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An Improved Genetic Algorithm for Berth Scheduling at Bulk Terminal

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Abstract: Berth and loading and unloading machinery are not only the main factors that affecting the terminal operation, but also the main starting point of energy saving and emission reduction. In this paper, a genetic Algorithm Framework is designed for the berth allocation with low carbon and high efficiency at bulk terminal. In solving the problem, the scheduler's experience is transformed into a regular way to obtain the initial solution. The individual is represented as a chromosome, and the sub-chromosomes are encoded as integers, the roulette wheel method is used for selection, the two-point crossing method is used for cross, and the exchange variation method is used for variation in the procedure of designing the Algorithm. Considering the complexity of berth scheduling problem and the diversity of constraints and boundary conditions, the genetic algorithm combines with system simulation to get the final scheme of berth allocation. This model and algorithm are verified to be practical by analyzing multiple sets of examples of shorelines with different lengths. When compared with the traditional algorithms in three aspects which includes berth offset distance, departure delay cost and energy consumption of portal crane, the result indicates that the improved algorithm is more effective and feasible. The study will help to lower energy consumption and resource waste, reduce environmental pollution, and provide a reference for low-carbon, green and sustainable development of the terminal.

Keywords: Bulk terminal; Berth scheduling; Genetic algorithm; Energy-saving

1 Introduction

With the increasing competition among ports, it has become one of the key factors to enhance their competitiveness by increasing the berths' utilization, accelerating ships' loading and unloading, improving efficiency and service [1–3]. Berth position, the important resource in the port transportation system, is one of the key factors that affecting their development. So, the berth allocation has become one of the important issues in ports' research now [4–6].

Scholars at home and abroad have made deep research on berth allocation, which covers forecasting of terminal throughput, optimization and configuration of ports' equipment, configuration of port's construction and handling operation line for single ship, simulation of ports' system, bottleneck analysis and its optimization, coordinated configuration for container truck and operating line, berth scheduling, ship loading and its optimization, etc. In recent years, research on energy efficient port has mainly focused on macro-scopic aspects such as law, policy, planning, and equipment technique, but barely on production and operation [7–10].

There are two approaches to the multi-objective berth allocation, one is the widely used traditional multi-objective optimization, the other is the improved [11–13]. Though the former follows the principle of algorithm of single-objective problem, it is not suitable for the large scaled. For example, Pareto Optimality needs to be optimized continuously. The results vary because there is not any relevance between each optimization, which not only wastes time, but also leads to an inefficient decision. The latter, the new-type and intelligent one, is applied to solve large, scaled problems and features advantages that not only processing large and scaled search space, but also producing multiple equilibrium solutions during the period of single optimization when compared to the traditional one [14–16].

A genetic algorithm (GA) is a search technique used in computing to find exact or approximate solutions to optimization and search problems [17–19]. Categorized as global search heuristics, the genetic algorithm is a particular class of evolutionary algorithm (EA) that uses techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover. The algorithm is implemented in a computer simulation in which a population of abstract representations (called chromosomes or the genotype of the genome) of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem evolves toward better solutions. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached. It find its wide application in bioinformatics, phylogenetics, computational science, engineering, economics, chemistry, manufacturing, mathematics, physics and other fields. The paper employs it to solve berth scheduling because of its parallelism, practicability, and robustness [20–23].

2 Construction of Berth Scheduling Model at Bulk Terminal

2.1 Model Assumption

The model is constructed on basis of the following assumptions: ① the ship will arrive at port at the given arrival time on time; ② the berthing length is 1.2 times the length of the ship; ③ every ship only has one chance to berth without regard to shifting; ④ the continuous shoreline is the same in depth, which is bigger than the depth of immersion; ⑤ every ship has been assigned the minimum and the maximum loading machinery respectively; ⑥ the loading machinery will move on the track and won't stride over each other; ⑦ the ratio of the loading machinery keeps constant without regard to the mutual interference among machinery; ⑧ the loading time is inversely proportional to the numbers of the loading machinery, which meets a certain proportion.

2.2 Parameter Definition

i, j - Ships number, C is the set of all ships, $i, j \in C$.

M - Set of cranes, $m \in M$.

L - Total length of shoreline.

l_i - Length of Ship i.

St_i - Arrival time of Ship i.

Et_i - Exiting time of Ship i.

Dt_i - Expected Departure time of Ship i.

Kt_i - Berthing time of Ship i.

X_i - Actual berthing position of Ship i.

E_i - Optimum berthing position of Ship i.

S_i - Start position for berthing Ship i.

B_i - End position for berthing Ship i.

α - Constant, if the exiting time is no greater than the expected, $\alpha = 0$, else, $\alpha = 1$.

ω_1 - Unit cost of berthing deviation distance.

ω_2 - Unit cost of delayed departure time.

ω_3 - Unit cost of energy consumption of cranes.

Cm_i - Number of cranes assigned to Ship i.

M - Energy consumption of one-crane-one-operation in one unit time.

y_{ik} - k Cranes assigned to Ship i.

Z_i - The maximum load of Ship i.

$CMmax_i$ - The maximum number of cranes assigned to Ship i.

$CMmin_i$ - The minimum number to cranes assigned to Ship i.

q_{im} - Operating quantity distributed to Crane M by Ship i. If $q_{im} = 0$, then the crane doesn't work for Ship i.

Vo-Operation efficiency of cranes.

2.3 Destination Function

The berth scheduling model of the continuous shoreline is described as follows: First, the ship to port is assigned a specific position along the shoreline based on C (namely, all the ships), then is arranged a berthing order based on St_i, finally is assigned cranes to load based on Z_i. The berth along the continuous shoreline is shown in Fig. 1.

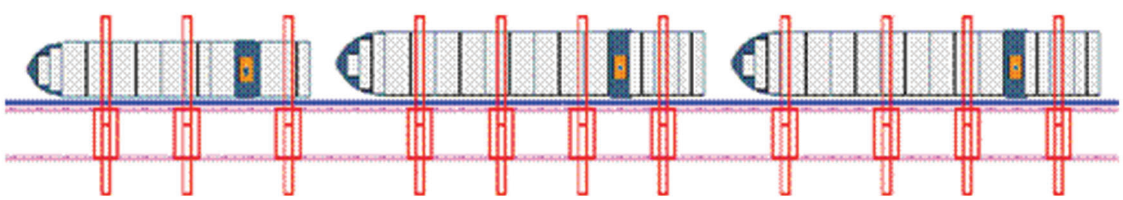

Figure 1: Schematic diagram of berth along the continuous shoreline

In view of the interrelationship between cranes and ship, the destination function is of multi-objectives. It includes the minimum distance cost influenced by deviation between the actual and the optimal berthing positions, the minimum departure delay cost, and the minimum energy consumption of cranes.

The minimum distance cost influenced by deviation between the actual and the optimal berthing positions is as follows.

$$f(1) = Min\omega_1 \sum_{i=1}^{c} |X_i - E_i| \tag{1}$$

The minimum delayed cost caused by departure is as follows.

$$f(2) = Min\omega_2\alpha \sum_{i=1}^{c} |Et_i - Dt_i| \tag{2}$$

The minimum energy consumption produced by cranes is as follows.

$$f(3) = Min \sum_{i=1}^{c} \sum_{k=1}^{m} Cm_i y_{ik} N \tag{3}$$

2.4 Constraint Conditions

The constraint conditions, namely assumptions that satisfy the model, are shown in the following.

$$Et_i - St_i \geq 0 \tag{4}$$

Eq. 4 indicates that the departure time must not be earlier than the arrival time.

$$(Et_i - Kt_i)(Kt_i - Et_i)Pi_j \geq 0 \tag{5}$$

Eq. 5 indicates that the ships' positions won't interleave if the time is not interleaved, that is, the positions of these two ships won't coincide within the same time.

$$CM\ \mathrm{min_i} \leq Cm_\mathrm{i} \leq CM\ \mathrm{max_i} \tag{6}$$

Eq. 6 indicates that the number of cranes assigned cannot be less than the maximum number of the accepted.

$$\left(B_i - S_j\right)\left(S_i - B_j\right)S_{ij} \geq 0 \tag{7}$$

Eq. 7 indicates that the ships' positions won't interleave if the time is not interleaved, that is, the positions of two ships won't coincide within the same time.

$$\sum_{i=1}^{c} X_i = C \tag{8}$$

Eq. 8 indicates that all the ships to port can berth.

$$\sum_{m=1}^{M} q_{im} = Z_i \tag{9}$$

Eq. 9 ensures that all the goods in Ship i can be unloaded thoroughly.

$$(Et_i - St_i) = Z_i/(V_0 \times Cm_i) \tag{10}$$

Eq. 10 indicates that the operation time is equal to the volume of goods that divided by the cranes' efficiency. In other words, it is directly proportional to the volume of goods, but is inversely proportional to the cranes' number.

$$x_i = 0 \text{ or } 1, \forall I = \{1, 2, \ldots, c\} \tag{11}$$

$$x_{ik} = 0 \text{ or } 1, \forall I = \{1, 2, \ldots, c\}, k = \{1, 2, \ldots, m\} \tag{12}$$

$$s_{ij} = 0 \text{ or } 1, \forall I = \{1, 2, \ldots, c\}, j = \{1, 2, \ldots, c\} \tag{13}$$

$$p_{ij} = 0 \text{ or } 1, \forall I = \{1, 2, \ldots, s\}, j = \{1, 2, \ldots, c\} \tag{14}$$

Equations from (11) to (14) are binary constraints, where, if $x_i = 1$ then Ship i berths, if $x_i = 0$ then Ship i doesn't berth; if $x_{ik} = 1$ then k cranes will be assigned to Ship i; if $S_{ij} = 1$ then Ship i and Ship j are time-interleaved, else $S_{ij} = 0$; if $P_{ij} = 1$ then Ship i and Ship j are position-interleaved, else $P_{ij} = 0$.

3 Algorithm Design for Berth Scheduling

3.1 Algorithm Framework

The weight factor transformation approach to the multi-objective problem is as follows: Assign ($I = 1,2, \ldots,n$) to every sub function ($I = 1,2,\ldots,n$), where ω_i means the corresponding importance in multi-objective optimization, then $u = \sum \omega_i f(x_i)$. It adds up the linear weights of all the destination functions. This convenient and efficient method will receive a feasible solution which can be used as an initial solution and applied to other methods.

It can be seen from the mathematical model that by assigning weights, the multi-objective problem is transformed to a single-objective one, and then is solved by use of genetic algorithm [24–26]. Specific solutions are as follows.

Step 1: To collect data. Berth position and cranes are assigned to Ship i based on the data collected.

Step 2: To wait for berthing. The berth position is judged whether to be available or not first. If it is, then ship i berths and the berthing time is determined. Else, Ship i has to wait for berthing at anchor.

Step 3: To wait for cranes. Ship i waits for loading and unloading after berthing. First, the number of free cranes (FC) is judged whether to be sufficient or not. If it is, then ship i is assigned appropriate cranes and starts to work, and the working time is determined. Secondly, the neighbor cranes are judged whether to be called or not. Ship i has to wait at berth and can't work until the minimum number of cranes is satisfied. We have to obey the rule that only neighbor cranes can be called.

In algorithm design, a job library is set to indicate whether the berths and cranes are in use or not and is controlled by event triggering. There are three trigger modes, the berth position is locked at berthing time, the crane is locked when starting to work, and the corresponding position and cranes is released at departure time.

3.2 Algorithm Implementation

3.2.1 Individual Coding

A genetic algorithm is employed here to obtain an optimal berth position and cranes' number for the berth scheduling along the continuous shoreline. The berth position, berthing time and cranes assigned will affect the departure delay time and the energy consumption of cranes. Binary is widely used in coding for genetic algorithm but not for berth scheduling, because it will make problems more complicated and is detrimental to computer processing [27–30].

Since the shoreline can only serve for one ship at the same time, repeated genes are not permitted. There are three decision variables in the model, the berth time Kt_i, the starting position S_i, and the cranes' number Cm_i. Individual in this paper is expressed by genome whose subchromosomes are coded by integer. That is, the individual gene value is expressed by integer, and the coding length is decided by the number of decision variables. The ship number is thus represented by the position of the individual gene whose subchromosome number of 1, 2, and 3 represent the berth consequence, the starting position, and the cranes' number respectively. For instance, let's code eight ships along a ten meters shoreline, as shown in Tab. 1. Ship 1 is the first to berth at the position of ten meters from the shoreline, and three cranes are assigned. Ship 2 is the third to berth at the position of one hundred and thirty meters from the shoreline and one crane is assigned, and so on.

Table 1: Example of genic coding for genome

Ship Number	1	2	3	4	5	6	7	8
Sub-chromosome 1	1	3	5	2	4	8	7	6
Sub-chromosome 2	10	130	240	600	980	412	753	350
Sub-chromosome 3	3	1	5	2	4	2	3	3

3.2.2 Population Initialization

Because the berth scheduling is complicated, there would be a large number of infeasible solutions if the initial population is generated randomly. In order to avoid this, a feasible but not optimal berth scheme is presented at first, which is shown specifically in the following.

Step 1: Let's suppose that there will be s ships to port in twenty-four hours. The maximum length of ship is M, and the minimum is N. The maximum berth positions available can be obtained from the total length of shoreline and the minimum length of ship.

Step 2: According to the initial parameters, ships awaiting are viewed as rectangles which is to be put in box, and then are checked, sorted, and decoded based on the estimated arrival time.

Step 3: The rectangles are arranged based on ships' load in the order from big to small.

Step 4: The maximum load is assumed to be i. Item with the maximum load is selected from Set s and put in the lower left corner of the box.

Step 5: When cut horizontally along the line above Ship i, the remaining space is divided into two parts. The space below is the first layer to be boxed.

Step 6: Items with the same load of i are searched in the remaining Set s. Item with the minimum load difference is selected (which is also assumed to be j), put in the first layer, and then arranged to the right adjoining j. Set s is scanned continuously to search for items with the minimum load difference and arranged to the right.

Step 7: Cut horizontally along the line above Ship j, rescan Set s, and search for item with the minimum load difference which will be arranged in the upper right. The process will be repeated till the first layer is occupied.

Step 8: Whether the item can be arranged in the next layer or not depends on the estimated arrival time. Set s is updated. Steps from 3 to 7 are repeated to select appropriate rectangular items which will be put into the two-dimension space.

In order to ensure the maximum daily throughput, after the first ship in every layer is confirmed, the arrival time of ships that arranged in the next layer is computed. If the load of ships that arranged in the next layer is more than that of the first layer, then ships in the next layer take the priority to be arranged. Meanwhile, whether the ships can be arranged in a certain layer depends on the estimated arrival time t, and then Set s is updated.

After subchromosome 1 and 2 are decided, subchromosome 3 is selected randomly from cranes' set C, which must obey the rules that number of cranes assigned to each ship is neither greater than the maximum number of cranes which each ship can accept nor smaller than the minimum one.

3.2.3 Design of Fitness Function

Fitness function in the genetic algorithm is a non-negative value, which is expected to be as large as possible in general. But the destination function in the paper aims at a minimum operation cost, so it has to be transferred to meet the requirements. Fitness function is usually expressed by an inverse destination function or by M, a considerable large number, that taking away the destination function. The latter method is employed to transfer the destination function and its corresponding fitness function.

$$\text{Fitness(x)} = \begin{cases} \text{M} - \text{f(x)}, \text{when } f(x) < M \\ 0, \text{other situations} \end{cases} \tag{15}$$

where, $f(x)$ is the original destination function that features the minimum costs of deviation distance for berthing, delayed time for departure, and energy consumption for loading and unloading, namely, $f = min (\omega_1 f_1' + \omega_2 f_2' + \omega_2 f_2')$

3.2.4 Selection Operation

Selection operation usually employs roulette method, in which, individual selection probability is proportional to its fitness. Suppose the group to be n, and the individual fitness to be f_i, and then probability i is computed by $p_i = f_i / \sum f_j$. The individual selection probability is positive correlated with the fitness. When the individual is selected from the group, the crossed individual is then determined by repeated selections. A uniform random number between 0 and 1 will be produced in each section. The number is employed to determine the selected individual which will be associated randomly to cross over. Here in the paper the roulette wheel method.is employed.

3.2.5 Crossover Operation

A two-point crossing is employed because of the complex destination and constraint. If the crossed offspring couldn't satisfy the constraint that the ship has one and only one berthing chance and the cranes allocated is not more than the maximum cranes, an infeasible solution will emerge. Other exchange or adjustment strategy will be used to transfer the infeasible solution to the feasible one. Specific crossover is shown in Fig. 2.

It can be drawn from the figure above that A and B are parent generation, and child generation $C1$ and $D1$ are generated from two-point crossing. It can also be drawn from the middle subgeneration of subchromosome 1 that Row 1 is the same as Row 5, and Row 4 is the same as Row 7. The middle subgeneration $D1$ can't satisfy the constraint that each ship only has one chance to berth.

3.2.6 Mutation Operation

In practice, exchange mutation is employed in berthing sequence, while substitution mutation is in berthing position, in which a position is selected randomly to substitute. The mutated chromosome should satisfy the constraint that the individual ship has one and only one berthing chance and the number of cranes assigned could neither be more than the maximum number of cranes needed nor less than the minimum number of cranes assigned. The specific mutation is as shown if Fig. 3.

3.2.7 Termination Condition

Different problems call for different termination criteria in the genetic algorithm. There are four commonly used criteria: ① MaxGen, the maximum genetic algebra, is given. The algorithm terminates when the iteration number reaches MaxGen; ② LB, the lower bound, is given. The algorithm terminates when the iteration number reaches $\mathcal{E}$, a required deviation in evolving; ③ the algorithm terminates when a continuous Generation K emerges, and a better solution is not evolved; ④ the combination of all the above.

Here in the paper, the maximum iteration number is used as termination condition in solving berth scheduling model. Each individual destination function is computed till the iteration number reach a preset value, and then the computation ends with a corresponding result.

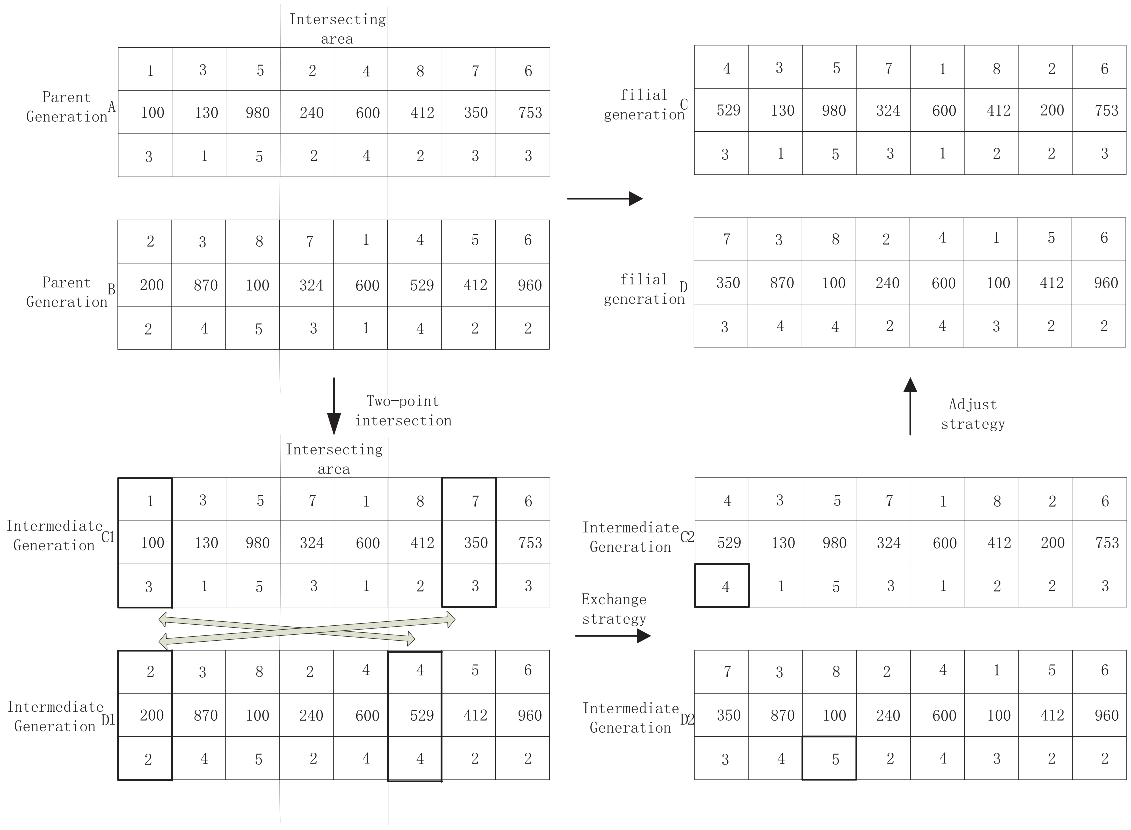

Figure 2: Schematic diagram of chromosomal crossover

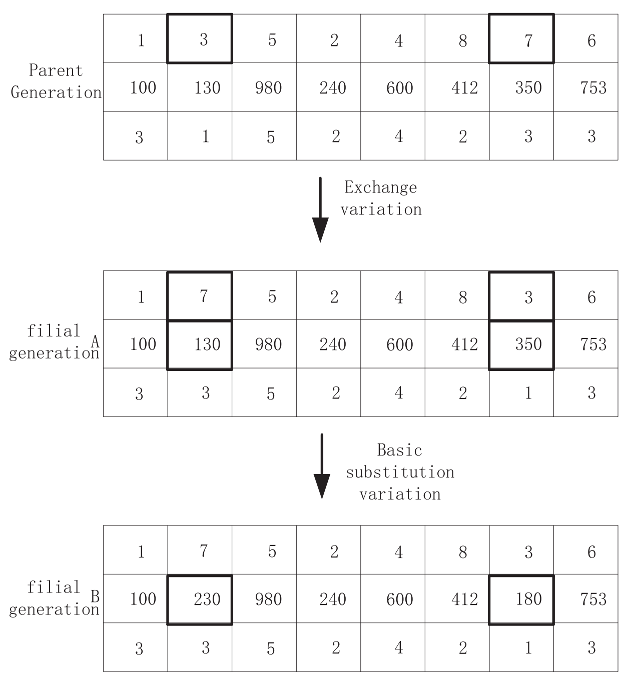

Figure 3: Schematic diagram of chromosomal mutation

4 Algorithm and Simulation

Complicated mathematical models and constraints are used in solving the complicated berth scheduling. Simulation is an effective way to estimate a complicated system, but not to provide an optimal strategy. Because some of the genes generated is infeasible, they need to be repaired or abandoned. It is easy for the simulation software but not easy for the genetic algorithm itself to repair genes by programming. For example, one ship crosses over the other in a certain time. Simulation will search for a practical berthing strategy by repairing genes. Here in the paper, both simulation and optimization algorithm are used in the specific example.

The implementation steps are as follows:

Step 1: Initialize the genetic algorithm to produce randomly initial data, the initial berth allocation scheme that includes service order of ships, berth position, and number of crane allocation.

Step 2: Let $I = 1$.

Step 3: Based on the information of Individual i, initialize the simulation model and run it. The constraint of the energy consumption module is expressed *via* the simulation module. If the simulated individual satisfies the constraint, all the cost consumed, namely the optimized target, will be computed by running the simulation. Otherwise, the simulation will terminate and feedback a biggish fitness function to the genetic algorithm.

Step 4: If $I < 1$ return to Step 3, else go to the next step.

Step 5: Evaluate scheme with the fitness values of the individual and produce the optimal value in the population.

Step 6: If the designated iteration times is not met, the genetic operation has to be performed again to produce a new solution, and then return to Step 2 to perform simulation optimization till the iteration times is met, and then produce the optimal result and scheme for berth allocation.

5 Example Analysis

The efficiency and reliability of the genetic algorithm are verified with experiments on different values, including lengths of continuous shoreline, numbers of ships to port in a certain time, and numbers of cranes which are not provided infinitely and are generally taken with one percent of the shoreline' length. In the experiment, the algorithm's performance is verified by shorelines with lengths of 400, 600, 800, 1000, 1200 and 1400 m. Each shoreline with the same length will be tested for three times, and an interval of 10 is employed to set the ships' number.

When the shoreline is 400 m long, the cranes' number is set to 4, the ships' number is 5, 15, and 25 for the three-time test respectively. A 600-m shoreline is set with 6 cranes and 8, 18 and 28 ships. A 800 m shoreline is set with 8 cranes and 11, 21 and 31 ships; a 1000 meter shoreline is set with 10 cranes and 13, 23 and 33 ships. A 1200-m shoreline is set with 12 cranes and 17, 27 and 37 ships. A 1400-meter shoreline is set with 14 cranes and 18, 28 and 38 ships. Each group of experiments will be verified for ten times, whose average value will be used to prove the efficiency and practicality of the algorithm. All the ships' load and length are shown in Tab. 2. The ship's load is supposed to be distributed evenly with its length.

Table 2: List of load' distribution with length

Ship's Length (m)	Load (t)	Proportion (%)
155	3500–5000	10.10
155	5000–8000	38.80
200	8000–13000	26.40
272	13000–21000	9.21
282	21000–31000	8.95
300	31000–43000	7.17

Tab. 3 shows the comparison between the result from the genetic algorithm and that from the traditional method when computed with the genetic module in the simulation software.

Table 3: Comparison of results from genetic algorithm and traditional method

Index		Berth deviation (m)		Cost of delay penalty (yuan)		Energy-consumption of cranes (kwh)	
Shoreline (Cranes)	Ships Number	Genetic Algorithm	Traditional Method	Genetic Algorithm	Traditional Method	Genetic Algorithm	Traditional Method
400m(4)	5	0	0	720.4	1608.8	18253.4	19751.6
	15	42	123	13501.4	15354.3	59325.8	61570.2
	25	131	251	18765.1	24355.6	103828.3	121313.6
600m(6)	8	0	0	0	0	36469.8	37153.8
	18	73	200	11500.2	13300.6	83255.5	89378.9
	28	108	300	12200.4	14533.6	122388.3	130331.6
800m(8)	11	273	563.7	6973.2	18683.8	58718.3	61864.3
	21	421.3	890	13506	51235.4	111281.6	122459.1
	31	510	1180	21328	67560	156310.6	180310.7
1000m(10)	14	305	975.3	9245.3	32325.5	69317.8	71384.2
	24	530	1170.5	22650.8	81352.6	120130.3	141301.5
	34	580	1260	23000	81650	160310.6	185667.8
1200m(12)	17	453	1021	21495.2	67166.8	76856.7	80491.1
	27	523	1174.5	52150.6	116325.3	130031.2	141042.5
	37	617	1247	72880	120000.75	200673.3	241226.6
1400(14)	20	0	0	0	0	82281.5	88174.4
	30	130	410	20040.4	22440.4	149380.5	158032.4
	40	315	1340	31380.2	83544.8	213310.2	255207.4

By comparing the berthing deviation, delay punishment, and energy consumption of cranes, we can draw a conclusion that the genetic algorithm is better than the traditional one, which indicates that the algorithm is effective and practical.

6 Conclusion

In order to achieve the goals for carbon peaking and carbon neutrality under the new developmnet philosophy in China, a multi-objective model with the minimum departure delay cost, the minimum berthing deviation cost, and the minimum energy consumption of cranes is established by analyzing the studies of scholars at home and abroad. The genetic algorithm is employed to improve the model, in which, individuals are represented by genome, each subchromosome is encoded with intege, roulette wheel method is used for selection, two point crossing is for crossover and exchange mutation is to ensure the algorithm's high-efficiency and stability. And then the improved genetic algorithm is integrated with simulation. Six shorelines with different lengths and eighteen types of berthing ships are designed to test the algorithm's practicability. The test shows that this model not only reduces the berthing deviation distance, but also saves the ships' operating time, the time in port and the cranes' energy consumption. The model is proved to be effective and, feasible and the berth scheduling will provide reference for the actual operation and management.

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