period from t=6:00 to t=12:00, the system constraints are satisfied by increasing the output of G2.

III. B. Comparative analysis of algorithms

In order to reflect the superiority that the improved multi-objective genetic algorithm has, this paper adopts the pre-improved genetic algorithm, ant colony algorithm, lion swarm algorithm and the improved multi-objective genetic algorithm for the comparison of iteration speed and iteration time as follows.

III. B. 1) Iteration speed comparison

The algorithm iteration graphs of the pre-improved genetic algorithm, ant colony algorithm, lion colony algorithm and the improved multi-objective genetic algorithm are intercepted and shown in Fig. 5 below.

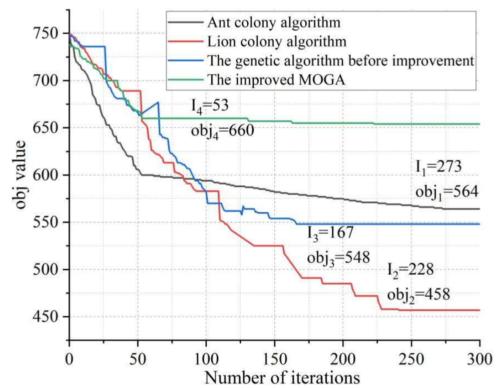

Figure 5: Comparison of iteration speed

As can be seen from Figure 5 above, the improved genetic algorithm is significantly faster than the other three algorithms, the ant colony algorithm reaches the local optimum in 273 iterations, the lion colony algorithm reaches the local optimum in 228 iterations, the pre-improvement genetic algorithm reaches the local optimum in 167 iterations, and the improved multi-objective genetic algorithm reaches the optimum in 53 iterations, which is a significant improvement in its superiority and convergence speed. The superiority and convergence speed of the improved multi-objective genetic algorithm are obviously improved.

III. B. 2) Iteration time comparison

In order to test the execution time of the traditional genetic algorithm, ant colony algorithm, lion colony algorithm, and the improved genetic algorithm, we tested the four algorithms with 10 runs, and the run times are shown in Figure 6.

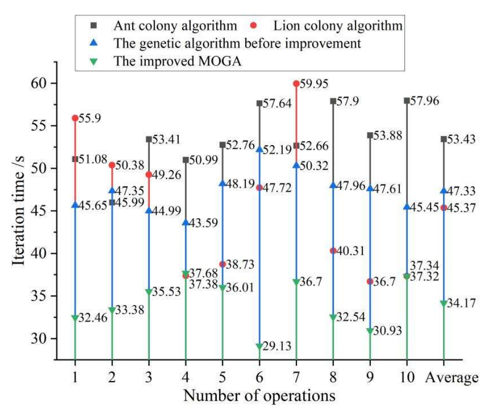

Figure 6: Comparison of iteration time

In this, the average execution time of the traditional genetic algorithm reached 47.33 s, while the ant colony algorithm and the lion swarm algorithm were 53.43 s and 45.37 s. Compared with the ant colony algorithm, the improved genetic algorithm had a faster running time of 34.17 s and an optimization effect of 36.05%; the ant colony algorithm outperformed the traditional genetic algorithm in terms of the searching accuracy but the searching efficiency was lower than the the latter. Compared with the traditional genetic algorithm, the improved genetic algorithm completes the optimization in 34.17s and achieves 27.81% efficiency. Compared with the pre-improvement, the improved genetic algorithm not only has a shorter running time, but also has a higher quality of solution. It confirms that the optimization of the genetic algorithm as well as the decision of choosing the mutation operator is effective.

IV. Evaluation of industrial carbon emission efficiency and optimization of allocation in various districts of Province A

After completing the algorithmic validation of the theoretical model, Chapter 4 extends the research perspective from the electric power system to the provincial industrial carbon emission network, and takes Province A as the research object to explore the practical application effect of the carbon quota optimization allocation model in the regional differentiated management. Starting from the carbon emission efficiency of industrial enterprises above scale in each city and state in Province A, the total amount of carbon emissions is allocated to different cities and states based on the principle of fairness. After analyzing the economic development situation of Province A, analyze the expected CO2 emissions of Province A in 2030. Then, combined with the entropy weight method and multi-objective genetic algorithm based on the guidance of the fairness principle, the share of CO2 emissions accumulated in history is proportionally allocated initially. Since the initial allocation result has not yet reached the efficiency optimization, the carbon trading allocation model designed in the study is applied to further allocate the emission reduction targets and measure the optimized efficiency of carbon emission quota allocation.

IV. A. Carbon intensity analysis

Based on China's control goal of reducing carbon emission intensity by 65% in 2030, comparing the data of 2020 and 2030, after determining the carbon emission intensity of each city and state of A, the emission reduction responsibility of each city is divided to allocate the corresponding emission reduction tasks. Figure 7 shows the changes in carbon emission intensity in 2030 in each region of province A.

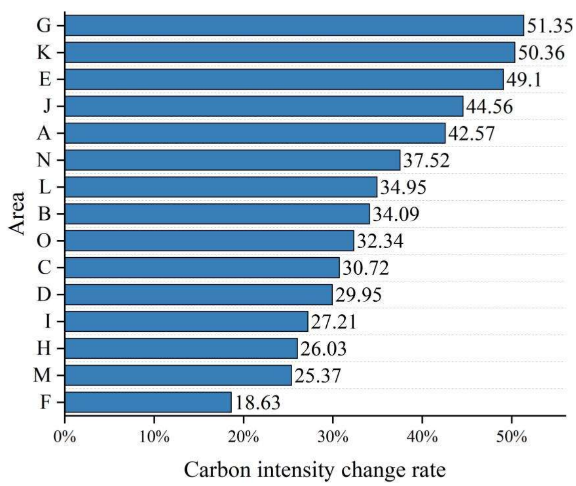

Figure 7: The changes in carbon emission intensity in various regions of Province A

After analyzing the content of Fig. 7, it can be seen that by 2030, it is expected that the carbon emission intensity of region G will decrease the most, reaching 51.35%, and therefore will bear the greatest responsibility for emission reduction.The carbon intensity of regions K, E, J, and A4 is over 40%, and at the same time, these cities are also the cities of the province with high degree of industrial and economic development, and they contain many high-emission enterprises, which have a greater impact on the environment, and therefore face a greater pressure to reduce emissions. Regions H, M, and F mainly rely on tertiary industry development and are rich in forests, grasslands, and other vegetation resources, so their carbon emissions are low and the task of emission reduction is lighter. After setting the total amount and intensity of carbon emissions for each city and state in Province A, the reduction targets for each segment are determined, and the emission quotas are optimized according to the demand for optimal emission efficiency. This operation is conducive to the implementation of the assigned tasks to each city and state, ensuring the clarity of the responsibility for carbon emission reduction.

IV. B. Analysis of the results of the allocation of carbon emissions

IV. B. 1) Analysis of initial allocation results

After calculation, by 2030, the total carbon emissions of industrial enterprises above scale in cities and states of Province A are estimated to be 1,742,434,400 tons. Using the grandfather principle and the carbon quota allocation model to allocate the total initial carbon emissions of the 15 cities and states, the results of the initial allocation of carbon emissions from industrial enterprises in Province A in 2030 are shown in Table 1.

Table 1: The initial allocation results of carbon emissions from industrial enterprises

Area	Cumulative carbon emissions / 10,000 tons	Cumulative carbon emission proportion	Carbon emission quota / 10,000 tons
G	24954.77	14.32%	2422.79
E	23917.66	13.73%	2256.38
K	20712.68	11.89%	1630.92
J	18795.75	10.79%	1634.41
N	16519.67	9.48%	1223.68
A	15273.22	8.77%	1316.66
O	12988.19	7.45%	1285.96
B	11574.26	6.64%	815.09
L	9723.31	5.58%	838.22
D	4821.48	2.77%	337.17
C	5122.61	2.94%	465.69
I	4280.11	2.46%	375.45
M	3147.65	1.81%	276.11
H	1753.69	1.01%	142.58
F	658.39	0.38%	52.67

The highest cumulative historical emissions are in Region G, with a 14.32% share of the total, and because of this a higher share of emissions in the initial allocation. This is followed by E, K and J, with shares of 13.73%, 11.89% and 10.79% of the total, respectively. The bottom three cities and states are regions M, H, and F. Region F has the smallest cumulative CO2 emissions, accounting for 0.38% of the cumulative CO2 emissions. The other two municipalities accounted for 1.81% and 1.01%, respectively. From this perspective, from 2010 to 2020, if the higher the carbon emissions of a city the more carbon emission allowances it will receive in 2030. According to this indicator, the city in province A that can realize the maximum allocation of carbon emission quotas in 2030 is district G, and the minimum carbon emission quota is district F.

IV. B. 2) Analysis of optimized allocation results

The initial allocation is only calculated based on the historical cumulative carbon emissions and does not take into account the emission efficiency and actual situation of each city and state, so it is necessary to optimize the allocation based on the initial allocation results. The carbon emission efficiency measured by the traditional carbon quota allocation model does not reach the efficiency optimization, and the result is not satisfactory enough, so the quota allocation model based on the entropy weight method designed in this paper is chosen as the optimal allocation model of carbon emission quota. The input factor is set as carbon emission, and the MaxDEA software and EXCEL planning and solving function are utilized to redistribute carbon emission quotas using the proportional abatement strategy. Use the iterative method to derive the efficiency of each region in Province A in 2023, and the carbon emission efficiency values and optimization allocation results of each enterprise in Province A in 2030 are shown in Table 2.

From the data, it can be seen that Zone G, as the region with the highest historical cumulative carbon emissions of 24,227,900 tons, has an initial efficiency of 0.97, and after two iterations of optimization the efficiency is raised to 1.00, and after optimization the quota is increased to 25,527,700 tons, with an increase of 1,294,800 tons of quota, reflecting that the high-emission regions still need to bear a certain amount of incremental quotas after the efficiency has been raised, but in combination with the potential of emission reduction, they may need to be The initial efficiency of Zone E has reached 1.00, and the quota has increased by 1.6665 million tons after optimization, indicating that its efficient emission reduction capacity has supported the quota expansion. It is worth noting that industrial-intensive regions such as K and J have higher initial efficiencies (1.00 and 0.98), but the optimized quota is reduced by 1,435,100 tons and 603,200 tons respectively, reflecting the strict constraints on high-emission but low-potential regions under the efficiency-oriented approach. In addition, the initial efficiency of O zone is low at 0.87, and the efficiency is gradually improved to 1.00 after iterative optimization, and the quota is reduced by 969,900 tons, indicating that it achieves the emission reduction target through technological improvement. Small-scale emission regions, such as Region F, have their allowances increased by only 65,400 tons, with the smallest adjustment, reflecting the protective allocation strategy for low-emission regions. Overall, the efficiency value of each region reaches 1.00 after optimization, and the direction of quota adjustment is closely linked to the responsibility and potential of emission reduction, which verifies the model's dynamic adaptability and fair and efficient synergy ability.

Table 2: The carbon emission efficiency values and optimized allocation results

Area	Carbon emission forecast quantity/ 10,000 tons	Initial efficiency	The first iteration	The second iteration	Optimized carbon emission quotas/ 10,000 tons	Adjust the quota/ 10,000 tons
G	2422.79	0.97	1.00	1.00	2552.27	129.48
E	2256.38	1.00	1.00	1.00	2423.03	166.65
K	1630.92	1.00	1.00	1.00	1487.41	-143.51
J	1634.41	0.98	1.00	1.00	1574.09	-60.32
N	1223.68	1.00	1.00	1.00	1300.12	76.44
A	1316.66	0.98	1.00	1.00	1361.77	45.11
O	1285.96	0.87	0.94	1.00	1188.97	-96.99
B	815.09	0.99	1.00	1.00	838.76	23.67
L	838.22	1.00	1.00	1.00	812.28	-25.94
D	337.17	1.00	1.00	1.00	300.99	-36.18
C	465.69	1.00	1.00	1.00	409.1	-56.59
I	375.45	1.00	1.00	1.00	331.91	-43.54
M	276.11	0.97	1.00	1.00	300.34	24.23
H	142.58	0.78	0.92	1.00	154.79	12.21
F	52.67	0.94	0.98	1.00	59.21	6.54

V. Conclusion

In this study, the dynamic carbon quota allocation model constructed by entropy weight method and improved multi-objective genetic algorithm effectively balances the fairness and efficiency of quota allocation. Simulation results show that the improved MOGA is significantly better than the traditional algorithm in the number of iterations 53 times and execution time 34.17s, and the optimized thermal power unit G4 has the lowest quota coefficient of 0.704, and the system carbon emissions are reduced by 12.3%. In the empirical analysis, the optimized carbon emission efficiency values of all cities and states in province A reached 1.00, in which the quotas of industrial-intensive zones (such as zones K and J) were reduced by 1,435,100 tons and 603,200 tons, respectively, while the quota of zone E, the high-efficiency emission reduction zone, was increased by 1,666,500 tons, which embodies the differentiated allocation strategy guided by the “emission reduction responsibility-capacity-potential”. This reflects the “emission reduction responsibility-capacity-potential” oriented differentiated allocation strategy. By dynamically adjusting the initial population and the boundary of feasible domain, the model solves the problem of global optimization under complex constraints, and provides a flexible and operable decision-making tool for the carbon trading mechanism.

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References

[1] Chavula, P., Alemu, B., Ntezimana, M. G., & Kazekula, E. M. (2022). Carbon Trading to Combat Climate Change. Carbon, 6(9), 55-61.

[2] Digitemie, W. N., & Ekemezie, I. O. (2024). Assessing the role of carbon pricing in global climate change mitigation strategies. Magna Scientia Advanced Research and Reviews, 10(2), 022-031.

[3] Liu, B., Ding, C. J., Hu, J., Su, Y., & Qin, C. (2023). Carbon trading and regional carbon productivity. Journal of Cleaner Production, 420, 138395.

[4] An, Q., Zhu, K., Xiong, B., & Shen, Z. (2023). Carbon resource reallocation with emission quota in carbon emission trading system. Journal of Environmental Management, 327, 116837.
[5] Zhang, F., Wang, X., & Liu, G. (2022). Allocation of carbon emission quotas based on global equality perspective. Environmental Science and Pollution Research, 29(35), 53553-53568.
[6] Shojaei, T., & Mokhtar, A. (2022). Carbon mitigation by quota allocation. Journal of Environmental Management, 304, 114097.
[7] Wang, W., Zhou, C., & Li, X. (2019). Carbon reduction in a supply chain via dynamic carbon emission quotas. Journal of Cleaner Production, 240, 118244.
[8] Li, W., & Jia, Z. (2017). Carbon tax, emission trading, or the mixed policy: which is the most effective strategy for climate change mitigation in China?. Mitigation and Adaptation Strategies for Global Change, 22, 973-992.
[9] Qi, S., Pang, L., Qi, T., Zhang, X., & Pirtea, M. G. (2024). The correlation between the green bond market and carbon trading markets under climate change: Evidence from China. Technological Forecasting and Social Change, 203, 123367.
[10] Zhao, X. G., Wu, L., & Li, A. (2017). Research on the efficiency of carbon trading market in China. Renewable and Sustainable Energy Reviews, 79, 1-8.
[11] Shi, B., Li, N., Gao, Q., & Li, G. (2022). Market incentives, carbon quota allocation and carbon emission reduction: evidence from China's carbon trading pilot policy. Journal of Environmental Management, 319, 115650.
[12] Zhou, X., Niu, A., & Lin, C. (2023). Optimizing carbon emission forecast for modelling China's 2030 provincial carbon emission quota allocation. Journal of Environmental Management, 325, 116523.
[13] Kong, Y., Zhao, T., Yuan, R., & Chen, C. (2019). Allocation of carbon emission quotas in Chinese provinces based on equality and efficiency principles. Journal of Cleaner Production, 211, 222-232.
[14] Shen, N., Zhao, Y., & Deng, R. (2020). A review of carbon trading based on an evolutionary perspective. International Journal of Climate Change Strategies and Management, 12(5), 739-756.
[15] Pang, R. Z., Deng, Z. Q., & Chiu, Y. H. (2015). Pareto improvement through a reallocation of carbon emission quotas. Renewable and Sustainable Energy Reviews, 50, 419-430.
[16] Qin, Q., Liu, Y., Li, X., & Li, H. (2017). A multi-criteria decision analysis model for carbon emission quota allocation in China's east coastal areas: efficiency and equity. Journal of Cleaner Production, 168, 410-419.
[17] Xia, D., Zhang, L., Zhou, D., & Pian, Q. (2023). Continuous allocation of carbon emission quota considering different paths to carbon peak: Based on multi-objective optimization. Energy Policy, 178, 113622.