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Multi-dimensional Optimization Research on the Path of Creating Blue Carbon Industry Clusters in Macao-Zhuhai Pole Based on Intelligent Algorithm

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ABSTRACT

This paper combines the development situation of blue carbon industry to formulate the multi-dimensional optimization model construction of blue carbon industry cluster path. First set the model decision variables and objective function, and divide the constraints. Select the genetic algorithm to solve the optimization model. Determine the research data sources and genetic algorithm parameters, and analyze the multidimensional optimization model. The sensitivity coefficients of each decision variable to the optimization model are 0.2~0.1, and its sensitivity level is III, which means that the selected decision variables meet the research requirements. Compared with the other three algorithms, this paper's genetic algorithm has superiority in four performance indicators, indicating that the genetic algorithm is more suitable for optimization model solving, and finally, the optimization model of this paper is put into the actual blue carbon industry, and it is found that there is a significant difference in the effect of carbon reduction, economic gain, green environmental protection, and satisfaction before and after the optimization ($P<0.05$), which verifies the effectiveness of this paper's optimization for practical application, and finally, according to the optimization results, the Finally, according to the optimization results, the corresponding optimization path is proposed.

Keywords: genetic algorithm; blue carbon industry; objective function; optimization model

1. Introduction

The construction of the blue economy partnership is a rational choice to strengthen international ocean cooperation and promote the sustainable development of the oceans under the great changes in the world. In this sense, it is an important issue to improve the global ocean governance system [1-3]. At the same time, from the domestic perspective, the development of blue economy and the promotion of sustainable development of the oceans is also an important task in the construction of China's new development pattern [4-6].

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Realizing the “dual-carbon” goal is a huge task and challenge for China in the future [7]. The ocean is the largest active “carbon reservoir” on earth, with a carbon sequestration capacity per unit area much higher than that of land, and the ecosystem has a huge potential for carbon storage [8-9]. Blue carbon, also known as ocean carbon sink, is defined as the processes, activities and mechanisms by which marine activities and marine organisms absorb carbon dioxide from the atmosphere and fix it in the ocean [10]. Nowadays, blue carbon has become a key field of carbon negative emissions (negative carbon) research, and blue carbon has the advantages of large carbon storage and long carbon storage time compared with forest carbon sinks, which is crucial to the global carbon cycle and regulation of climate change [11-12].

China actively develops blue carbon basic theory research and application practice, has implemented several blue carbon national key research and development program projects, issued a series of policy documents around the world, from the technical theory to put forward the land and sea integration of emission reduction and sinks, micro-biological carbon pump, coastal wetland ecological service function and sinks, seawater aquaculture environmental negative emissions and other programs to enhance the blue carbon capacity [13-15]. At the same time, the marine economy has become an important engine of China's economic growth, and the importance of promoting the low-carbon development of the marine economy has become more and more prominent in the “dual-carbon” strategic layout [16-18]. Under the urgent background of global warming, promoting marine activities to reduce emissions and increase sinks, and guiding the marine industry to a friendly environment is an important way to cope with the greenhouse effect [19-21].

From the perspective of green and sustainable development of blue carbon industry, the article designs a multidimensional optimization model for blue carbon industry cluster road. Firstly, the decision variables are determined, and the total economic volume (GDP), total energy consumption $(Energy)$, and total carbon emission (CO_2) are taken as the objective functions, the constraints of the optimization solution are set, and the mathematical modeling work is finally completed. Within the scope of intelligent algorithm, it is proposed to use genetic algorithm to solve the above optimization model, take the 2014~2024 Statistical Yearbook of a Province of a certain city as the main data source of this research, use data analysis software to analyze the arithmetic example of the multidimensional optimization model of the blue-carbon industry cluster, and put forward three optimization strategies, so as to make the development of the blue-carbon industry more rationalized.

2. Research on multi-dimensional optimization of blue carbon industry based on intelligent algorithm

2.1. *Blue carbon industry*

There is currently a distinction between narrow and broad definitions of blue carbon development and application in academia and management. The narrowly defined development model focuses on marine carbon sequestration and sink enhancement, through the protection and restoration of the three internationally recognized blue carbon ecosystems, namely mangrove forests, salt marshes and seagrass beds, and the enhancement of blue carbon capacity in the areas of fisheries carbon sinks, carbon sequestration, and micro-biological carbon pumps [22-23]. In a broad sense, the development model can be understood as "the total value of marine biological, abiotic and other marine activities that absorb, fix and store carbon dioxide", in which marine activities are the key areas of the blue carbon industry, aiming to integrate the improvement of carbon sink capacity with the low-carbon development of the marine field and the application of marine zero-carbon technology, so as to achieve a sustainable marine development model oriented by blue carbon promotion. Blue carbon economy and blue carbon industry are based on the broad concept of blue carbon to carry out research, in Weihai, Zhoushan and other places released the action plan for the development of blue carbon economy, more focus on the combination of local characteristics of the marine industry, is committed to promoting the ecology of the marine industry, marine ecological industrialization, the formation of the marine ecological industrial economy with the core concept of blue carbon development.

2.2. Multi-dimensional optimization model of blue carbon industry cluster road

2.2.1. Model construction methodology. From the perspective of multidimensional optimization of blue carbon industrial cluster road, the optimization goal is to achieve what the optimal combination state of industrial ecological structure looks like when carbon emissions are minimized and economic growth is maximized, so as to point out the direction for the rationalization of industrial ecological structure, advanced and ecological adjustment. Therefore, the multidimensional optimization model of blue carbon industrial cluster road to be constructed in this paper is very different from the existing models in terms of the object to be solved, the goal and the dimension and complexity of the elements to be considered. First, the question to be predicted to answer is clear, that is, to answer to achieve the economic and social development goals, what is the optimal blue carbon industrial cluster road multidimensional. Secondly, the optimization goal is a multi-factor, multi-dimensional complex system, different from the single industry economic structure prediction, the multi-dimensional optimization of the industrial cluster path includes economic growth, energy consumption, carbon emissions and absorption, and so on, many interrelated elements. The third is to make the optimization prediction more instructive.

2.2.2. Constructing decision variables. Combining the above blue carbon industry definition and model construction method, the decision variables of the multidimensional optimization model of blue carbon industry cluster path are defined:

Time dimension: 2018, 2023, 2028.

Indicator dimension: GDP (blue carbon industry output value), Energy (energy), CO_2 (blue carbon industry carbon emissions), Nonfossil Energy (non-fossil energy).

The above total 3×27×4=324 dimensions, which is denoted as x(industry, year, type), where industry denotes the industry dimension, type denotes the indicator dimension, and year denotes the time dimension.

2.2.3. Objective function. Based on the above decision variables and the definition of the blue carbon industry, the aggregate objective functions for the three scenarios of total economic volume (GDP), total energy consumption $(Energy)$, and total carbon emissions (CO_2) are determined as follows.

1) Economic total (GDP) objective function. Define $y(2018, GDP)$ as the total amount GDP in 2018, then there is an objective function:

$$y(2020, GDP) = \sum_{i=1}^{27} x(i, 2018, GDP) \tag{1}$$

Ditto:

$$y(2025, GDP) = \sum_{i=1}^{27} x(i, 2023, GDP) \tag{2}$$

$$y(2030, GDP) = \sum_{i=1}^{27} x(i, 2028, GDP) \tag{3}$$

2) Total energy consumption $(Energy)$ objective function. Definition $y(2018, Energy)$ is the total energy consumption in 2018, then there is an objective function:

$$y(2020, Energy) = \sum_{i=1}^{27} x(i, 2018, Energy) \tag{4}$$

Ditto:

$$y(2025, Energy) = \sum_{i=1}^{27} x(i, 2023, Energy) \tag{5}$$

$$y(2030, Energy) = \sum_{i=1}^{27} x(i, 2028, Energy) \tag{6}$$

3) Total carbon emissions Objective function. Definition $y(2018, CO_2)$ is the total carbon emissions in 2018, then there is an objective function:

$$y(2020, CO_2) = \sum_{i=1}^{27} x(i, 2020, CO_2) \tag{7}$$

Ditto:

$$y(2025, CO_2) = \sum_{i=1}^{27} x(i, 2023, CO_2) \tag{8}$$

$$y(2030, CO_2) = \sum_{i=1}^{27} x(i, 2028, CO_2) \tag{9}$$

2.2.4. Constraints. From the above decision variables, objective functions, constraints and development states, it can be seen that the industrial ecological structure to be predicted is a multidimensional, multiconstrained and time-varying dynamic system, so, according to the method of looking for optimization model construction, this paper constructs the TBATS model, which is a fusion model of multiple models, including the BOX-COX transformation model, the ARMA error correction model, the trend prediction model and the seasonal component model, and these models are fused into a total time series model. The final optimized model is:

$$x(industry, type, year) = \eta_1 \times y^{(\omega)}_{step1t} + \eta_2 \times y^{(\omega)}_{step5t} \tag{10}$$

Among them:

$$y_t^{(\omega)} = \begin{cases} \dfrac{y_t^{\omega} - 1}{\omega} & \omega \neq 0 \\ \log y_t & \omega = 0 \end{cases} \tag{11}$$

$$y_t^{\omega} = \ell_{t-1} + \phi b_{t-1} + \sum_{i=1}^{T} s^{(i)}_{t-m_i} + d \tag{12}$$

$$\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha d \tag{13}$$

$$b_t = (1-\phi) b + \phi b_{t-1} + \beta d_t \tag{14}$$

$$s_t^{(i)} = s^{(i)}_{t-m_t} + \gamma_i d_t \tag{15}$$

$$d_t = \sum_{i=1}^{p} \varphi_i d_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{16}$$

In the formulas listed above, formula (10) is the total time series model, $y^{(\omega)}_{s\kappa plt}$ is the value of $y_i^{(\omega)}$ when the step size is 1, $y^{(\omega)}_{nspst}$ is the value of $y_i^{(\omega)}$ when the step size is 5, and η_1, η_2 is the weighting factor. Equation (11) is the Box-Cox transform model, where $y_i^{(\omega)}$ is the optimized value in Box-Cox transform with respect to parameter ω. Equation (12) is the ARMA error correction model where $y_i^{(o)}$ is the optimized value in Box-Cox transform at moment t. Equations (13) to (16) are the parameter estimation formulas in the ARMA error correction model, where: m_1, m_2, m_T denotes the seasonal period. ℓ_i and b_i denote the level and trend at the tth moment, respectively. $s_t^{(i)}$ denotes the ith seasonal component at moment t, d_t denotes a process of the ARMA model: ε_i is the Gaussian distribution $(\varepsilon_i \sim N(0,\sigma^2))$ of the white noise process. ϕ is the damping parameter: α, β, γ_i is the smoothing parameter, which are both row vectors, θ is the column vector, and T is the period.

2.3. Optimized model solution

With the continuous development and progress of computer technology, a new research field has been born outside the traditional model solving field, computational mathematics, which mainly relies on computer algorithms and computational power to achieve the purpose of model solving, and computational mathematics has been widely used in various fields. The main algorithms in multi-objective optimization model solving include genetic algorithm that simulates biological evolution, ant colony algorithm that simulates the characteristics of ants searching for food, immune algorithm that simulates the immune process and so on, based on the requirements of this research, this paper adopts the genetic algorithm for optimization model solving.

2.3.1. Genetic Algorithm Basics. The computational process of genetic algorithm is to simulate the adaptive search in nature, without the need to provide the initial solution, under the principle of survival of the fittest, continuous selection, mutation, and ultimately through a certain number of iterative processing to obtain the final excellent individual. Genetic algorithms provide a general framework for solving problems for all complex problems, with high solution space search efficiency as well as search stability [24-25]. Genetic algorithm is more widely used in various types of complex problems optimization, image processing, data mining, industrial manufacturing and other related fields.

The first of the constituent elements of a genetic algorithm is the genetic coding of the actual problem; normally, the solution vector $x \in X$ is referred to as an individual or a chromosome, and a chromosome is composed of discrete genes, each of which controls one or more features of the chromosome. In the earliest implementations of genetic algorithms, the gene codes were patterned as binary bits, and normally a chromosome code represents a unique solution in the solution set space x.

2.3.2. Mathematical modeling of genetic algorithms. According to the basic components of the genetic algorithm, the basic mathematical model of the genetic algorithm can be expressed as shown in Equation (17):

$$SGA = (C.E.P_0.M.\Phi.\Gamma.\Psi.T) \tag{17}$$

Among them,

T Labeling genetic operation termination conditions.

Ψ Labeled variation operator.

Γ Labeled cross operator.

Φ Label the choice operator.

M Labels the population size, i.e., the size of the unsetting population, which is predominantly 20-100 in practical calculations.

P_0 Label the initial population.

E Labeling the fitness evaluation function.

C Label the way individuals are coded.

2.3.3. Genetic algorithm optimization solution process. Genetic algorithm optimization solution process shown in Figure 1, genetic algorithm as the earliest intelligent evolutionary solution algorithm, to the present in various fields of deformation has been very rich, but a variety of deformation of the most primitive algorithmic basis is the basic genetic algorithm, the basic genetic algorithm is designed to carry out a finite number of iterations and get the final solution results to show the optimal solution in the form of the Pareto solution set, including the construction of the initial population specifically, Fitness calculation, selection, crossover, mutation and so on several aspects, divided into 6 steps, genetic algorithm solution of the general specific computational flow steps are as follows.

Step1: Randomly generate the initial population of chromosome coding, and the individual size of the initial population is the set number N.

Step2: Calculate the fitness level of the first N individuals according to the objective function, determine whether the fitness meets the termination criterion, terminate if the condition is met, otherwise continue to Step3 for execution.

Step3: Select the individual with high adaptation level according to the adaptation level and eliminate the individual with low adaptation level.

Step4: For the individuals selected by Step3, perform crossover operation to generate new individuals.

Step5: Perform mutation on the individuals generated by Step4 according to probability to generate new individuals.

Step6: Return to execute Step2 with the execution results of Step3 and Step4 as the new generation population.

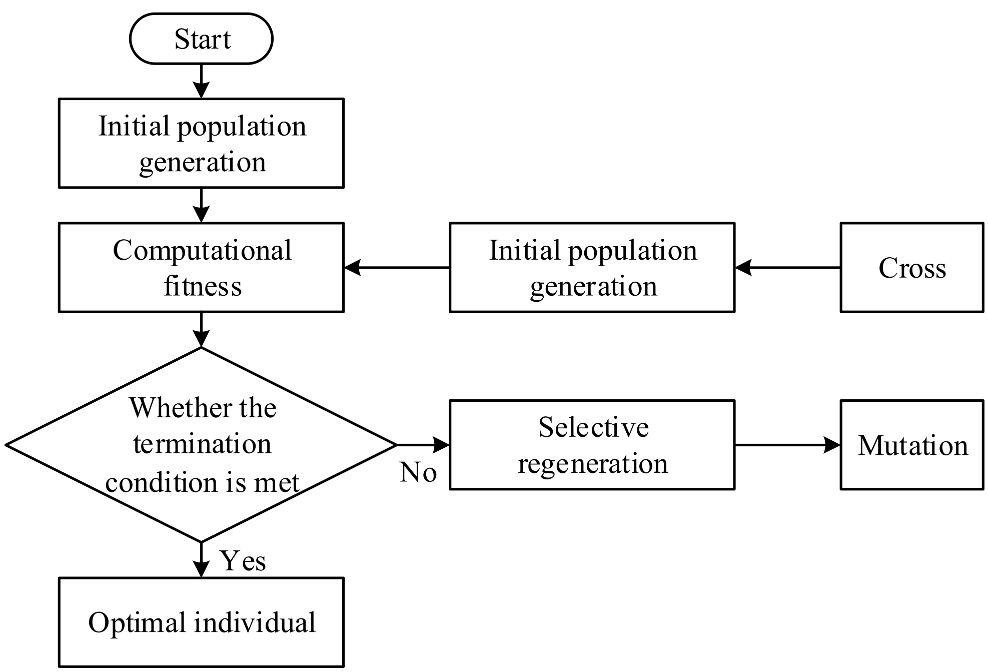


Fig. 1. Basic genetic algorithm solution flow

3. Example analysis of multi-dimensional optimization model

This chapter introduces a Macao-Zhuhai pole to build blue carbon industry as a case study, firstly, combines the data of this case study, secondly, analyzes the optimization results of the multidimensional path optimization model, and then solves the pair of dimensional optimization model by using genetic algorithms, and finally, using the optimization results, puts forward three optimization strategies.

3.1. Model validation analysis

3.1.1. Parameter sensitivity analysis. In order to verify the validity of the above decision variables, the sensitivity of time, total economy (GDP), total energy consumption (Energy), and total carbon emission (CO_2) to the optimization of blue carbon industrial clusters is analyzed. Based on the basic parameters, the values of time, total economy (GDP), total energy consumption (Energy), and total carbon emission (CO_2) are decreased or increased by 5% and 10% respectively, and the values of other parameters remain unchanged, and the parameter sensitivity coefficients are calculated as follows:

$$E = \frac{\Delta A}{A} / \frac{\Delta F}{F} \tag{18}$$

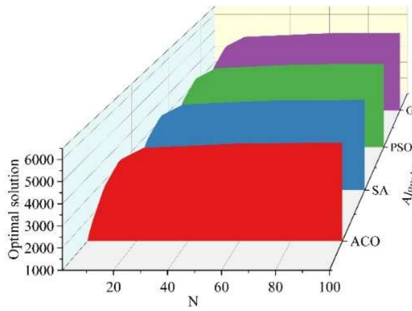
Where E indicates the sensitivity coefficient of parameter A (time, total economy, total energy consumption, total carbon emission) to the risk factor F (-10%, -5%, 5%, 10%).

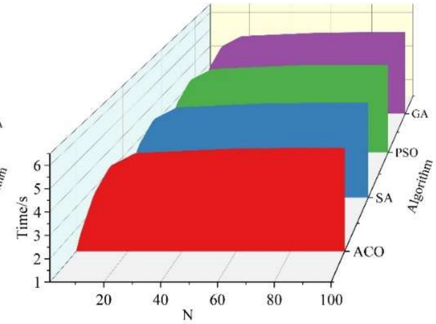
The results of the sensitivity analysis of the parameters of the optimization model of the blue carbon industry cluster are shown in Table 1, with $0 \le |E| < 0.05$ indicating no sensitivity (sensitivity level Ⅰ), $0.05 \le |E| < 0.2$ being low sensitivity (sensitivity level Ⅱ), $0.2 \le |E| < 1$ being sensitive (sensitivity level Ⅲ), and $1 \ge E$ indicating high sensitivity (sensitivity level Ⅳ). It can be seen that time, total economic volume (GDP), total energy consumption (Energy), total carbon emissions (CO_2) on the optimization of blue carbon industrial clusters sensitive coefficient value of 0.2 ~ 1, indicating that the decision-making variables on the optimization model sensitive level of sensitive level Ⅲ, to verify that the decision-making variables in the optimization model of the actual effective and feasible.

Table 1. Parameter sensitivity analysis results

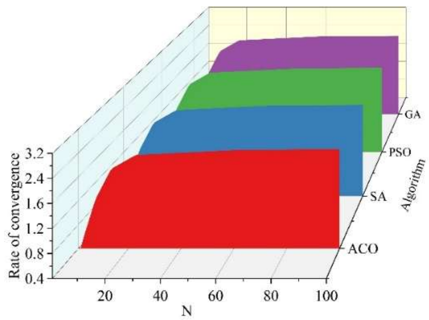
Rate of change	-10%	-5%	5%	10%
Time	0.3447	0.2907	0.2084	0.2718
GDP	0.4358	0.2779	0.6326	0.3158
Energy	0.2844	0.9714	0.9778	0.8607
CO_2	0.7794	0.9438	0.5526	0.6944

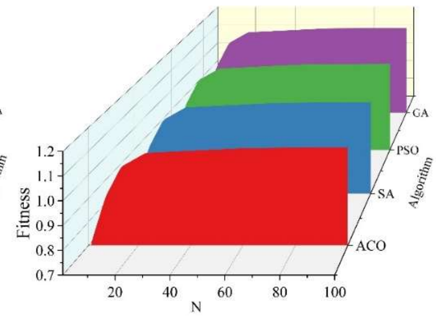
3.1.2. Comparative analysis of intelligent algorithm solving performance. Although the above analysis shows that the genetic algorithm is able to solve the optimal solution of the optimization model, it has not proved the priority of the genetic algorithm in the optimization model solution, in this regard, three control algorithms are set up, which are Ant Colony Algorithm (ACO), Simulated Annealing Algorithm (SA), and Particle Swarm Algorithm (PSO), and a comparative performance analysis is carried out for the solution performance of the intelligent algorithms based on the convergence speed, precision, recall, and the value of F1 The comparison results of intelligent algorithm solving performance are shown in Fig. 2, where (a)~(d) are the optimal solution, running time, convergence speed, and fitness value, respectively. Comprehensive Figure 2 (a) ~ (d) can be seen, compared with the ant colony algorithm (ACO), simulated annealing algorithm (SA), particle swarm algorithm (PSO), the genetic algorithm in the optimal solution, running time, convergence speed, the adaptability value of the best performance, indicating that genetic algorithms are more suitable for optimizing the model solving.





(a)Optimal solution (b)Running time

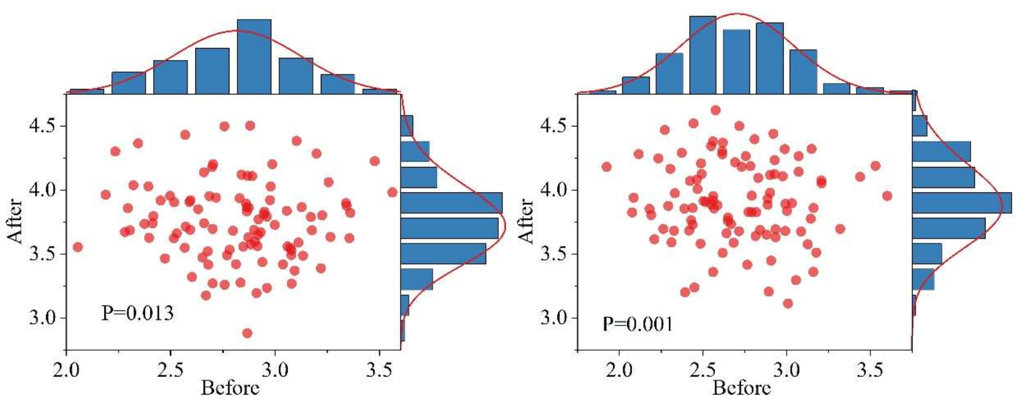




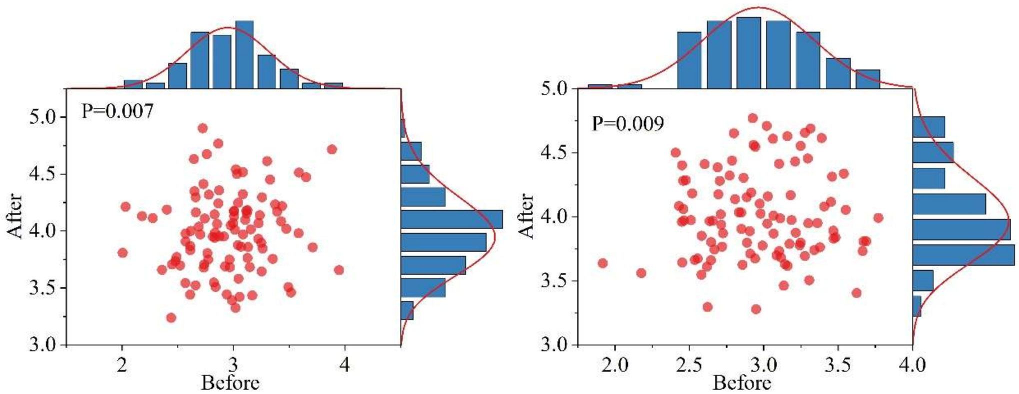
(c)Convergence rate (d)Fitness

Fig. 2. Performance comparison of intelligent algorithms

3.1.3. Comparative analysis before and after optimization. The optimization model of this paper is put into the actual blue carbon industry, and 100 users are invited as the research subjects to obtain the research data through the form of scale test, and then with the help of independent sample t-test, the comparison results before and after the optimization are discussed in depth from the four dimensions of the carbon reduction effect, economic gain, green environmental protection, and satisfaction, and the results of the comparison analysis before and after the optimization are shown in Fig. 3, in which (a) to (d) are the four indicators of the carbon reduction effect, economic gain, green environmental protection, and satisfaction, respectively. (a) ~ (d) are the four indicators of carbon reduction effect, economic gain, green environmental protection, and satisfaction. Comprehensive Figure 3 (a) ~ (d) can be concluded that the carbon reduction effect, economic returns, green environmental protection, satisfaction of the four indicators of the value of the significant difference, P < 0.05, that is, to prove that this paper's optimization model is put into the actual blue carbon industry, can produce a significant role in promoting the rapid development of the blue carbon industry to the direction of the green and sustainable.



(a)Carbon reduction effect (b)Economic gain



(c)Green and environmental protection (d)Satisfaction

Fig. 3. Comparative analysis before and after optimization

3.2. Multi-dimensional optimization model solution and optimization strategy

3.2.1. Data sources. The data used in this chapter are from the Fisheries Statistics Yearbook of a Province and the Statistical Yearbook of a Province. Some of the data need to be separately extracted and processed from a city. For the consideration of sample neatness, authenticity, timeliness and accessibility, this paper selects 2014-2024 as the range of research years. The research data presentation statistics are shown in Table 2, where Y1~Y3 denote the three objective functions in the multidimensional optimization model, respectively. It can be clearly seen that the descriptive indicators of total economic volume Y1, total energy consumption Y2, and total carbon emission Y3 show an increasing trend year by year, which provides data support for the following optimization model solution.

Table 2. Research data statement statistics

Year	Y1/Ten thousand yuan	Y2/Tons	Y3/Tons
2014	1353	4953	4810
2015	1003	4090	3319
2016	1043	4229	3623
2017	1115	4932	3898
2018	1203	4942	3913
2019	1353	4953	4105
2020	1539	5474	4166
2021	2084	5513	4376
2022	2113	5720	4522
2023	2212	5727	4810
2024	2681	5881	4947

3.2.2. Data analysis. Multi-dimensional optimization of blue carbon industry cluster paths is a complex process, which involves the balance and trade-off of multiple objectives. In practice, the design of parameters has a direct impact on the performance of the algorithm. If the parameters are not reasonably designed, the advantage of the algorithm will be significantly reduced, which may lead to the inability to find a satisfactory solution or a significant increase in the computation time, thus affecting the efficiency and effectiveness of the whole optimization process. In order to ensure that the genetic algorithm can run efficiently and find high-quality solutions, this study carefully designs and adjusts its relevant parameters. These parameters include population size, crossover and variance probability, etc., which have an important impact on the performance of the algorithm, with a crossover ratio of 0.65, a variance number of 66, a population number of 100, and a maximum number of iterations of 100. By optimizing these parameters, it is hoped to improve the algorithm's searching ability, so that it is able to find a closer-to-optimal solution in a shorter period of time.

The above research data are input into the optimization model, and after the genetic algorithm optimization training, the optimal solution of the iterative training of the objective function is obtained, and the optimization results of the path of the blue carbon industry cluster are shown in Table 3. Through careful observation, it can be clearly seen that with the increase in the number of iterations, all three indicators show a decreasing trend. This phenomenon initially indicates that the genetic algorithm used in the model can effectively optimize the objective function in the process of continuous iteration, so as to optimize the multiple objectives of total economic output (GDP), total energy consumption (Energv) and total carbon emissions (CO_2). After a certain number of iterations, the values of the three objective functions gradually tend to stabilize, specifically the convergence of each indicator, it can be seen that when the number of iterations is about 45 times, the total energy consumption (Energv) objective function began to stabilize, which indicates that the algorithm in 45 iterations or so has been able to find a relatively good solution in terms of the total amount of economy (GDP). Similarly, when the number of iterations is about 60, the objective function of total carbon emissions (CO_2) also stabilizes, indicating that the algorithm has reached a better balance in terms of carbon emissions around 60 iterations. And when the number of iterations is about 50 times, the total blue carbon industry economy (GDP) also stabilizes, which indicates that the algorithm also gets a relatively reasonable solution in the total blue carbon industry economy around 50 iterations.

Table 3. Blue carbon industrial cluster path optimization results

N	Y1	Y2	Y3	N	Y1	Y2	Y3	N	Y1	Y2	Y3	N	Y1	Y2	Y3
1	4992	4833	4870	26	1899	1834	2060	51	1444	1539	1371	76	1444	1539	1368
2	4683	4326	4658	27	1877	1825	2030	52	1444	1539	1371	77	1444	1539	1368
3	4374	3820	4447	28	1856	1815	2001	53	1444	1539	1370	78	1444	1539	1368
4	4065	3506	4235	29	1834	1805	1971	54	1444	1539	1370	79	1444	1539	1368
5	3756	3437	3971	30	1812	1796	1942	55	1444	1539	1370	80	1444	1539	1368
6	3448	3368	3791	31	1791	1786	1912	56	1444	1539	1369	81	1444	1539	1368
7	3139	3300	3696	32	1769	1776	1883	57	1444	1539	1369	82	1444	1539	1368
8	2954	3216	3584	33	1748	1767	1854	58	1444	1539	1369	83	1444	1539	1368
9	2822	3058	3428	34	1726	1757	1824	59	1444	1539	1369	84	1444	1539	1368
10	2690	2899	3271	35	1705	1748	1791	60	1444	1539	1368	85	1444	1539	1368
11	2557	2790	3115	36	1683	1738	1755	61	1444	1539	1368	86	1444	1539	1368
12	2425	2703	2958	37	1661	1728	1718	62	1444	1539	1368	87	1444	1539	1368
13	2293	2616	2802	38	1640	1717	1682	63	1444	1539	1368	88	1444	1539	1368
14	2161	2530	2646	39	1618	1692	1646	64	1444	1539	1368	89	1444	1539	1368
15	2136	2443	2489	40	1597	1666	1610	65	1444	1539	1368	90	1444	1539	1368
16	2114	2356	2355	41	1575	1640	1574	66	1444	1539	1368	91	1444	1539	1368
17	2093	2269	2325	42	1554	1615	1537	67	1444	1539	1368	92	1444	1539	1368
18	2071	2182	2296	43	1532	1589	1501	68	1444	1539	1368	93	1444	1539	1368
19	2050	2096	2266	44	1511	1564	1465	69	1444	1539	1368	94	1444	1539	1368
20	2028	2009	2237	45	1489	1539	1429	70	1444	1539	1368	95	1444	1539	1368
21	2006	1922	2207	46	1467	1539	1393	71	1444	1539	1368	96	1444	1539	1368
22	1985	1873	2178	47	1456	1539	1372	72	1444	1539	1368	97	1444	1539	1368
23	1963	1863	2148	48	1456	1539	1372	73	1444	1539	1368	98	1444	1539	1368

24	1942	1853	2119	49	1455	1539	1371	74	1444	1539	1368	99	1444	1539	1368
25	1920	1844	2089	50	1444	1539	1371	75	1444	1539	1368	100	1444	1539	1368

Another important role of the Pareto solution set is that it can flexibly adjust the resource allocation according to the preferences and objectives of the blue carbon industry cluster and guide the project towards a particular optimal resource arrangement. As a commonly used algorithm in the field of multidimensional optimization, the optimization results of genetic algorithm are usually presented in the form of Pareto solution set, which contains multiple optimal paths, and the three-dimensional image of Pareto solution set is shown in Figure 4. In this study, 300 data points are selected from a large number of solution sets, which represent the optimal equilibrium under the three main constraints of total economy (GDP), total energy consumption (Energv) and total carbon emission (CO_2). Through in-depth analysis of these scenarios, a more precise basis for decision-making on blue carbon clusters can be derived, and it is found that the three objective functions show a monotonically increasing situation.

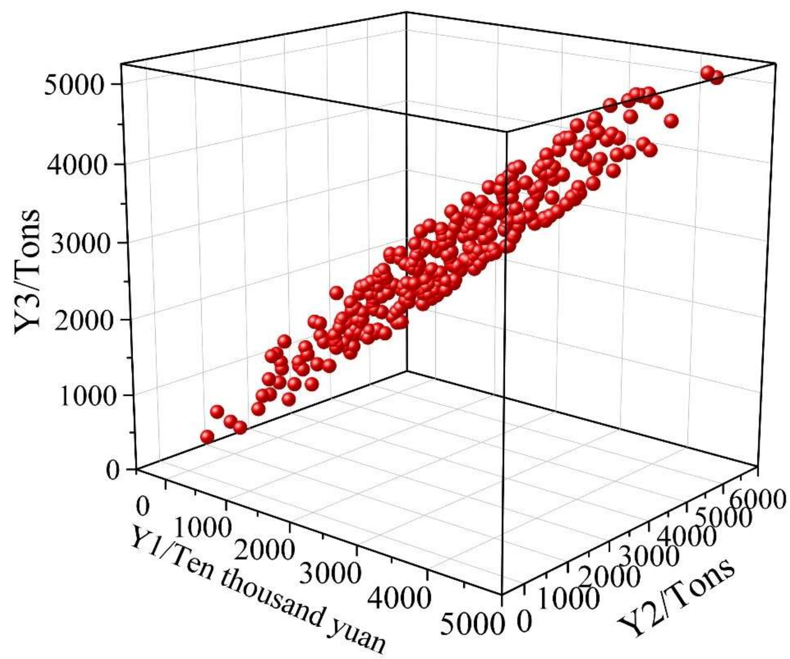


Fig. 4. Pareto solves 3D images

In order to observe the relationship between the objective functions more intuitively, the two-dimensional image of the Pareto solution set is shown in Fig. 5, where (a) ~ (c) are Y1-Y2, Y1-Y3, and Y2-Y3, respectively. It can be clearly seen that the monotonically increasing degree between Y1-Y2 is much stronger and its fluctuation range is smaller, while the opposite is true for Y1-Y3 and Y2-Y3. As a matter of fact, they can completely allocate resources more rationally and optimize the blue carbon industry scheme according to the objective function role relationship. Such an approach not only helps to save resources and reduce waste, but also effectively reduces carbon emissions, which is in line with the concept of sustainable development and is of great significance in promoting the sustainable development of blue carbon industry.

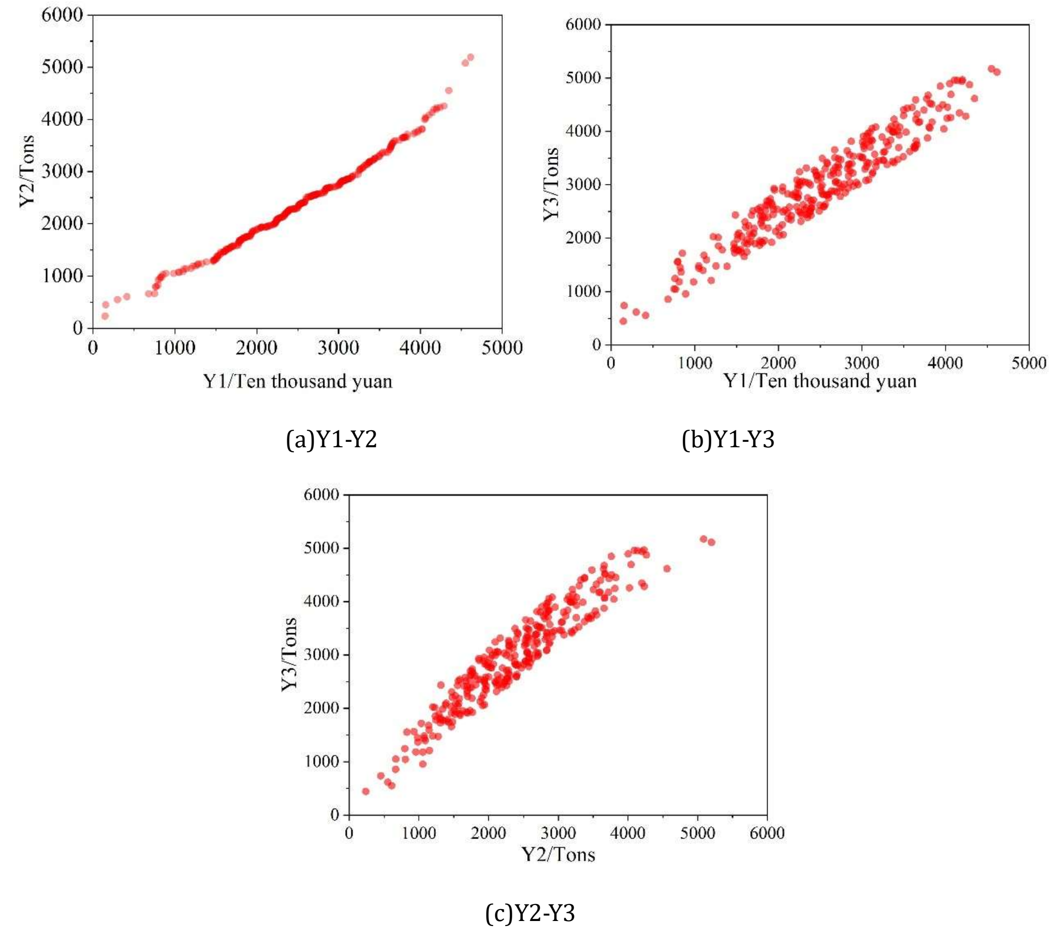


Fig. 5. Pareto solution set two-dimensional image

3.2.3. Optimization strategies:

1) Strengthening the investigation of blue carbon resources in the coastal zone. According to the relationship between total economy (GDP), total energy consumption (Energv) and total carbon emission (CO_2), it can be seen that enterprises should actively adopt native species that are diverse and suitable for use as pioneering species, reasonably match them to carry out functional restoration, improve the absorption of carbon content by the species, and reduce the total amount of energy consumption, so as to make the development of industrial clusters further safeguarded. Ensure that the development and management of blue carbon resources are more efficient, promote local economic development, protect the national ecological environment, and realize the balance between economic development and blue carbon protection.

2) Establishing a refined control system for blue carbon resources. We should give full play to the synergistic role of government and market compensation, and build a multi-dimensional, multi-level and diversified ecological compensation structure, so as to improve the risk sharing mechanism of ecological compensation funds, and then improve the efficiency of ecological compensation. Cultivate, develop and expand blue carbon industries such as marine eco-tourism, recreational fisheries, and carbon sink technical services with "emission reduction and sink increase" as the core. Integrate green finance policies and the development of blue carbon economic industries, explore multiple financing methods such as "leverage" and "blue carbon ecological products + green funds" with ecological restoration funds as "leverage", encourage banks, fund companies and insurance institutions to increase the development of carbon sink projects, develop blue carbon financial products and their derivatives, activate ecological assets, and improve the supply rate of ecological resources. Unify the

carbon inclusive market, include the value of ecological services other than carbon sequestration in the blue carbon ecosystem into the carbon inclusive blue carbon pricing, and focus the blue carbon inclusive income on low- and middle-income groups that contribute to the protection and restoration of blue carbon, so as to rationalize the total industrial economy (GDP), total energy consumption (Energv) and total carbon emissions (CO_2).

3) Carrying out blue-carbon resource protection and restoration actions. Encourage and guide enterprises, social organizations and natural persons to carry out blue carbon resource protection and restoration actions in ecological control zones and coordinated development zones, and explore and establish incentive mechanisms and subsidy policies to promote the protection and restoration of blue carbon ecosystems according to local conditions. Develop a specialized platform for fine control of blue carbon resources, introduce advanced technologies such as blockchain, IoT and big data, strengthen the construction of new digital infrastructure, and promote the development of total economic volume (GDP), total energy consumption (Energv) and total carbon emissions (CO_2) in a more idealized direction.

4. Conclusion

In this paper, the decision-making variables and objective functions are determined in the creation of blue carbon industry in the AZZ Pole, the corresponding constraints are delineated, and among the existing intelligent algorithms, it is proposed to use the genetic algorithm to solve the multidimensional optimization model, and the development of blue carbon industry is discussed in depth.

1) Through the parameter sensitivity analysis, the validity of the multidimensional decision-making set up in this paper is verified. In addition, compared with the other three optimization algorithms, the genetic algorithm excels in the four aspects of the optimal solution, running time, convergence speed, and adaptability value, which verifies that the genetic algorithm is more adapted to the optimization model solving. Deploying the optimization model of this paper to the actual blue carbon industry, it is found that there is a significant difference between before and after optimization ($P<0.05$), i.e., it is confirmed that the optimization model of this paper promotes the sustainable development of the blue carbon industry.

2) In the process of calculating the optimal solution, it is found that the three objective functions are all stable within 70 generations, and the optimal solutions are 1444, 1539, and 1368, respectively, and it is also found that there is a monotonically increasing development trend among the three objectives, and three optimization strategies are proposed to promote the high-quality development of the blue carbon industry.

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