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Study on the Intelligent Promotion Path of Green Port under the Carbon Peak and Carbon Neutral Strategy Based on Multi-Objective Genetic Algorithm

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ABSTRACT

Under the background of carbon peak carbon neutrality, the competition among ports is not only the competition among terminal scale, throughput, and service level, but also the competition of low energy consumption and low pollution, and with the development of China's carbon trading mechanism, the cost of carbon emission has become more and more a part of the enterprise that cannot be ignored. In this paper, the berths and shore bridges of the port are taken as the target variables, and the fuel consumption in the process of ships traveling to the port is inferred according to the assumed conditions, and the BAP model under the carbon peak carbon neutrality is deduced, and the relevant constraints are proposed. The initial population is randomly generated, and the first generation of offspring population is obtained through the selection, crossover and mutation operations of multi-objective genetic algorithm, which then continues until the end conditions of the program are satisfied. Through the empirical method, comparing the effect of carbon cost optimization scheme generated by multi-objective genetic algorithm and traditional method, the value of the objective function under the multi-objective genetic algorithm model decreased by 10.48%, the operation cost of the port decreased by 4.54%, the cost of the ship's in-port time decreased by 24.9%, and the ship's average in-port time decreased by 11.01%, as compared with the traditional allocation scheme. The multi-objective genetic optimization model of berth shore bridge considering carbon cost can shorten the ship's time in port, which reduces the carbon emission from the side and achieves the promotion purpose of green port. In the model sensitivity analysis, with the increase of carbon trading price, the four indicators F, F1, F2 and T also showed linear growth, with the growth rate of 17.24%, 18.44%, 14.37% and 18.02%, respectively, and the model sensitivity is good.

Keywords: BAP model, Constraints, Multi-objective Genetic Algorithm, Carbon Peak Achievement and Carbon Neutralization, Carbon Emissions

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1. Introduction

As the global climate change problem is becoming more and more prominent, carbon neutrality has become a common goal of governments and enterprises, among which the "dual-carbon" policy has become more and more eye-catching. Waterway transportation is an important link in world trade, but its emissions have a non-negligible impact on the environment [1]. Therefore, the construction of green ports is particularly important. Green ports are sustainable ports that obtain a good balance between environmental impacts and economic benefits [2-3]. This kind of port is guided by the green concept and is committed to building a new type of port with healthy environment, ecological protection, rational use of resources, low energy consumption and low pollution, and realizing the harmonious coexistence between the port and the natural environment [4-6]. Green port not only focuses on the economic benefits of the port itself, but also pays more attention to its impact on the environment, and strives to find the best balance between port development and environmental protection [7-9].

Low-carbon environmental protection is the primary characteristic of green ports. Measures such as the adoption of clean energy, the implementation of shore power systems, and the promotion of low-sulfur fuel use are used to reduce pollution when ships call at ports, while improving the efficiency of energy use [10-13]. In this process, the use of intelligent logistics management system, intelligent terminal management system and other means to optimize the logistics process can achieve the maximum use of resources and recycling [14-16]. The use of modern information technology means, such as big data, Internet of Things, artificial intelligence, etc., realizes the intelligence of port operation and management [17-19]. Through intelligent security systems and intelligent energy management systems, the efficiency and safety of port management can be improved, while reducing energy consumption and emissions [20-22].

In this paper, the ship arrival time is used as a decision variable to optimize the ship fuel consumption and carbon dioxide emissions by integrating them into the objective function of the traditional berth allocation model. Assuming the berth allocation plan time, the fuel consumption of the ship traveling to the port is speculated, from which the carbon peak carbon neutral BAP model is inferred. In the same way, an objective function with corresponding constraints is proposed for the shorebridge allocation in the harbor. Subsequently, the initial population is generated and non-dominated sorted, and the first generation of offspring population is obtained by the three basic operations of selection, crossover, and mutation of the multi-objective genetic algorithm. And so on, until the generated population meets the end conditions of the program, completing the solution to the multi-objective genetic algorithm. Taking a port as an example, the optimal solution of the model considering carbon cost is obtained by means of empirical verification.

2. Multi-objective Genetic Algorithm Based Port Berth-Shore Bridge Allocation

2.1. Modeling

2.1.1. Berth allocation under peak carbon neutralization. Different from the traditional berth allocation model, this paper takes the ship arrival time as a decision variable, and integrates the ship fuel consumption and carbon dioxide emission into the objective function of the traditional berth allocation model for optimization. However, a problem that cannot be ignored is that ships control their arrival time by changing their speed when docking, which can minimize their waiting time, but will affect their departure time, and then affect the ship schedule. In order to prevent the optimization result that all ships approach the port with the lowest speed to reduce fuel consumption and carbon dioxide emission, and at the same time shorten the operation time in port, this paper modifies the objective function of minimizing the average time of arrival of the ship to minimizing the average delay time of departure of the ship.

Let V: the set of arriving ships (containing n ships), L: the length of the shoreline, l_i: the ship's length (taking into account the safety distance of the ship's berthing), h_i: the operating time of the ship i, x_i: the berthing position, M: a sufficiently large constant. Decision variables: y_i: the berthing time of the ship. a_i: the arrival time of the ship i, a_i should take a value between $[\underline{a}, \overline{a}_i], \underline{a}$ and $\overline{a}_i$ determined by the maximum and minimum speed of the ship respectively. Auxiliary Decision Variables: $\sigma_{ij} : \sigma_{ij} = 1$ means that vessel i berths to the left of vessel j, otherwise $\sigma_{ij} = 0; i, j \in V, i \neq j; \delta_{ij} : \delta_{ij} = 1$ means that vessel i berths before vessel j, otherwise $\delta_{ij} = 0; i, j \in V, i \neq j$.

Assume that the berth allocation plan starts at moment zero, when the ship is at a distance of m_i (nautical miles) from the port. From the ISM, the functional relationship between the fuel consumption f_i per sailing day of ship i and the adopted speed v_i can be expressed in equation (1):

$$f_i = c_i^1 + c_i^0 \cdot v_1^3 \tag{1}$$

Where c_i^0 is the skill factor of the ship i and c_i^1 is the auxiliary diesel consumption per voyage i of the ship.

The fuel consumption F_i of a ship i during its journey from a distance of m_i nautical miles from the port to the port can be expressed as:

$$F_i = \frac{1}{24}\left[c_i^1 + c_i^0 \cdot \left(\frac{m_i}{a_i}\right)^2\right] \cdot a_i = \frac{1}{24}(c_i^1 \cdot a_i + c_i^0 \cdot m_i^3 \cdot a_i^{-2}) \tag{2}$$

This leads to the following BAP model under carbon peak carbon neutralization:

$$\min f_1 = \frac{1}{24}\sum_{i \in V}(c_i^1 \cdot a_i + c_i^0 \cdot m_i^3 \cdot a_i^{-2}) \tag{3}$$

$$\min f_2 = \frac{1}{n}\sum_{i \in V}(y_i + h_i - d_i)^* \tag{4}$$

$$s.t \;\; x_i + l_i \leq L, i \in V \tag{5}$$

$$x_i + l_i \leq x_i + M(1 - \sigma_{ij}), i, j \in V, i \neq j \tag{6}$$

$$y_i + h_i \leq y_i + M(1 - \delta_{\bar{y}}), i, j \in V, i \neq j \tag{7}$$

$$1 \leq \sigma_{ij} + \sigma_{ji} + \delta_{ij} + \delta_{ji} \leq 2, i, j \in V, i < j \tag{8}$$

$$a_i \leq y_i, i \in V \tag{9}$$

$$\underline{a_i} \leq a_i \leq \overline{a_i}, i \in V \tag{10}$$

$$x_i \geq 0, \sigma_{ij}, \delta_{ij} \in [0,1], i, j \in V, i \neq j \tag{11}$$

The objective function (11) is to minimize the fuel consumption of the ship during its approach to the port [23]. Since the ship's CO2 emissions are proportional to the amount of fuel used, this objective is consistent with minimizing the ship's carbon emissions during the voyage. The ratio coefficient between CO2 emissions from ships and the amount of oil used has minor differences in various literatures, this paper adopts the ratio of the Intergovernmental Panel on Climate Change, i.e., the combustion of 1 tonne of marine oil produces 3.17 tonnes of CO2 The objective function (4) is to minimize the average delay of ship departures from the port, and it is important to note that in this paper we do not consider ships without delays, but only delayed departures are optimized. So here the parameter n is the total number of delayed ships.

2.1.2. Allocation of shore bridges in ports. Let T be the set of time periods, $|T|=t$, C be the set of available shore bridges, $|C|=c$, E_i be the amount of boxes loaded and unloaded by the ship, etb_i be the expected berthing time of the ship i, etu_i be the expected departure time of the ship i, $C\min_i$ be the minimum number of shore bridges that can be allocated to the ship i, which is determined by the agreement between the shipping company and the port company. $C\max_i$ is the maximum number of shore bridges that can be assigned to a vessel i and is determined by the length of the vessel and the safety distance of the shore bridges, and v_0 is the efficiency of individual shore bridge operations (TEUA/h). Decision variable nc_i is the number of operational shore bridges assigned to the vessel i, dependent variable th_i is the operation start time of the vessel i, which in this paper is assumed to start only when the required shore bridges are all ready, dependent variable tf_i is the operation completion time of the vessel i, and dependent variable $\theta_{ijk}=1$ is the time of completion of the operation of the vessel, if the shore bridges k serve the vessel i during the time period j, otherwise $\theta_{ijk}=0$ the shore bridge assignment sub-model is as follows:

$$\min f_3=\frac{1}{n}\sum_{i\in V} nc_i \tag{12}$$

$$C\min_i \le nc_i \le C\max_i, \forall i\in V \tag{13}$$

$$tf_i = th_i + nc_i\cdot\frac{E_i}{v_0}, \quad \forall i\in V \tag{14}$$

$$tf_i \le etu_i, \forall i\in V \tag{15}$$

$$\sum_{k\in C}\theta_{ijk}=nc_i, \forall i\in V, j=th_i,\cdots,tf_i \tag{16}$$

$$\sum_{k\in C_j}\sum_{j=1}^{sib_j-1}\theta_{ijk}=0, \forall i\in V \tag{17}$$

$$\sum_{k\in C}\sum_{j=\sin_i+1}^{t}\theta_{ijk}=0, \forall i\in V \tag{18}$$

$$\sum_{i\in V}\theta_{ijk}\le 1, \forall j\in T, k\in C \tag{19}$$

$$\sum_{k\in C}\sum_{i\in V}\theta_{ijk}\le c, \forall j\in T \,\&\, \theta_{jk}, m_{jk}\in\{0,1\}, \forall i\in V, j \tag{20}$$

The objective function (12) indicates that the ship waiting for the average operation required to minimize the total number of shore bridges, it should be noted that the utilization of shore bridges can be repeated, that is to say, assuming that the berthing position is similar or the same before and after the two ships can be assigned to the same number of shore bridges, constraints (13) indicates that the number of assigned shore bridges of each ship to take the range of values. Constraint (14) indicates that the ship operation time is directly proportional to the amount of containers loaded and unloaded by the ship, and inversely proportional to the number of assigned bridges, constraint (15) ensures that all the loading and unloading operations need to be completed within a specified time window, and constraint (16) indicates that the number of operational bridges remains unchanged during the ship operation. Constraints (17) and (18) indicate that no shorebridge operates on a ship outside the specified time window, constraint (19) indicates that a single shorebridge can serve a maximum of one ship per time period, constraint (20) ensures that the number of all operating shorebridges cannot exceed the total number of shorebridges in each time period, and constraint (21) defines the dependent variables.

2.2. Model solving

First, the initial population is randomly generated, and the first generation of offspring population is obtained by three basic operations of genetic algorithm: selection, crossover, and mutation after non-dominated sorting [24]. Secondly, starting from the second generation, the parent population is merged with the offspring population for fast non-dominated sorting, and at the same time, the crowding degree is calculated for the individuals in each non-dominated layer, and the appropriate individuals are selected according to the non-dominated relationship as well as the crowding degree of the individuals to form a new parent population. Finally, a new offspring population is generated by the basic operation of genetic algorithm. And so on until the conditions for the end of the program are met. The specific operations are as follows and the corresponding program flowchart is shown in Figure 1.

1) Population initialization. An initial parent population P_t with an initial population size of L was randomly generated, and for each individual, a two-layer chromosome code was used according to equation (21):

$$G^L = \begin{pmatrix} G^1_{k_1} & G^1_{k_2} & \dots & G^1_{k_i} & \dots & G^1_{k_n} \\ G^2_{q_1} & G^2_{q_2} & \dots & G^2_{q_i} & \dots & G^2_{q_n} \end{pmatrix} \tag{21}$$

where G^L is the set of chromosome codes, G^1_{ki} denotes the first level of genes at position i of the chromosome, i.e., the berthing position of the ith ship, taken as a random integer between [1, 6]. G^2_{qi} denotes the second level gene at chromosome position i, i.e., the number of service bridges of the ith ship, which is a random integer between $q_{i\min}$ and $q_{i\max}$.

2) Crossover operation. In this paper, we use the simulated single-point binary crossover method, for two individuals $G^1(G^m_{k_i})$ and $G^2(G^m_{q_i})$ in the two parent populations P_i, two offspring $H^1(H^m_{k_i})$ and $H^2(H^m_{q_i})$ are obtained by Eq. (21), which generates the offspring population Q_i:

$$\begin{cases} H^m_{k_i} = 0.5\left[(1+\beta)G^m_{k_i} + (1-\beta)G^m_{q_i}\right] \\ H^m_{q_i} = 0.5\left[(1-\beta)G^m_{k_i} + (1+\beta)G^m_{q_i}\right] \end{cases} \tag{22}$$

where $i = 1, 2, \dots, n, m = 1, 2$, β are the propagation factors, generated dynamically and randomly from the distribution coefficients η and the random number $\varphi \in [0,1]$, as shown in Eq. (23):

$$\beta = \begin{Bmatrix} (2\varphi)^{\frac{1}{(1+\eta)}} & 0 \prec \varphi \le 0.5 \\ \left(\dfrac{1}{2-2\varphi}\right)^{\frac{1}{(1+\eta)}} & 0.5 \prec \varphi \le 1 \end{Bmatrix} \tag{23}$$

3) Selection operation. Combine the parent population P_t and the offspring population Q_t into a new population R_t with a population size of 2M, and use the objective function as the fitness function to perform non-dominated sorting on R_i. The main steps are: calculate the number of dominated individuals n_p for each individual p in R_i and the dominated solution set S_p for individual p, put the individuals of $n_p = 0$ into set F_i, and eliminate the domination of the individuals in F_i over the remaining individuals. Calculate the number of dominated individuals n_l for each of the remaining individuals t, put the individuals of $n_l = 0$ into set F_2, eliminate the domination of the individuals of F_2 over the remaining individuals, and repeat the above steps until all the individuals of R_t have been partitioned, and set F_u is the set of individuals corresponding

to the Pareto rank of u. For Z individuals in the same set F that do not dominate each other, a crowding degree is calculated. The specific steps are: take d_u to denote the crowding degree, take $d_0 = 0, d_1 = d_Z = \infty$ and arrange all the objective function values f_k in ascending order, and note $f_{k\max}, f_{k\min}$ the maximum and minimum values of the individual objective function values, respectively. The formula for calculating the crowding degree is shown in equation (24):

$$d_u = d_0 + \frac{f_k(u+1) - f_k(u-1)}{f_{k\max} - f_{k\min}}(u = 2,3,...Z-1) \tag{24}$$

4) Population renewal. An elite retention strategy is used to prioritize individuals with greater crowding in R_t until the population size reaches L.
5) Mutation operation. Based on the reinforcement learning fixed-point mutation strategy, the set of all genes on the parent population P_{t+1} is used as the initial action set, the objective function is calculated to obtain the initial state set, and the state-action pair $Q(s,a)$ is used as the Q matrix element [25]. The fixed-point mutation process is used to select the positions of P_{t+1} key genes, and the mutation operation is carried out by uniform mutation, and the reward function R_n is calculated to update the Q matrix state until the Q matrix converges, and the converged action set is used as the offspring population Q_{t+1}, and the steps (2)~(4) are repeated until the maximum number of iterations.

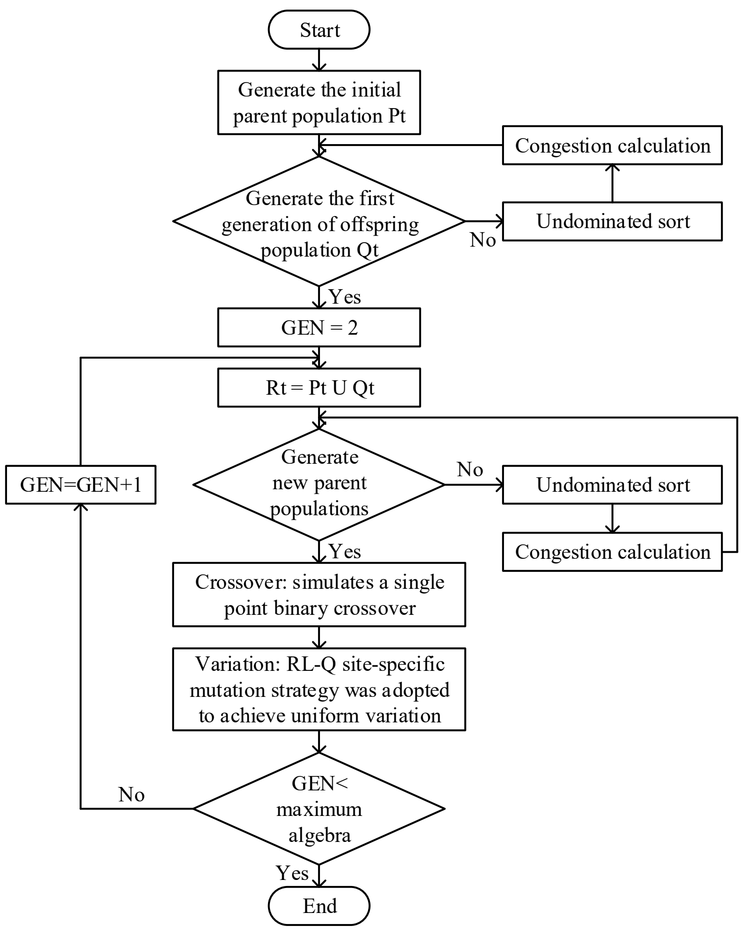


Fig. 1. Flowchart of the NSGA-II algorithm

3. Example verification - a port as an example

3.1. Analysis of calculation results

3.1.1. Optimal solution of the model considering the cost of carbon. Figure 2 shows the optimal solution of the model considering the carbon cost, after the multi-objective genetic algorithm calculation, the objective function value of the optimal solution is obtained as 120,486.64 yuan, the cost of shore and bridge operation is 134,856 yuan, the cost of the ship's time in port is 90,485 yuan, and the average time of the ship's time in port is 40.65 hours.

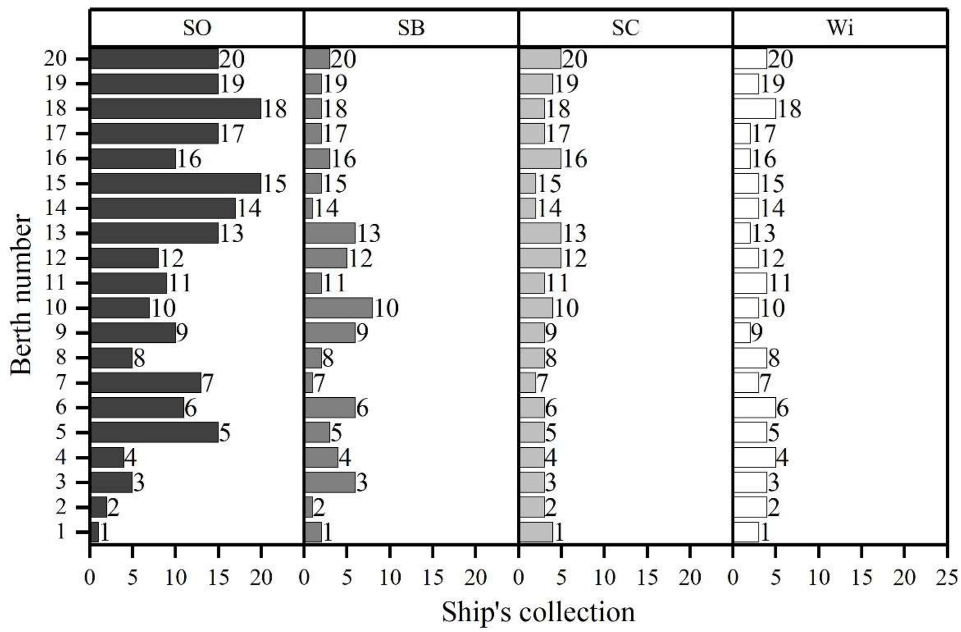
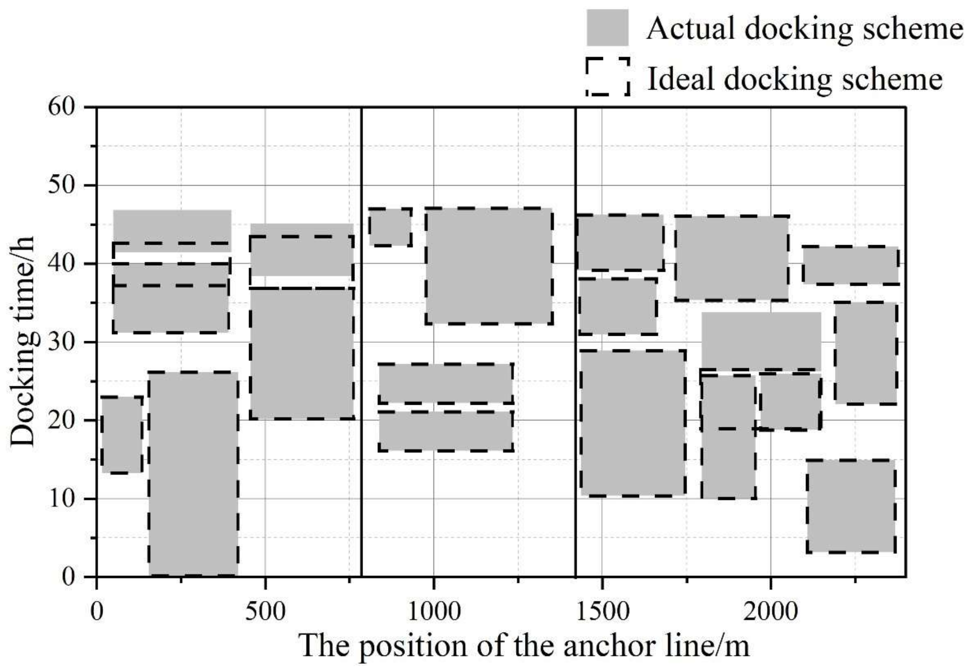


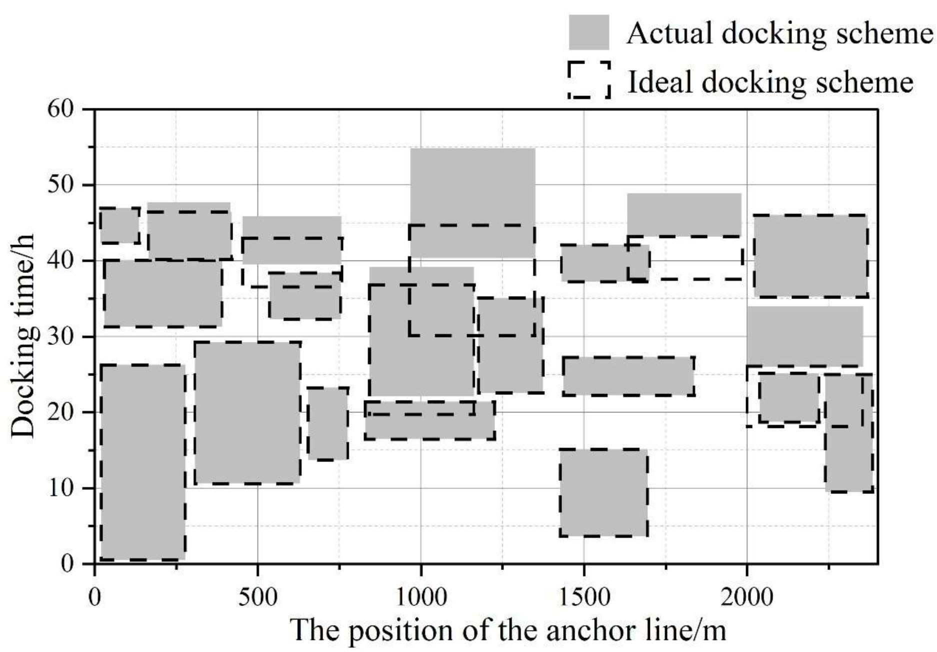
Fig. 2. The optimal solution to the carbon cost model

Note: SO indicates the berthing sequence of the ship, SB indicates the berthing berth of the ship, SC indicates the number of shore Bridges configured by the ship, Wi indicates the preferred berth of the ship. F is the objective function value, F1 is the operation cost of the shore bridge, F2 is the cost of the ship's time in port. T represents the average time a ship is in port,F=120486.64 yuan,F1=134856 yuan,F2=90485 yuan,T=40.65 hours.

3.1.2. Berth-Shore Bridge Configuration. The traditional basic berth scheduling method ignores the transshipment scheduling of container flow that occurs in multi-port scenarios, and decision makers usually focus on minimizing the ship's in-port time when formulating the berth window plan, and determine the correspondence between the ship and the port berths based on the time cost according to the ship's route list. However, in the production practice of large multi-port transshipment hub port, the distance between ports is far and a large number of transshipment boxes need to be transferred in a one-way ship, two-way ship, one-way ship, two-way ship docked in different ports will produce containers between ports and mutual towing transshipment to reduce the carbon cost of inter-port transportation of containers to be treated by the port to scheduling ships to formulate the berth plan is an important factor. Under the large-scale ship example (number of ships = 20), the proposed multi-objective berth allocation scheduling scheme considering inter-port transshipment is compared with the traditional berth allocation scheduling scheme based on the minimum carbon cost as shown in Fig. 3, Fig. (a) shows the scheme based on the minimum carbon cost, and Fig. (b) shows the scheme considering inter-port transshipment. The final realization rate of the minimum carbon cost scheme based on multi-objective genetic algorithm is 85%, and the realization rate of the scheme considering inter-port transit is 70%.



(a) based on the minimum carbon cost plan



(b) consider inter-terminal transit options

Fig. 3. Comparison of berth allocation and scheduling schemes for large scale cases

3.1.3. Comparative analysis. In order to visually demonstrate the superiority of the multi-objective genetic algorithm's carbon cost optimization scheme over the traditional first-come-first-served berth allocation scheme, this paper compares them. Table 1 shows the comparison of the berth-shore-bridge allocation scheme under the multi-objective genetic algorithm scheme with the traditional first-come-first-served port berth-shore-bridge allocation scheme. Compared with the traditional allocation scheme, the value of the objective function under the multi-objective genetic algorithm model decreases by 10.48%, the operating cost of the port decreases by 4.54%, the cost of the ship's in-port time decreases by 24.9%, and the average ship's in-port time decreases by 11.01%.

It can be seen that the berth shorebridge optimization model considering carbon cost is superior to the traditional first-come-first-stop-first-service scheme, which can shorten the ship's in-port time and reduce the carbon emission from the side to achieve the promotion of green port.

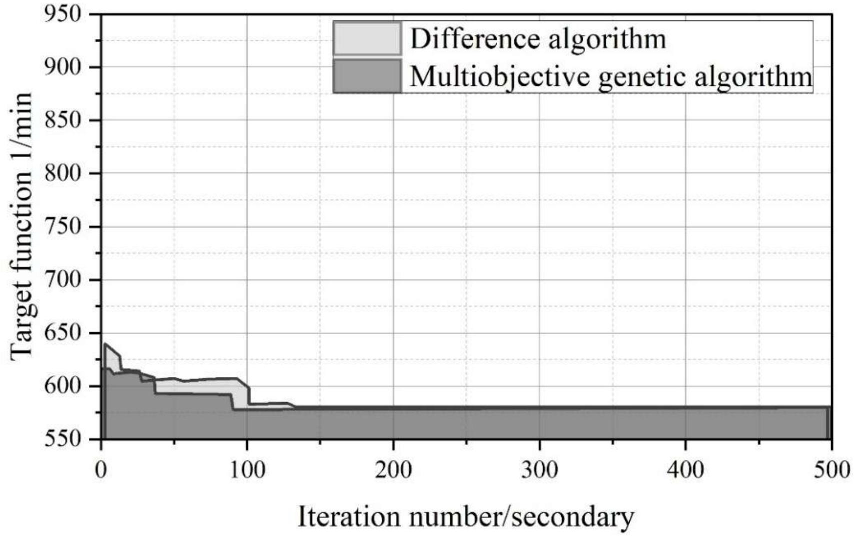
Table 1. Scheme contrast

/	Multitarget inheritance Assembly of ships																			
S	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
SO	1	2	5	4	15	11	13	5	10	7	9	8	15	17	20	10	15	20	15	15
SB	2	1	6	4	3	6	1	2	6	8	2	5	6	1	2	3	2	2	2	3
SC	4	3	3	3	3	3	2	3	3	4	3	5	5	2	2	5	3	3	4	5
Wi	3	4	4	5	4	5	3	4	2	3	4	3	2	3	3	2	2	5	3	4
F=120486.64 yuan,F1=134856 yuan,F2=90485 yuan,T=40.65 hours.																				
/	Tradition Assembly of ships																			
S	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
SO	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
SB	3	3	2	5	4	5	1	2	4	5	3	4	2	2	3	1	2	4	2	2
SC	6	4	4	3	3	3	2	4	2	3	3	3	5	2	2	2	4	3	3	6
Wi	4	2	3	5	5	6	1	5	5	6	2	5	6	3	3	4	3	2	3	4
F=134597.28 yuan,F1=141265 yuan,F2=120486 yuan,T=45.68 hours.																				

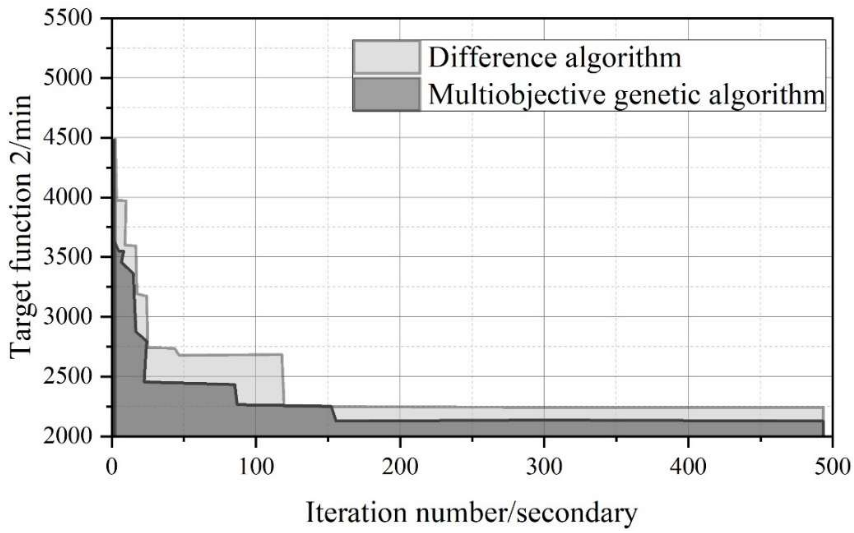
3.2. Model testing

3.2.1. Pareto Optimal Solution Analysis. A series of Pareto optimal solutions are obtained by solving with the NSGA-II algorithm, which demonstrate the equilibrium state of the inbound and outbound ship berth-coast bridge problem in the context of multi-objective function optimization. When these optimal solutions are analyzed in detail, the trends of several key parameters are focused on to gain a deeper understanding of the model's performance when dealing with the ship berth-shore bridge problem in a ship port. Fig. 4 shows the comparison of the running results of the difference algorithm and the NSGA-II algorithm with the objective functions 1-3 in Figs. (a)-(c), respectively.

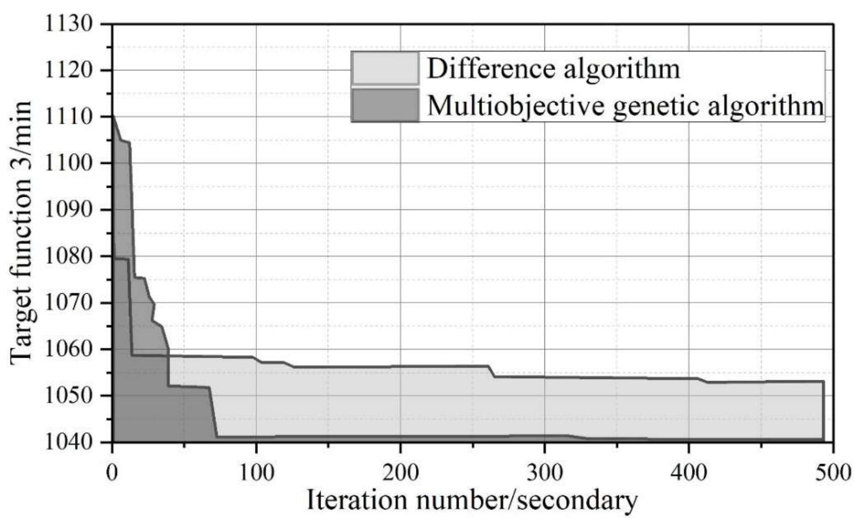
In the detailed analysis of the Pareto optimal solution, it is found that the NSGA-II algorithm has significant superiority in the multi-objective optimization problem. Not only does it have better performance in the three objectives of total inbound and outbound ship scheduling time, total ship waiting time in port and total tugboat berthing operation time, but also the change trends of each parameter are relatively balanced in the solution sets with different trade-offs, which shows that the model effectively handles the problem of coordinated scheduling of inbound and outbound ships and tugboats. This provides strong support for the model in practical applications. In the comparative test results, comparing the NSGA-II algorithm with the difference algorithm, for example, in the objective function 3, the NSGA-II algorithm used 90 iterations to the objective function, and at the same time, the running time was 1040 min. this shows that the NSGA-II algorithm has a higher solving efficacy in the ship co-scheduling problem. The comprehensive analysis of the Pareto optimal solution and the comparative test results conclude that the model has a high degree of rationality and effectiveness in the ship cooperative scheduling problem. However, it should be noted that the model has some limitations, such as the challenge of computational complexity when dealing with large-scale problems. Therefore, in future research, further improvement of the algorithm can be considered to enhance its computational efficiency or explore customized optimization strategies for specific problems.



(a)Objective function 1



(b)Objective function 2



(c)Objective function 3

Fig. 4. The difference algorithm is compared with the operation of the NSGA-Ⅱ algorithm

3.2.2. Sensitivity analysis. In order to verify the validity of the model constructed in this paper, this section conducts a sensitivity analysis of some parameters in the model. Since the solution of the model is the combination of berth and bridge configurations, which will be directly reflected to the objective function of the model, i.e., cost, the sensitivity analysis in this section only discusses the effects of changes in some parameters on the model cost and the average time of ships in port, including the unit carbon emission cost and the efficiency of the bridge operation.

There are two forms of carbon emission cost, one is carbon trading cost and the other is carbon tax, which is defined in this paper to be approximately equal to the regional carbon trading price. Carbon trading price is a floating value, this paper discusses the impact of carbon trading price on the model solution, respectively, take the carbon trading price of 60, 90, 120, 150, 180, 210 yuan per ton, and get the results of the numerical changes as shown in Table 2 below. With the growth of carbon emission cost, the four indicators F, F1, F2 and T also grow linearly, with growth rates of 17.24%, 18.44%, 14.37% and 18.02% respectively.

Table 2. Sensitivity analysis table based on changes in carbon cost

Carbon emission cost, (Yuan/ton)	The objective function value,F (yuan)	Port operation This F1 (Yuan)	Cost of ship's time in port F2 (Yuan)	Average time in port T (hours)
16.5	120486.64	134856	90485	40.65
60	124945.54	137486.36	94247.46	40.96
90	128749.64	143487.65	95486.13	41.65
120	134587.12	149648.48	97356.65	42.82
150	141446.96	157845.98	103489.42	43.46
180	144967.15	159178.65	105348.15	45.59
210	146487.54	162845.48	107665.26	48.34

In order to more intuitively represent the extent to which the change in carbon cost affects each indicator, this paper plots the change in each indicator with the change in carbon cost, as shown in Fig. 5, with F3 being the average time in port for ships. Because the average time of ships in port is relatively small, this paper represents it on the secondary axis (right Y-axis).

According to Figure 5, it can be seen that the values of each indicator have increased to a certain extent with the increasing cost of carbon emissions. The difference is that with the increase of carbon emission cost, the changes of objective function value, port operation cost, and ship's time in port cost tend to be relatively flat, and the change of ship's time in port is getting bigger and more obvious, and the average time in port is raised from 45 to 49 hours when the average time in port is increased from carbon emission cost of 180 yuan/tonne to 210 yuan/tonne.

The change of carbon emission cost has a higher degree of influence on the ship's time in port, the higher the carbon emission cost, the longer the ship's time in port, and the greater the degree of change. Container port operators should pay more attention to the operation and management of ports, actively respond to the development and implementation of the Carbon Peak and Carbon Neutral policy, and optimize the operation of container ports from various perspectives, such as resource allocation and management, and the optimization of import and export operations, in order to cope with China's increasingly developing carbon trading market.

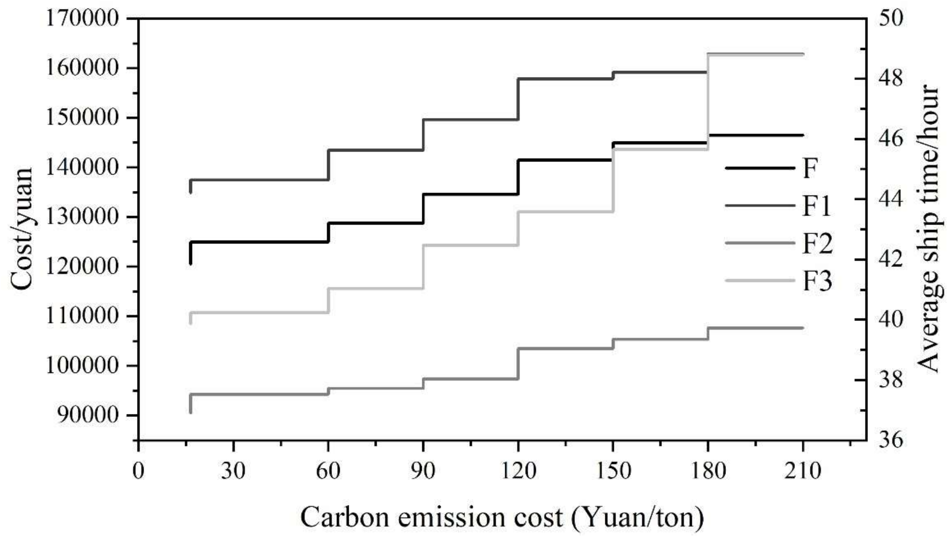


Fig. 5. Sensitivity analysis on the cost of carbon emissions

3.2.3. Robustness test. As a discrete dynamic system, the berth schedule of a multi-port transshipment port is susceptible to random factors such as ship handling time. In order to verify the robustness of the proposed modeling scheme and the solution results, multiple sets of experiments are conducted by adjusting the variance of random factors. The robustness of the example results is also analyzed by comparing with the traditional scheme from the three indicators of total cost, delay rate and inter-port transit rate, and Fig. 6 shows the model optimization effect under the uncertainty scenario.

Figure 6 shows the optimization effect of the model under the uncertainty scenario. As can be seen from Figure 6, with the increase of the uncertainty of the ship handling time, the optimization effect of the model scenario on the total cost of carbon emission and the inter-port transit rate are kept at a high level, between 13%~23% and 15%~40%, respectively, and there is no obvious increase in the delay rate, which reflects the robustness of the model's optimization effect. Meanwhile, the experimental results show that the model scenarios have more significant optimization effects under the scenarios with lower uncertainty levels. Therefore, for port transshipment ports, it is necessary to ensure that the docked ships have stable processing time to reduce their uncertainty to enhance the optimization effect of total port operation. Usually, the enhancement of ship informationization level and port shoreside loading and unloading efficiency is an effective way to reduce the uncertainty of ship handling time.

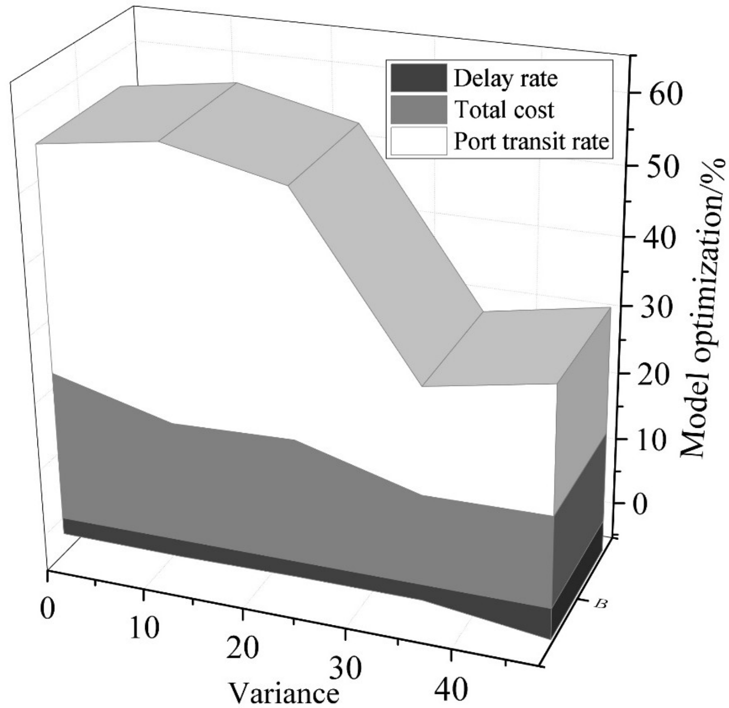


Fig. 6. The model optimization effect of the uncertain situation

4. Green Port Construction Strategy under the Peak Carbon and Carbon Neutral Strategy

4.1. Basic Concepts of Peak Carbon Neutrality in Ports

4.1.1. Peak Carbon Neutral. "Carbon peaking" refers to the peak of net carbon dioxide emissions (emissions minus offsets) at a certain point in time, and gradually declining after that point. "Carbon neutrality" means that the net emission of carbon dioxide is zero for a certain period of time, that is, the carbon dioxide emissions generated are offset with the carbon emission production achieved through carbon removal technologies such as energy conservation and emission reduction, afforestation, and industrial carbon sequestration, so as to achieve "zero emissions".

According to the Greenhouse Gas Protocol (GHG Protocol) jointly developed by the World Resources Institute and the World Business Council for Sustainable Development, there are three sources of carbon emissions for enterprises: (1) the amount of greenhouse gases directly emitted by the company's production, such as fuel combustion, company vehicle use emissions, etc. (2) Indirect greenhouse gas emissions from the Company's purchased electricity. (3) Other indirect greenhouse gas emissions, such as carbon emissions from the production of purchased materials and carbon emissions from related transportation activities. Therefore, when analyzing the "carbon peak and carbon neutrality" of the port industry, it is necessary to consider the above three carbon emission sources as a whole.

The "carbon peak" of the port industry generally refers to the process in which the port operating enterprises consider the direct, indirect and other carbon emissions generated in the process of port economic development and production activities in a certain period of time, and make the carbon dioxide emissions of the port industry reach a historical peak and then continue to decline through energy conservation and emission reduction, transformation of energy consumption structure, carbon sequestration technology, etc. "Carbon neutrality" in the port industry refers to achieving net-zero carbon dioxide emissions in the production, service and operation of ports. Therefore, the progress of "carbon peak and carbon neutrality" is an important indicator to measure whether the port has achieved green development, low-carbon development and zero-carbon development.

4.1.2. Importance of green port construction under the peak carbon neutral strategy:
1) The construction of green and low-carbon ports is a vivid practice of implementing the idea of ecological civilization. The proposal of the dual-carbon target highlights China's great determination of green development, and at the same time embodies the responsibility and commitment of China as the world's largest developing country. Promoting the construction of green ports and achieving the goal of "carbon peak and carbon neutral" in the port industry is a vivid practice of implementing the idea of ecological civilization, and a concrete measure to take new steps in green development.
2) The construction of green and low-carbon ports is a concrete measure to help China fully realize the goal of "peak carbon and carbon neutrality", and the green and low-carbon action in transportation is one of the ten key tasks of China's "Peak Carbon and Carbon Neutrality" implementation plan. Ports, as one of the important components, are a key area to focus on.
3) The construction of green and low-carbon ports is an important way to promote the sustainable development of ports and enhance their comprehensive competitiveness. Ports, as an important hub of the transportation industry, have an irreplaceable role in foreign exchanges with the advantages of large capacity and low cost of waterborne transportation, and are equipped with global connectivity and linkage.

4.2. Green Port Construction Strategy

4.2.1. Raising the political profile. The "dual-carbon" strategy is a major decision made by the Chinese government based on the current development situation, and is an important initiative to realize sustainable and high-quality economic and social development in China. The promotion of a "dual-carbon" strategy in the port industry is of strategic importance for the long-term sustainable development of ports. Therefore, it is necessary to further improve the position, unify the thinking and understanding, promote the re-enhancement of the ideological understanding, and fully understand the necessity and urgency of building a green and low-carbon port and realizing the goal of "dual-carbon" ports.

4.2.2. Planning leadership. Currently, carbon neutrality in the transportation sector has been included as one of the ten key tasks for Peak Carbon 2030. As an important link in transportation, ports should strengthen top-level design and carry out unified planning and deployment of green and low-carbon port construction at a strategic level. At the same time, it is also necessary to take into full consideration the characteristics of ports in each region, fully embodying the unity of commonality and individuality, and, while clarifying the common goals and paths, supporting enterprises to formulate their own goals and measures in accordance with their own construction situation and development characteristics. It is necessary to play the leading role of the government in promoting the realization of the goal of "carbon peak and carbon neutrality", to do a good job of top-level planning and design at the government level, to implement and enforce the plan at all levels, to strengthen the overall management of port enterprises, to formulate rigorous and powerful supervisory measures, and to press down on the main responsibility of each port enterprise.

4.2.3. Categorization. The report of the 20th CPC National Congress proposes to establish before breaking, and to implement the carbon peak action in a planned and step-by-step manner. The port industry should take the green and low-carbon transformation as the lead, enhance the energy efficiency utilization level of port transportation equipment as the basis, optimize the energy structure of the port, improve efficiency as the key, from energy saving and emission reduction, technology upgrading, energy substitution, ecological carbon sinks and green finance, etc., classify and implement measures, highlight the key points, and fully promote the work of green and low-carbon port construction.

5. Conclusion

This paper establishes an objective function as well as constraints based on the two conditions of berths and bridges of the port in the context of the carbon neutral strategy of Carbon Dakota. Population initialization, crossover operation, selection operation, population update and mutation operation are carried out sequentially to solve the multi-objective genetic algorithm model. A port is taken as an example to validate the example of green port promotion under multi-objective genetic algorithm. The objective function value of the optimal solution of the model considering the cost of carbon emission is 120,486.64 yuan, the cost of shore and bridge operation is 134,856 yuan, the cost of the ship's in-port time is 90,485 yuan, and the average in-port time of the ship is 40.65 hours. Comparing the berth-shorebridge configurations of multi-objective genetic algorithm and traditional differential algorithm, the final realization rate of the minimum carbon cost scheme based on multi-objective genetic algorithm is 85%, and the realization rate of the scheme considering inter-port transshipment scheme is 70%, and the realization rate of the scheme of the multi-objective genetic algorithm is better than that of the traditional algorithm. Pareto optimal solution, sensitivity, and robustness analysis are applied to test the model performance, respectively. The NSGA-II algorithm used 90 iterations to reach the objective function in objective function 3, and at the same time, the running time was 1040 min. this indicates that the NSGA-II algorithm has a higher solution efficacy in the ship co-scheduling problem. With the increasing carbon emission cost, the value of each index increases to some extent. The average time in port is raised from 45 hours to 49 hours when the average time in port increases from carbon emission cost of 180 yuan/ton to 210 yuan/ton.

References

[1] Hua, C., Chen, J., Wan, Z., Xu, L., Bai, Y., Zheng, T., & Fei, Y. (2020). Evaluation and governance of green development practice of port: A sea port case of China. Journal of cleaner production, 249, 119434.

[2] Lam, J. S. L., & Li, K. X. (2019). Green port marketing for sustainable growth and development. Transport Policy, 84, 73-81.

[3] Wan, C., Zhang, D., Yan, X., & Yang, Z. (2018). A novel model for the quantitative evaluation of green port development–A case study of major ports in China. Transportation Research Part D: Transport and Environment, 61, 431-443.

[4] Xiao, G., Wang, Y., Wu, R., Li, J., & Cai, Z. (2024). Sustainable maritime transport: A review of intelligent shipping technology and green port construction applications. Journal of Marine Science and Engineering, 12(10), 1728.

[5] Iris, Ç., & Lam, J. S. L. (2019). A review of energy efficiency in ports: Operational strategies, technologies and energy management systems. Renewable and Sustainable Energy Reviews, 112, 170-182.

[6] Lin, C. Y., Dai, G. L., Wang, S., & Fu, X. M. (2022). The evolution of green port research: a knowledge mapping analysis. Sustainability, 14(19), 11857.

[7] Teerawattana, R., & Yang, Y. C. (2019). Environmental performance indicators for green port policy evaluation: Case study of Laem Chabang port. The Asian Journal of Shipping and Logistics, 35(1), 63-69.

[8] Yau, K. L. A., Peng, S., Qadir, J., Low, Y. C., & Ling, M. H. (2020). Towards smart port infrastructures:

Enhancing port activities using information and communications technology. Ieee Access, 8, 83387-83404.

[9] Du, K., Monios, J., & Wang, Y. (2019). Green port strategies in China. In Green ports (pp. 211-229). Elsevier.

[10] Fahdi, S., ELKHECHAFI, M., & HACHIMI, H. (2019, April). Green port in blue ocean: Optimization of energy in Asian ports. In 2019 5th International Conference on Optimization and Applications (ICOA) (pp. 1-4). IEEE.

[11] Marzantowicz, Ł., & Dembińska, I. (2018). The reasons for the implementation of the concept of green port in sea ports of China. Logistics and Transport, 37, 121-128.

[12] Sogut, M. Z., & Erdoğan, O. (2022). An investigation on a holistic framework of green port transition based on energy and environmental sustainability. Ocean Engineering, 266, 112671.

[13] Wang, W., Huang, L., Gu, J., & Jiang, L. (2019). Green port project scheduling with comprehensive efficiency consideration. Maritime Policy & Management, 46(8), 967-981.

[14] Su, Z., Liu, Y., Gao, Y., Park, K. S., & Su, M. (2024). Critical Success Factors for Green Port Transformation Using Digital Technology. Journal of Marine Science and Engineering, 12(12), 2128.

[15] Zhang, Z., Song, C., Zhang, J., Chen, Z., Liu, M., Aziz, F., ... & Yap, P. S. (2024). Digitalization and innovation in green ports: A review of current issues, contributions and the way forward in promoting sustainable ports and maritime logistics. Science of the Total Environment, 912, 169075.

[16] Chen, J., Huang, T., Xie, X., Lee, P. T. W., & Hua, C. (2019). Constructing governance framework of a green and smart port. Journal of Marine Science and Engineering, 7(4), 83.

[17] Muradian, A., Kuzkin, O., & Remzina, N. (2023). Logistics of Smart Port in Ukraine: Problems and Prospects in the Conditions of Sustainable Development. Problemy Ekorozwoju, 18(2), 229-241.

[18] El Imrani, O. (2024, May). Optimization of Port Logistics performance through Innovative Technology Management. In 2024 IEEE 15th International Colloquium on Logistics and Supply Chain Management (LOGISTIQUA) (pp. 1-7). IEEE.

[19] Mahmud, K. K., Chowdhury, M. M. H., & Shaheen, M. M. A. (2023). Green port management practices for sustainable port operations: A multi method study of Asian ports. Maritime Policy & Management, 1-36.

[20] Liu, M., Lai, K. H., Wong, C. W., Xin, X., & Lun, V. Y. (2024). Smart ports for sustainable shipping: concept and practices revisited through the case study of China's Tianjin port. Maritime Economics & Logistics, 1-46.

[21] Deng, Y., & Han, J. (2024). Energy Management of Green Port Multi-Energy Microgrid Based on Fuzzy Logic Control. Energies, 17(14), 3601.

[22] Alzate, P., Isaza, G. A., Toro, E. M., Jaramillo-Garzón, J. A., Hernandez, S., Jurado, I., & Hernandez, D. (2024). Operational efficiency and sustainability in smart ports: a comprehensive review. Marine Systems & Ocean Technology, 1-12.

[23] Vikas Srivastava,Aditi Paul & Somnath Sinha. (2024). MMOF: A Multi-Metric Objective Function for Congestion Detection Under Varying Transmission Ranges in RPL-Based WSN. SN Computer Science(8),1112-1112.

[24] Zhibao Guo,Hamid Reza Karimi,Baoping Jiang,Zhengtian Wu & Yukun Cheng. (2024). Enhanced intelligent water drops with genetic algorithm for multi-objective mixed time window vehicle routing. Neural Computing and Applications(prepublish),1-15.

[25] Han Xu,Chen Xue,Quan Chen,Jun Yang & Bin Liang. (2024). Continuous Multi-Target Approaching

Control of Hyper-Redundant Manipulators Based on Reinforcement Learning. Mathematics(23),3822-3822.