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Optimized Allowance Allocation and Decision Support Based on L-BFGS Algorithm under a New Carbon Emission Trading Mechanism

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ABSTRACT

As the global climate change problem is getting more and more serious, carbon emission quota allocation is more and more emphasized by countries all over the world, while the traditional carbon quota allocation program has the problem of single objective. In order to improve the scientificity and acceptability of the carbon quota allocation scheme, this paper constructs indicators and forms multi-objective functions to formulate the carbon quota allocation scheme from the three perspectives of efficiency, fairness and sustainability, and builds a multi-objective optimization model for carbon quota allocation and decision support. Aiming at the solution problem of the carbon quota allocation model, an improved hybrid swarm algorithm based on Gaussian perturbation, tournament selection strategy and proposed Newtonian local optimization search operator (L-BFGS) is proposed. The model is used to explore the quota allocation scheme for cities in the Bohai Economic Rim in 2030. In the three single-target pre-allocation schemes based on the principles of efficiency, fairness, and sustainability, the difference between the cities with the largest and smallest quotas is 319 Mt, 289 Mt, and 256 Mt, respectively, which lacks scientificity and rationality. In contrast, the allocation results of the multi-objective pre-allocation scheme proposed by the carbon quota allocation model in this paper are relatively balanced and the difference is small, which can eliminate the conflict between multiple principles.

Keywords: L-BFGS algorithm, multi-objective optimization, Gaussian perturbation, bee colony algorithm, carbon quota allocation

1. Introduction

In recent years, with the increasing awareness of environmental protection, the carbon emissions trading market, as an ecological economic model, is gradually being emphasized by governments and

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enterprises, and is regarded as one of the effective ways to solve the problem of global climate change, and in the carbon emissions trading market, the allocation of quotas is a crucial mechanism [1-4]. Through rational allocation of carbon emission rights, enterprises can be effectively incentivized to reduce carbon emissions and promote low-carbon transition [5-6].

Quota allocation can guide enterprises to take the initiative to reduce emissions, and by allocating a certain number of carbon emission quotas to enterprises, it can make enterprises face the pressure to reduce emissions, thus incentivizing them to take effective emission reduction measures [7-8]. This market-based approach not only promotes enterprises to consciously carry out carbon emission reduction, but also reduces the cost of emission reduction and promotes the development and application of low-carbon technologies [9-11]. In addition, quota allocation is of great significance in promoting the formation and development of carbon emission market. Reasonable quota allocation mechanism can ensure the balance of supply and demand in the market, avoid excessive fluctuations in the price of carbon emission rights, and attract more participants to enter the carbon emission market through quota allocation to promote the prosperity and development of the market [12-15]. Quota allocation plays a crucial role in the carbon emissions trading market, and only by establishing a fair, reasonable, and transparent quota allocation mechanism can we effectively promote carbon emission reduction, promote the healthy development of the carbon emissions market, and realize the national carbon emission reduction goals [16-19]. Therefore, it is necessary to strengthen supervision and management, optimize the quota allocation mechanism, and promote the carbon emissions trading market toward a more healthy and sustainable development [20-21].

In order to realize scientific and reasonable carbon quota allocation, this paper follows the three principles of fairness, efficiency and sustainable development, constructs the indicators of fairness, efficiency and sustainability respectively, and forms the corresponding multi-objective function. Aiming at the singularity problem of the traditional carbon quota allocation scheme, from the perspective of multi-objective optimization, the carbon quota allocation model of non-linear planning is constructed, and the corresponding carbon emission scheme is derived by assigning different weights. Facing the nonlinear solution problem of the carbon quota allocation model, an improved hybrid swarm algorithm is proposed. The introduction of Gaussian perturbation based on the current global optimal solution can prevent the algorithm from falling into local optimality and accelerate the convergence of the algorithm. A tournament selection strategy is adopted on the follower bees to avoid the precocity phenomenon of the algorithm, and the L-BFGS algorithm is used for local optimization to achieve fast convergence of the algorithm. Numerical simulation experiments are carried out to test the effectiveness of the improved hybrid swarm algorithm in this paper. Finally, the interactive carbon quota allocation model proposed in this paper is utilized to explore the carbon quota allocation scheme for the cities in Bohai Rim Economic Zone in 2030.

2. Carbon quota allocation model based on L-BFGS algorithm

Carbon quota allocation plays an important role in the development and structural optimization of the production industry, and a reasonable carbon quota allocation under the emerging carbon emissions trading mechanism is a prerequisite for the effective operation of the carbon emissions trading market. In order to optimize the allocation of carbon emissions, this chapter will construct a carbon quota allocation model based on the L-BFGS algorithm to provide optimization and decision support for the carbon quota allocation work.

2.1. Carbon Quota Allocation and Decision Support Modeling

To accomplish the total carbon emission reduction target, the first step is to determine the target of each province, i.e., assuming that there are N provinces (in this paper, we take $N=30$), among which the carbon emission value C_i of the i th province ($i=1,2,\cdots,N$, same as the following) in the base year and the value of the country's total carbon emissions $C=\sum_{i=1}^{n} C_i$ are known quantities, and the carbon emission quota X_i for the i th province in the next year and the total carbon emission control value are the unknown quantities sought.

2.1.1. Sustainability, efficiency and equity indicators:

1) Sustainability indicators for carbon allowance allocation. If only the absolute fall of carbon credits is considered under the principle of sustainability, then the distance $\sqrt{\sum_{i=1}^{N}(X_i-C_i)^2}$ normalized that is, to obtain the objective function of sustainability:

$$\alpha=\frac{\sqrt{\sum_{i=1}^{N}(X_i-C_i)^2}}{2\sum_{i=1}^{N} C_i} \tag{1}$$

Where α is called the sustainability index.

2) Efficiency index of carbon quota allocation. Considering the GDP of each province in the base year as G_i, the total national GDP value $G=\sum_{i=1}^{n} G_i$, and the projected target value of each province's GDP in the next year of the base year, $G_i^{'}$, where the projected target value of $G_i^{'}$ is directly given based on the projected economic growth rate of each province in the base year, and the summation yields the total national GDP value $G^{'}=\sum_{i=1}^{n} G_i^{'}$. Then the carbon emission coefficients per unit economic volume for each province in the base year $\overline{\eta}_i=\frac{C_i}{G_i}$ and the carbon emission coefficients for the following year $\overline{\xi}_i=\frac{X_i}{G_i^{'}}$ On the basis of efficiency equity should be compared to the base year of the carbon emission factor can not be decreased, that is, the constraint: $\overline{\xi}_i,, \overline{\eta}_i$.

Because the overall efficiency of each province should eventually converge to unify to reach the national overall emission efficiency coefficient $\overline{\xi}=\frac{X}{G^{'}}$, the M provinces that have not reached the national average emission coefficient need to be whipsawed and solved for first:

$$M=\frac{1}{2}\sum_{i=1}^{N}\left(1+\frac{|\overline{\xi}_i-\overline{\xi}|}{\overline{\xi}_i-\overline{\xi}}\right) \tag{2}$$

The objective function of the efficiency principle is then given:

$$\beta=\frac{\sum_{i=1}^{N}(\overline{\xi}_i-\overline{\xi})\left(1+\frac{|\overline{\xi}_i-\overline{\xi}|}{\overline{\xi}_i-\overline{\xi}}\right)}{2M} \tag{3}$$

Where β is the efficiency index, the smaller the target value β, the more efficient. This objective function is generally obtained iteratively in other models, and here in this paper, we directly give the provinces that have not reached the average emission efficiency coefficient, and set the value of the overall national emission efficiency coefficient $\overline{\xi}$ as the most efficient. The value of $1+\frac{|\overline{\xi}_i-\overline{\xi}|}{\overline{\xi}_i-\overline{\xi}}$ in the equation can only take 0 or 2, which means that the i th province can or cannot reach the national average emission factor $\bar{\xi}$, respectively. The equation $(\bar{\xi}_i - \bar{\xi})(1+\frac{|\bar{\xi}_i - \bar{\xi}|}{\bar{\xi}_i - \bar{\xi}})$ represents the fall-off of the i th province from the overall national emission efficiency factor $\bar{\xi}$, and β is the sum of the fallout of all provinces that do not meet the national average emission efficiency factor $\bar{\xi}$, the smaller its value, the more efficient it is. The value of $\beta = 0$ is the extreme ideal value, indicating that the emission efficiency is consistent across provinces.

3) Fairness indicator of carbon quota allocation. The country to fulfill the carbon emission target, the quota that needs to be allocated to the province for free in this year needs to have a national total control coefficient μ, in this paper, we take $\mu = 0.8$, that is, the value of the total quota that is initially issued for free needs to be satisfied:

$$X \le \mu C \tag{4}$$

The initial quotas of each province need to have a certain guarantee, i.e., the principle of fairness, this paper gives the i th province corresponds to the next year's minimum carbon emission proportion coefficient ρ_i, this paper, in order to simplify the discussion, uniformly take the $\rho_i = 0.6$, in order to reflect the principle of fairness, the bottom line, the value of the quota is not less than the previous year's ρ_i times and not exceed the previous value, i.e:

$$\rho_i C_i \le X_i \le C_i \tag{5}$$

2.1.2. Carbon quota allocation model under the perspective of multi-objective optimization. In this paper, a nonlinear programming model is developed to minimize the sustainability objective function considering only carbon emission values:

$$\min \quad \alpha = \frac{\sqrt{\sum_{i=1}^{n}(X_i - C_i)^2}}{2\sum_{i=1}^{n} C_i} \tag{6}$$

$$s.t. \begin{cases} X \le \mu C \\ \bar{\xi} \le \bar{\eta} \\ \rho_i C_i \le X_i \le C_i \end{cases} \tag{7}$$

A nonlinear programming model that minimizes the efficiency objective function in the case of GDP is considered with constant constraints:

$$\min \quad \beta = \frac{\sum_{i=1}^{N} |\bar{\xi}_i - \bar{\xi}|(1+\frac{|\bar{\xi}_i - \bar{\xi}|}{\bar{\xi}_i - \bar{\xi}})}{2M} \tag{8}$$

Taking into account the three principles of sustainability, efficiency and equity:

$$\min \theta = k_1\alpha + k_2\beta \tag{9}$$

where $k_1, k_2 \in [0,1]$ and satisfies $k_1 + k_2 = 1$. Given different values of the weighting coefficients (k_1, k_2), the optimal solutions are discussed one by one, in which if $(k_1, k_2) = (0,1)$ or (1,0) is set, the conclusion is obtained as the value of the carbon emission allowance obtained by the principle of sustainability only and efficiency only, with the fairness being guaranteed, and the value of the carbon emission allowance obtained by the principle of sustainability only, k_1, k_2 is a compromise when taking (0.5, 0.5).

2.2. Carbon Quota Allocation Model Solution

2.2.1. Standard swarm algorithm. The bee colony algorithm (ABC algorithm) searches for the optimal nectar source by simulating the intelligent behavior of bees in foraging [22]. The swarm in the algorithm is categorized into leading, following and scouting bees. They share information and interact with each other to complete the search for food sources. When solving the optimization problem, the location of the food source is the solution space, the set of feasible solutions of the optimization problem is called a population, each individual (feasible solution) in the population corresponds to a food source, and the degree of superiority of the food source depends on the fitness value of the optimization problem to be optimized, and the number of feasible solutions is equal to the sum of the leading bees and the following bees. The D-dimensional vector $(V_i1, V_2, \cdots, V_{id})^T$ is used to denote the i th individual. Firstly, initialize the population to generate N solutions, half of which with better fitness values as leading peaks, and the other half as following bees; then enter the loop, the leading bees perform a neighborhood search for the food source, and update the position of the food source if the nectar quality (fitness value) of the new food source (solution) is superior to that of the previous solution, otherwise the position remains unchanged; the following bees select the food source according to the selection probability, and perform a neighborhood search around it, to retain the better solution.ABC algorithm obtains the optimal solution by such repeated search.

The search formula for the food source update by the leading bee and the following peak is:

$$X_{id} = V_{id} + rand(0,1) \times (V_{id} - V_{kd}) \tag{10}$$

Where: V_{id} is the d -dimensional solution of the i th individual of the current leading bee population, $d \in \{1, 2, \cdots, D\}$, $i \in \{1, 2, \cdots, N/2\}$, and k is chosen randomly; rand() is the random number on the interval [0, 1] used to control V_{id} 's neighborhood generation range.

The following bees in the ABC algorithm make food source selection through the feedback from the leading bees on the yield of the food source, and the greater the yield the greater the probability that the food source will be selected. The yield is expressed through the fitness value. The selection probability is as follows:

$$P_i = \frac{fit_i}{\sum_{i=1}^{NP/2} fit_i} \tag{11}$$

Where: fit_i is the fitness function value corresponding to the i th individual.

In order to avoid the loss of population diversity and prevent the population from falling into local optima, there is an important parameter limit in the ABC algorithm, which makes the probability of the algorithm searching for an optimal solution increase. Assuming that a particular solution remains unchanged for successive limit generations, the i th leading bee abandons the current solution and converts to a scout bee, and the scout peak generates a new solution through equation (11):

$$V_{id}^0 = V_{id}^{\min} + rand(0,1) \times (V_{id}^{\max} - V_{id}^{\min}) \tag{12}$$

where: $i = 1, 2, \cdots, N; d = 1, 2, \cdots, D$; $V_{id}^{\max}$ and $V_{id}^{\min}$ are the maximum and minimum values of the variables.

2.2.2. Improved Hybrid Swarm Algorithm:

1) Gaussian Perturbation Search [23]. Aiming at the problem that the standard bee colony optimization algorithm converges slowly in the late stage of evolution and is prone to fall into local optimum, the social cognition part of the search equation is improved by replacing it with a Gaussian perturbation term, and the evolution model is as follows:

$$\begin{cases} X_{id} = V_{id} + r_1(lbest_{id} - V_{ix}) + r_2 gauss_{id} \\ \quad gauss_{id} = r_3 gaussian(\mu, \sigma^2) \end{cases} \tag{13}$$

Where: r_1, r_2 and r_3 are random numbers obeying a uniform distribution in the interval (0, 1); the second part of the equation is the learning of the leading peak on its own experience, which represents the self-cognitive ability, and individuals in the population are affected by the locally optimal individuals, which ensures the diversity of the individuals in the population, but it will result in the lack of learning ability to the global optimal individual in the population, which leads to a lower probability of searching for the global optimal individual; in order to strengthen the social learning ability, a Gaussian perturbation term is added, which is controlled by the current global optimal individual, which both improves the social learning ability and increases the search for the global optimal individual. However, it will cause the population to lack the ability to learn from the global optimal individual, resulting in a lower probability of searching for the global optimal individual; in order to strengthen the social learning ability of the population, a Gaussian perturbation term controlled by the current global optimal individual is added, which not only improves the social learning ability of the individuals in the population, but also increases the diversity of the population, and further strengthens the ability of the individuals to escape; $gauss_{id}$ represents the Gaussian perturbation term generated by the ith individual of the population at the current iteration. The Gaussian perturbation produced at the current iteration, μ indicates that the mean is taken as 0; σ standard deviation is taken as $|gbest_{id}|$.

2) Tournament selection strategy. In the ABC algorithm, the following bees perform food source selection according to the roulette selection strategy, and the greater the food source yield, the greater the probability that the food source is selected. The selection probability is shown in equation (13). This roulette selection strategy can quickly select and retain the better individuals and eliminate the poorer individuals at the beginning of the algorithm operation; however, as the number of iterations increases, the individual fitness values gradually converge, the population diversity decreases, and the algorithm is prone to fall into local optimality.

The tournament selection strategy is a selection process based on a local competition mechanism, where k individuals are randomly selected for comparison in the current scout bee population, and the fitness function is the absolute value of the objective function, the individual with a small fitness value is selected and awarded a score of 1, and the parameter k is the size of the competition. The process is repeated for all individuals. The one with the highest final score also has the largest weight. Such a selection mechanism uses the fitness value as a relative criterion rather than an absolute criterion, which can avoid the premature phenomenon of the algorithm to some extent. The selection probabilities are as follows:

$$P_i = \frac{c_i}{\sum_{i=1} c_i} \tag{14}$$

Where: c_i is the score of each individual.

3) Limit field proposed Newton algorithm. In this paper, an improved algorithm in the proposed Newton's algorithm is chosen - Limit Domain Proposed Newton's Goan Method (L-BFGS), whose correction formula is as follows [24]:

$$H_{k+1} = V_k^T H_k V_k + \rho_k s_k s_k^T \tag{15}$$

where $\rho_k = \frac{1}{\gamma_i^T s_i}$. The correction process for H is as follows.

When $k+1 \le m$:

$$\begin{aligned} H_{k+1} = V_k^T V_{k-1}^T \cdots + H_0 V_0 \cdots V_{k-1} V_k + V_k^T \cdots V_1^T \rho_0 s_0 s_0^T V_k \\ + V_k^T V_{k-1}^T \cdots V_2^T \rho_1 s_1 s_1^T V_2 \cdots V_{k-1} V_k \\ + \cdots + \\ V_k^T V_{k-1}^T \rho_{k-2} s_{k-2} s_{k-2}^T V_{k-1} V_k \\ + V_k^T \rho_{k-1} s_{k-1} s_{k-1}^T V_{k-1} V_k + \rho_k s_k s_k^T \end{aligned} \tag{16}$$

when $k+1>m$:

$$\begin{aligned} H_{k+1} = V_k^T V_{k-1}^T \cdots V_{k-m+1}^T H_0 V_{k-m+1} \cdots V_{k-1} V_k \\ + V_k^T V_{k-1}^T \cdots V_{k-m+1}^T \rho_0 s_0 s_0^T V_{k-m+1}^T \cdots V_{k-1} V_k \\ + V_k^T V_{k-1}^T \cdots V_{k-m+2}^T \rho_1 s_1 s_1^T V_{k-m+2}^T \cdots V_{k-1} V_k + \cdots + \rho_k s_k s_k^T \end{aligned} \tag{17}$$

The computational steps of the L-BFGS algorithm are as follows.

(1) Choose the initial point $V_0, k=0$, set H_0 to be l, l is the unit matrix with precision ε_{end}, and positive integer m.

(2) Calculate the gradient of the objective function $f(V)$ at V_k with $g_k = \nabla f(V_k)$ to determine the search direction $d_k, d_k = H_k g_k$.

(3) Starting from V_k, search in the direction of d_k to find α_k such that $f(V_k+\alpha_k d_k) = \min_{t \geq 0} f(V_k + \alpha_k d_k)$, such that $V_{k+1} = V_k + \alpha_k d_k$. Judgment Judgment $f(V_{k+1}) \leq \varepsilon_{end}$, if it holds output V_{k+1}, otherwise go to step (5).

(4) Judge $\| f(V_{k+1}) \| \leq \varepsilon_{end}$, if it holds output V_{k+1}, otherwise go to step (5).

(5) Take $m = \min\{k+1, m\}$, update m times H_0 according to the correction formula to get a new correction formula H_k, where $S_k = V_{k=1} - V_k, y_k = \nabla f(V_{k+1}) - \nabla f(V_k)$, let $k = k+1$, go to step (2).

4) Steps to improve the hybrid swarm algorithm solution:

(1) Initialize the population, set the number of evolutionary generations Z_L, the flag vector $bas(i)=0$, the population size N, the maximum number of iterations max cycly of the improved swarming algorithm, the fitness of the objective function fit_i, and the precision of the local optimization transformation ε. An initial population is generated and the fitness of each individual is calculated. The harmonic balance equation adaptation function is as follows:

$$fit_i = | f(V_i) | \tag{18}$$

If the fitness value $fit_i \leq \varepsilon (i = 1, 2, \cdots, NP)$ of an individual, go to step f) for local optimization, otherwise proceed to the next step.

(2) The leading bee performs a neighborhood search based on equation (12) to generate a new solution X and calculates the fitness function value of each solution vector. Perform greedy selection, if the fitness value of X_i is less than V_i, replace V_i with X_i, and take X_i as the current optimal solution, otherwise keep V_i.

(3) Calculate the selection probability P_i according to Eq. (13), follow the bees to select the food source according to P_i, perform the neighborhood search to generate the new solution X_i, calculate the fitness function value of each solution vector and perform the greedy selection as in step (2).

(4) Determine whether there is a solution that needs to be discarded, if so, the scout bee generates a new solution to replace it according to equation (11).

(5) Judge whether the local optimization transformation accuracy ε is reached, if so, go to step f), otherwise go to step b).

(6) Use the obtained current better solution as the initial value $V^{(0)}$ of the L-BFGS algorithm, and continue the iteration. When the accuracy ε_{end} is satisfied or the maximum number of iterations max cycly is reached, the algorithm ends and the current solution is output; if not, go to step (2).

3. Numerical simulation experiments on algorithms

In order to verify the effectiveness of the improved hybrid swarm algorithm proposed in this paper in constructing the carbon quota allocation model, it is compared with a representative multi-objective optimization algorithm.

3.1. Experimental setup

The ZDT family of functions is selected as the test set in this chapter. The boundary of each function is shown in Table 1. In the table M denotes the number of targets in the test set, D is the maximum dimension of the test function. Range is the range of values of the decision variables of the test function. In the table $[[0]*D]$ indicates that all dimension values are 0, and the values of other dimension numbers are $[-5]*(D-1)=[-5,-10,-15,\ldots-5*D-1]$.

The Inverse Generating Distance (IGD) is used to evaluate the distribution and convergence of all algorithms.The IGD metric evaluates the performance of an algorithm by assessing the degree of agreement between the set of Pareto solutions generated by the algorithm and the true Pareto bounds. The mean and standard deviation of the IGD results are computed for each function.The mean of the IGD indicates the performance of the algorithm and the standard deviation indicates the stability. On each algorithm, all functions were run independently 25 times.

The performance of the improved hybrid swarm algorithm of this paper is evaluated by two sets of experiments. The first set of experiments is to compare with some classical multi-objective optimization algorithms, and the second set is to verify the effectiveness of each strategy of the improved hybrid bee colony algorithm in this paper. In order to ensure the fairness of the experiments, some public parameters are unified, the population size SN in the two objectives of the test function ZDT series for 200, taking into account the different algorithms of the number of calculations per iteration, unified to the number of evaluations of the objective function MaxFEs as a termination condition, the ZDT series of test functions for 5 × 104.

All experiments were conducted on a computer configured with an Intel Core i5-5200U CPU 2.6GHz processor and 4.0GB RAM.

Table 1. Parameters of the function

Test function name	M	D	Range([up], [low])
ZDT1	2	30	$[[0]*D],[[1]*D]$
ZDT2	2	30	$[[0]*D],[[1]*D]$
ZDT3	2	10	$[[0]*D],[[1]*D]$
ZDT4	2	10	$[0,[-5]*(D-1)],[1,[5]*(D-1)]$
ZDT6	2	10	$[[0]*D],[[1]*D]$

3.2. Analysis of the results of the comparison experiment

In order to verify the performance of this paper's improved hybrid swarm algorithm under IGD metrics, it is compared with several multi-objective evolutionary algorithms, namely NSGA-II, MOEA/D, MOPSO, and MOABC. The IGD results of this paper's improved hybrid swarm algorithm and the other five algorithms are shown in Table 2. It can be seen that the improved hybrid bee colony algorithm in this paper has excellent performance on both objective problems. The results show that the improved hybrid swarm algorithm in this paper has better allocation performance on simple PFs. For ZDT1, ZDT2, ZDT4 and ZDT6, the improved hybrid swarm algorithm of this paper achieves the best performance among the compared algorithms.

Table 2. Results comparison of IGD indexes of six algorithms

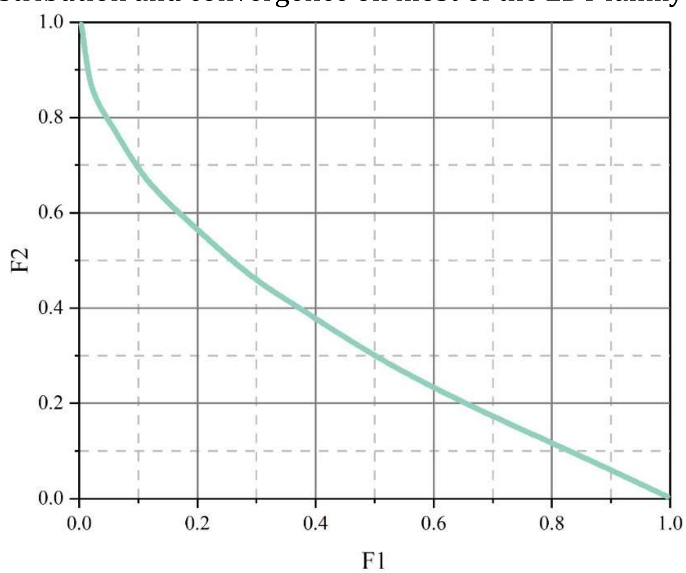
Problem	MOEA/D		NSGA-II		MOPSO		SPEA2		MOABC		Algorithm of this article	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
ZDT1	0.00373	0.00269	0.00235	0.0000803	0.492	0.194	0.00235	0.00006960	0.324	0.0554	0.00196	0.0000821
ZDT2	0.0038	0.0022	0.00237	0.0000786	1.41	0.364	0.00238	0.0000652	9.85	2.47	0.00197	0.0000201
ZDT3	0.0164	0.0219	0.00265	0.0000681	0.478	0.13	0.00263	0.0000705	0.244	0.0289	0.00301	0.0000751
ZDT4	0.525	0.196	0.862	0.379	13	4.94	0.85	0.288	0.201	0.082	0.00194	0.0000013
ZDT6	0.00309	5.34E-04	0.00185	0.0000618	0.191	1	0.00184	0.00005610	0.0275	0.0822	0.00149	0.0000011

The average ranking values of all the algorithms obtained by Friedman's test are shown in Table 3. As shown in the table, the improved hybrid bee colony algorithm of this paper has the highest ranking among all the six multi-objective algorithms with an average ranking of 1.52.

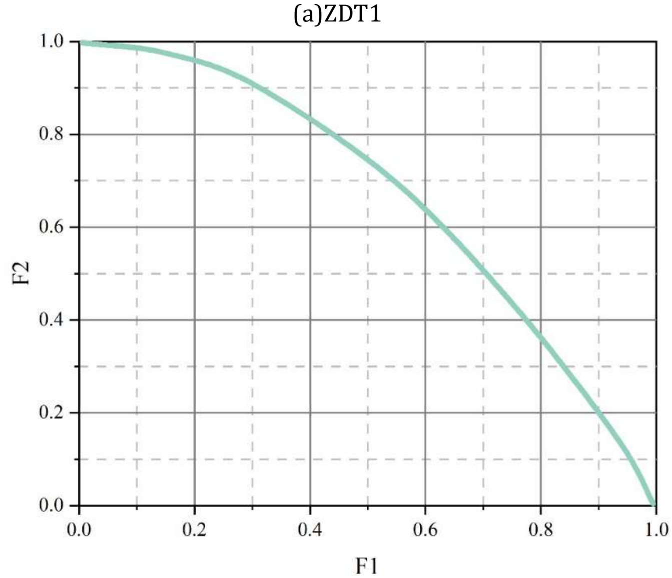
Table 3. The average IGD ranking of six algorithms

Algorithm	Mean ranking
MOEA/D	3.62
NSGA-II	2.88
MOPSO	5.75
SPEA2	2.86
MOABC	4.83
Algorithm of this article	1.52

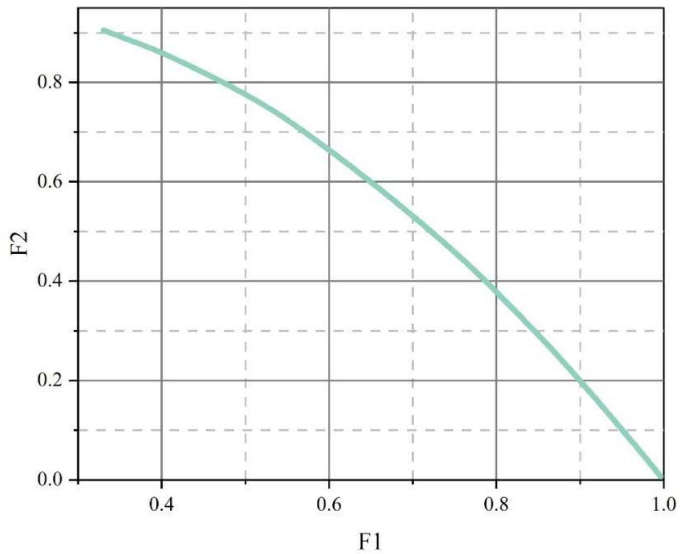
In the above analysis, the improved hybrid swarm algorithm in this paper in obtained excellent IGD results compared to MOEA/D, NSGA-II, MOPSO, SPEA2 and MOABC. In order to observe the quality of the final Pareto solution, the Pareto frontiers of the improved hybrid swarm algorithm of this paper obtained on some of the ZDT series of functions are given, as shown in Fig. 1. Figures (a) to (d) represent ZDT1 to ZDT4 in turn. As can be seen from the figure, the improved hybrid swarm algorithm in this paper has good distribution and convergence on most of the ZDT family of functions.



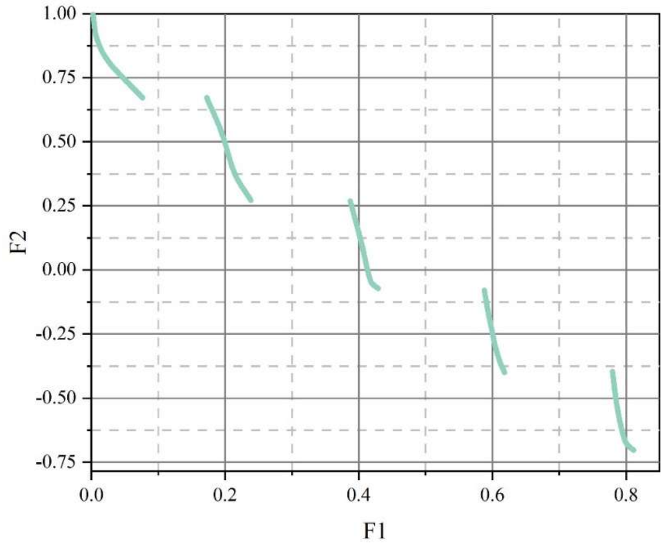
(a)ZDT1



(b)ZDT2



(c)ZDT3



(d)ZDT4

Fig. 1. Pareto Frontier of algorithm of this article in partial functions.

3.3. Comparative experimental analysis of the performance of different strategies

In order to study the role of different strategies in this paper's improved hybrid swarm algorithm, the algorithms of this paper's improved hybrid swarm algorithm combined with the strategies of MOABC, ABC-MF, ABC-MF-EO, and ABC-MF-RP are constructed. The IGD results of different algorithms are listed, as shown in Table 4. The results show that the improved hybrid swarm algorithm of this paper obtains the best IGD values in different test functions, i.e., the algorithm of this paper has good stability while improving the optimization performance of different test functions.

Table 4. Results of IGD values under different strategies

Problem	MOABC		MOABC-MF		ABC-MF-EO		ABC-MF-RP		Algorithm of this article	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
ZDT1	0.324	0.0554	0.00318	0.000128	0.00321	0.000214	0.00197	0.00000652	0.00197	0.0000821
ZDT2	9.85	2.47	0.00	0.0001	0.00	0.0001	0.00	0.0000	0.00	0.0000

			38	2	384	22	197	683	197	201
ZDT3	0.244	0.0289	0.00344	0.0005810	0.00338	0.000134	0.00303	0.0000943	0.00301	0.0000751
ZDT4	0.201	0.082	0.0033	0.000603	0.0032	0.0001580	0.00194	0.00000107	0.00194	0.0000013
ZDT6	0.0275	0.00822	0.00304	0.0000831	0.0306	0.0001200	0.0015	0.00000156	0.0015	0.0000011

Friedman test is used to calculate the average ranking of each algorithm under different strategies, as shown in Table 5. As shown in the table, the improved hybrid swarm algorithm in this paper has obtained the best ranking with an average ranking of 1.58. This means that the improved hybrid swarm algorithm in this paper is the most competitive algorithm among the different algorithms.

Table 5. Average rank values

Algorithm	Mean ranking
MOABC	4.78
ABC-MF	3.53
ABC-MF-EO	3.17
ABC-MF-RP	1.85
Algorithm of this article	1.58

4. Analysis of the allocation of carbon emission allowances to cities in the Bohai Rim Economic Zone

The Bohai Economic Rim is a major industrialized region in China, and is also a key regulatory region for emission reduction. With the rapid development of regional economy, the contradiction between economic development and carbon emission in the Bohai Rim Economic Zone has become more and more prominent. In this study, Tianjin, Beijing and all prefecture-level cities in Hebei, Shandong and Liaoning provinces are selected as research objects, and the carbon quota allocation model proposed in this paper is utilized to explore the quota allocation scheme among cities in 2030.

4.1. Comparative analysis of different allocation options

Based on the principles of equity, efficiency and sustainability, the carbon quota allocation model in this paper is applied to obtain the results corresponding to the three pre-allocation scenarios. After obtaining the three pre-allocation scenarios, this study further compares the carbon emission quotas obtained by each city in the three pre-allocation scenarios, as shown in Table 6. It can be found that there are obvious differences in the three pre-allocation results of 19 cities, including Beijing and Tangshan. Among the three kinds of pre-allocation programs, the difference between the largest and smallest quotas allocated to Tianjin, Chengde, Zhangjiakou, and Beijing is above 200 Mt, which is 237 Mt, 229 Mt, 212 Mt, and 211 Mt, respectively; the difference between the three kinds of pre-allocations in Dandong is above 100 Mt, and the difference between the three kinds of pre-allocations in the rest of the cities is less than 100 Mt.

It can be found that the difference between the cities with the largest and smallest quotas in the three pre-allocation schemes is 319Mt, 289Mt, 256Mt respectively, and the extreme difference of the optimized allocation result is 234Mt. According to the different preferences of each city, the results obtained by only considering a single principle of allocation tend to be more extreme, and the allocation scheme is not sufficiently scientific and reasonable, and it is difficult to reach a consensus among cities in Davao, which makes the scheme less operable and the policy more difficult to implement. It is difficult to reach a consensus among cities in Davao, and the program is not operable and has limited policy significance. In contrast, a multi-principle allocation that integrates the principles of equity, efficiency, feasibility and sustainability is relatively balanced and can minimize the distortion of an allocation that considers only a single principle and take into account a wider range of dimensions.

Table 6. Comparison of results of allocation schemes

Number	City	Carbon emission quotas(Mt)					
		Pre-allocation scheme based on fairness	Pre-allocation scheme based on efficiency	Pre-allocation scheme based on sustainability	Max-Min	Preference choice	Optimal allocation results
1	Beijing	331	183	119	211	Fairness	248
2	Tianjin	301	302	65	237	Efficiency	231
3	Shijiazhuang	150	144	71	79	Fairness	140
4	Tangshan	88	155	98	67	Efficiency	115
5	Qinhuangdao	35	49	69	34	Sustainable	52
6	Xian Handan	100	125	61	64	Efficiency	96
7	Xingtai	133	90	60	73	Fairness	109
8	Baoding	121	137	135	16	Efficiency	132
9	Zhangjiakou	73	56	268	212	Sustainable	78
10	Chengde	69	41	271	229	Sustainable	89
11	Cangzhou	84	122	71	51	Efficiency	93
12	Langfang	66	98	34	64	Efficiency	67
13	Hengshui	74	54	41	32	Fairness	65
14	Shenyang	144	157	81	76	Efficiency	128
15	Dalian	142	127	208	81	Sustainable	160
16	Anshan	60	67	71	11	Sustainable	67
17	Fushun	27	46	116	89	Sustainable	43

18	Benxi	20	36	87	67	Sustainable	34
19	Dandong	25	34	157	132	Sustainable	37
20	Jinzhou	33	50	64	31	Sustainable	48
21	Yingkou	32	52	45	20	Efficiency	44
22	Fuxin	15	37	66	52	Sustainable	35
23	Liaoyang	24	49	32	25	Efficiency	36
24	Hsun Panjin	23	53	23	30	Efficiency	34
25	Tieling	31	62	106	74	Sustainable	60
26	Chaoyang	30	47	121	91	Sustainable	53
27	Koh Hulu Island	28	47	82	54	Sustainable	45
28	Jinan	129	109	52	77	Fairness	116
29	Qingdao	178	127	127	52	Fairness	155
30	Zibo	92	74	41	50	Fairness	83
31	Zaozhuang	52	49	34	18	Efficiency	53
32	Dongying	69	75	48	27	Efficiency	65
33	Yantai	143	113	151	38	Sustainable	136
34	Weifang	141	138	116	25	Fairness	133
35	Jining	120	101	71	49	Fairness	112
36	Tai 'an	76	65	50	26	Fairness	72
37	Weihai	68	63	74	11	Sustainable	69
38	Sunshine	37	38	58	21	Sustainable	45
39	Laiwu	12	13	14	2	Sustainable	14
40	Linyi	140	125	125	16	Fairness	131
4	Dezh	80	79	60	20	Efficie	77

1	ou					ncy	
42	Liaocheng	76	72	49	26	Fairness	72
43	Binzhou	60	78	54	24	Efficiency	65
44	Heze	92	86	79	13	Fairness	87
Extreme difference		319	289	256	-	-	234

The contribution of the three pre-allocation scenarios of the principles of equity, efficiency and sustainability to each city is shown specifically in figure 2. In general, the principles of equity, efficiency and sustainability are both conflicting and consistent across cities. The principle of equity is highlighted in 11 cities, including Beijing, Xingtai, Tianjin, Jinan, Zibo, Qingdao, and Shijiazhuang, and specifically, the allocation results based on the principle of equity account for the largest percentage of results compared to the other two principles. In the case of Beijing, for example, the results show that the proportion of equity reaches 52.2%. 11 cities (e.g. Langfang, Tangshan, Tianjin, Shenyang) have the advantage of reflecting the principle of efficiency, as shown by the fact that they receive the largest amount of emission allowances in the pre-allocation scenario based on efficiency, and most of these cities are located in Hebei and Liaoning. The sustainability principle dominates in 13 cities (e.g., Dandong, Chengde, Zhangjiakou, Fushun, and Benxi), especially in Chengde, where the proportion of sustainability-based allocation is 71.0%. In addition, there is uniformity in the three pre-allocation results for the remaining cities, with each principle contributing to the emission allowances in much the same way.

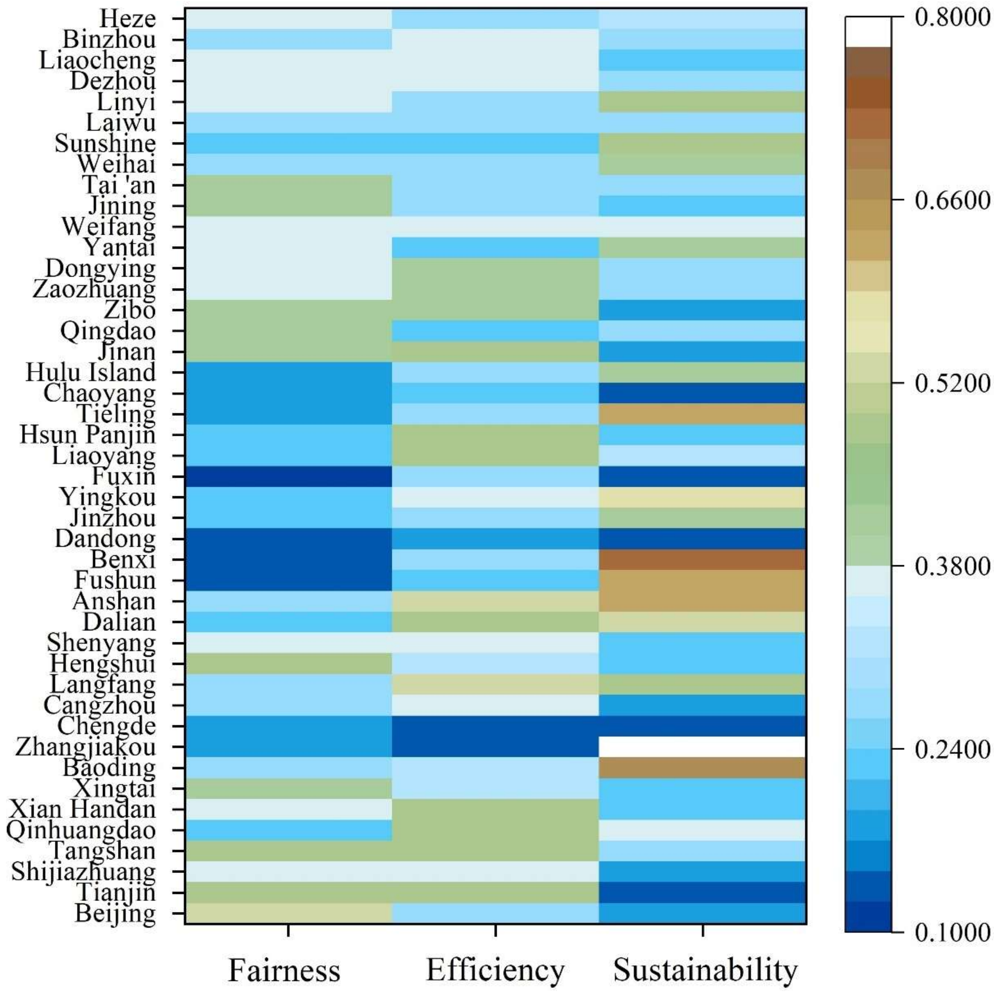


Fig. 2. The contribution of different carbon quota allocation schemes to each city

Under the three pre-allocation scenarios based on the principles of equity, efficiency and sustainability, the carbon allocation satisfaction of each city is shown in Figure 3. The number numbers 1 to 44 in the figure correspond to the cities in the Bohai Economic Rim, respectively, with reference to the number numbers corresponding to each city in the table above. The average value of carbon allocation satisfaction based on the efficiency principle is the largest (0.53), followed by the sustainability principle (0.44) and the equity principle (0.40). Therefore, in terms of average allocation satisfaction, the efficiency principle-based pre-allocation scheme is the most feasible among the three pre-allocation schemes. However, in the pre-allocation scheme based on the principle of efficiency there are 13 municipalities with low satisfaction (below 0.2), of which 6 municipalities have a carbon allocation satisfaction equal to 0. In the pre-allocation scheme based on the principle of fairness, there are only 8 municipalities with a satisfaction level lower than 0.2. In addition, this extreme in the pre-allocation scheme based on sustainability is even worse than that of the principles of fairness and efficiency, since 18 municipalities have a carbon allocation satisfaction is lower, below 0.1.Among the three allocation scenarios, the standardized variance of carbon allocation satisfaction is the smallest in the fair allocation scenario, at 0.12.In terms of minimum guarantees of satisfaction with carbon allocation across cities, the pre-allocation scenario based on the principle of fairness may be more feasible, in that it ensures that a smaller number of cities maintain a lower level of satisfaction with their allocations, even though the average satisfaction with their allocations is the lowest.

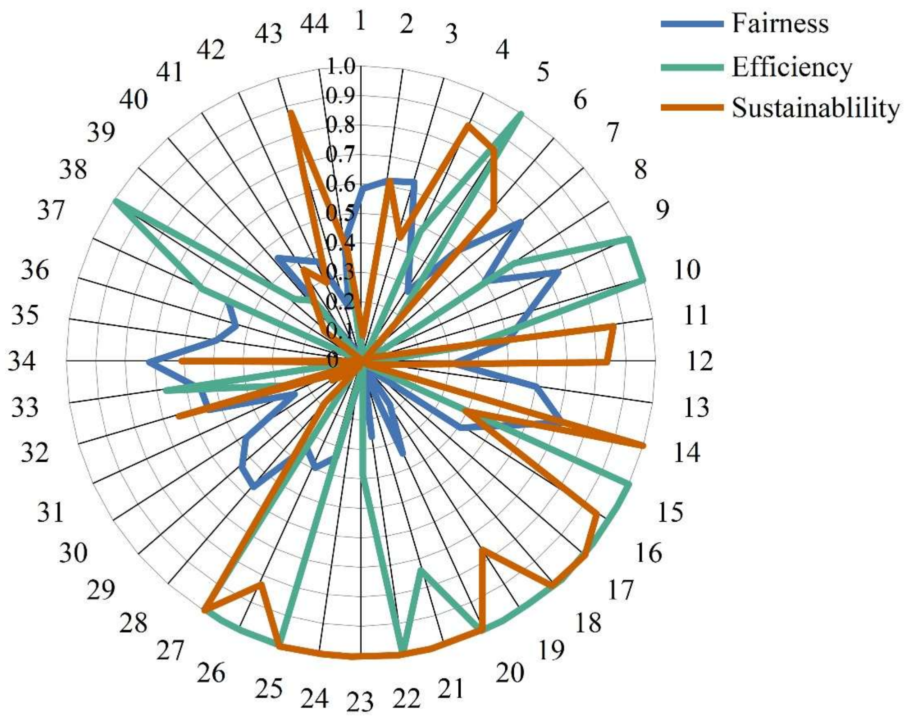


Fig. 3. Trends in carbon allocation satisfaction among cities

4.2. Analysis of the results of the optimal allocation of carbon emission allowances

In order to optimize the allocation results based on a single principle, a carbon emission quota allocation model for the Bohai Economic Rim under the multi-objective perspective is established based on the carbon quota allocation model in this paper. The minimum carbon allocation satisfaction of each city $a = 0.3$ is set as the base case, and the results of different scenarios are shown in Table 7. As can be seen from the table, the carbon emission allowances of 17 cities, including Shijiazhuang, Chaoyang, Huludao, Jinan and Liaocheng, are roughly equal in different scenarios. At the same time, the satisfaction levels of these cities are close to the upper and lower limits of the constraints, which means that the carbon allocation satisfaction constraints determine their allocation results.

In this study, Scenario 1 (equal weight) is set as the basic scenario, and the allocation results are used as the final carbon emission quotas for each city in 2030. Among them, Beijing, Tianjin, Dalian, Shijiazhuang, Yantai, Weifang and Linyi have the largest carbon emission quotas, totaling 1,180 Mt, accounting for up to 31% of all cities. Compared with the initial carbon emissions obtained based on historical emissions, the final allocation results in the equal-weight scenario show that 15 out of 44 cities decreased their carbon emission allowances including Langfang, Tangshan and Cangzhou, while 10 cities (Qinhuangdao, Anshan, Fushun and Benxi) remained stable and the remaining 19 cities, such as Beijing, Qingdao and Yantai, increased their final emission allowances.

Table 7. Carbon emission quotas of each city under different decision preferences

City	Carbon emission quotas(Mt)				
	Initial carbon emissions	Scenario 1: Equal weight	Scenario 2: Preference fairness	Scenario 3: Preference efficiency	Scenario 4: Preference for sustainability
Beijing	162	248	260	248	248
Tianjin	267	231	255	251	231

Shijiazhuang	161	140	140	140	140
Tangshan	173	115	105	126	109
Qinhuangdao	53	52	46	47	53
Xian Handan	131	96	98	103	84
Xingtai	93	109	111	109	109
Baoding	145	132	128	129	134
Zhangjiakou	60	78	78	78	78
Chengde	38	89	89	89	89
Cangzhou	135	93	90	100	86
Langfang	108	67	67	75	65
Hengshui	57	65	65	65	65
Shenyang	154	128	135	136	128
Dalian	113	160	154	143	180
Anshan	64	67	64	62	67
Fushun	43	43	43	43	43
Benxi	34	34	34	34	34
Dandong	31	37	37	37	37
Jinzhou	48	48	44	46	48
Yingkou	49	44	40	43	46
Fuxin	35	35	30	35	35
Liaoyang	47	36	32	37	36
Hsun Panjin	51	34	30	37	31
Tieling	60	60	53	60	60
Chaoyang	45	53	53	53	53
Hulu Island	45	45	44	45	45
Jinan	114	116	116	116	116

Qingdao	133	155	159	155	155
Zibo	77	83	83	83	83
Zaozhuang	48	53	53	53	53
Dongying	78	65	67	65	60
Yantai	118	136	139	124	144
Weifang	145	133	136	131	130
Jining	101	112	112	112	112
Taian	65	72	72	72	72
Weihai	65	69	69	62	73
Sunshine	38	45	43	41	48
Laiwu	11	14	14	14	16
Linyi	121	131	135	127	130
Dezhou	81	77	77	77	77
Liaocheng	71	72	72	72	72
Binzhou	81	65	63	66	63
Heze	76	87	90	82	85

Measuring the carbon allocation satisfaction of different cities under different scenarios, as shown in Table 8. It can be found that some cities are insensitive to changes in the weights of different principles, and 14 cities, including Shijiazhuang, Zhangjiakou, Chengde, Hengshui, Fushun, Benxi, Dandong, Jinan, Zibo, Zaozhuang, Jining, Tai'an, Dezhou, Liaocheng, etc., have equal carbon allocation satisfaction under different scenario preferences. Meanwhile, the satisfaction of these cities is close to the upper limit (1) and lower limit (0.3) of the constraint, implying that the carbon allocation satisfaction constraint determines their allocation results.

Table 8. The satisfaction of carbon allocation under different preference scenarios

City	Satisfaction			
	Scenario 1: Equal weight	Scenario 2: Preference fairness	Scenario 3: Preference efficiency	Scenario 4: Preference for sustainability
Beijing	0.3	0.34	0.3	0.3
Tianjin	0.3	0.41	0.39	0.3
Shijiazhuang	0.3	0.3	0.3	0.3
Tangshan	0.6	0.53	0.68	0.56
Qinhuangdao	0.95	0.7	0.74	1
Xian Handan	0.47	0.49	0.53	0.38
Xingtai	0.3	0.32	0.3	0.3
Baoding	0.59	0.56	0.57	0.61

Zhangjiakou	1	1	1	1
Chengde	1	1	0.99	1
Cangzhou	0.59	0.56	0.66	0.52
Langfang	0.33	0.34	0.47	0.3
Hengshui	0.3	0.3	0.3	0.3
Shenyang	0.32	0.49	0.51	0.3
Dalian	0.77	0.69	0.57	1
Anshan	0.94	0.76	0.61	1
Fushun	1	1	1	1
Benxi	1	1	1	1
Dandong	1	1	1	1
Jinzhou	1	0.8	0.9	1
Yingkou	0.67	0.43	0.61	0.79
Fuxin	1	0.83	0.99	1
Liaoyang	0.53	0.34	0.57	0.53
Hsun Panjin	0.44	0.31	0.55	0.35
Tieling	1	0.85	1	1
Chaoyang	1	0.98	1	1
Hulu Island	1	0.95	1	1
Jinan	0.3	0.3	0.3	0.3
Qingdao	0.3	0.34	0.3	0.3
Zibo	0.3	0.3	0.3	0.3
Zaozhuang	0.3	0.3	0.3	0.3
Dongying	0.49	0.52	0.49	0.42
Yantai	0.47	0.52	0.3	0.58
Weifang	0.39	0.54	0.31	0.3
Jining	0.3	0.3	0.3	0.3
Taian	0.3	0.3	0.3	0.3
Weihai	0.52	0.52	0.39	0.58
Sunshine	0.76	0.47	0.3	1
Laiwu	0.3	0.3	0.3	0.47
Linyi	0.34	0.4	0.3	0.34
Dezhou	0.3	0.3	0.3	0.3
Liaocheng	0.3	0.3	0.3	0.3
Binzhou	0.37	0.32	0.41	0.3

Heze	0.37	0.39	0.33	0.36
Average value	0.57	0.54	0.55	0.58

To summarize, the carbon quota allocation model proposed in this paper has a smaller difference in the allocation results in different situations, which is better than the single-principle allocation scheme. For example, in the multi-objective model, the carbon quota of Heze is equal to 37Mt, while in comparison, the largest carbon quota in the single-principle allocation scheme is 6.26 times of the smallest quota. Some cities have serious conflicts in the principles of equity, efficiency and sustainability, and the single-principle-based scheme inevitably distorts the allocation results. However, the carbon quota allocation model in this paper can effectively integrate the principles of equity, efficiency, sustainability and feasibility, eliminating conflicts between multiple principles and becoming more rational and less discrepant in different scenarios.

5. Conclusion

In this paper, based on the three important principles of fairness, efficiency and sustainability of carbon emission quota allocation, corresponding to the construction of indicators and the formation of multi-objective functions, a carbon quota allocation and decision support model is constructed, and an improved hybrid swarm algorithm based on Gaussian perturbation, tournament selection strategy, and the proposed Newtonian local optimization search algorithm (L-BFGS) is proposed to achieve the solution of the model's nonlinear problems. Numerical simulation experiments are carried out to test the effectiveness of the improved hybrid swarm algorithm in this paper. Compared with the multi-objective evolutionary algorithms such as NSGA-II, MOEA/D, MOPSO, MOABC, etc., the improved hybrid swarm algorithm of this paper has a better distributional performance on simple PFs, and the average ranking reaches 1.52. On most of the ZDT family of functions, the improved hybrid swarm algorithm of this paper has a good distributional and convergence properties. And under different strategies, the improved hybrid swarm algorithm of this paper still obtains the best IGD values in all the different test functions, with an average ranking of 1.58, which is the most competitive among all the algorithms.

Using the carbon quota allocation model proposed in this paper, the quota allocation scheme among cities in the Bohai Rim Economic Zone in 2030 is explored and analyzed. In the case of the fair, efficient and sustainable pre-allocation scheme with a single objective, the difference between the cities with the largest and smallest quotas is 319Mt, 289Mt and 256Mt, respectively, and the extreme difference of the optimized allocation result is 234Mt, which makes the resulting allocation scheme insufficient in terms of science and rationality. Under the three pre-allocation schemes of the principles of equity, efficiency and sustainability, the average value of carbon allocation satisfaction based on the principle of efficiency is the largest (0.53), followed by the principle of sustainability (0.44) and the principle of fairness (0.40), but the standardized variance of carbon allocation satisfaction in the equitable allocation scheme is the smallest 0.12, which is a more feasible scheme that ensures that fewer cities maintain a lower level of allocation Satisfaction. Using the carbon allowance allocation model in this paper to optimize the allocation results based on the single principle, the satisfaction of each city is close to the upper limit (1) and lower limit (0.3) of the constraints, and the difference in the allocation results is smaller, which is superior to the single-principle allocation scenario, and it can better integrate the principles of fairness, efficiency, sustainability, and feasibility, and eliminate the conflict between multiple principles.

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