OPTIMIZATION OF CONTAINER PORT LOGISTICS OPERATION EFFICIENCY BASED ON RESOURCE SCHEDULING

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Abstract - Container port is an important transit station in container multimodal logistics, and its efficiency of cargo handling will directly affect the efficiency of the whole logistics. This paper briefly introduces the container port and the berth-shore bridge allocation model of the container port and proposes to use a genetic algorithm for the allocation model to perform the optimization calculation. The adaptive cross-variance probability was used to improve the traditional genetic algorithm to enhance the optimization capability of the algorithm. An example analysis was carried out with three wharves in Beibu Gulf port, Guangxi. The improved algorithm was also compared with the particle swarm optimization (PSO) algorithm. The results showed that the improved genetic algorithm converged fastest and had a lower adaptive value after stabilization when the allocation model was optimized; the increase in the number of vessels to be served at the wharves increased the optimization time of the algorithm and the total loading and unloading time of the optimized allocation scheme; the improved genetic algorithm was faster in the optimization process of the allocation model, and the obtained allocation scheme had less total loading and unloading time.

Keywords: Container, Port, Resource scheduling, Genetic algorithm.

1. Introduction

The principle of using the container for the transportation of goods [1] is packing, i.e., the goods are loaded together in large-capacity containers, and the containers are loaded and unloaded during transportation [2].

Compared with traditional freight ways, container freight has advantages of being easy to load and unload, suitable for various transport forms, and providing protection for the goods. Containers can be transported by sea, land, and air, and water transport is the least expensive and has the largest capacity for long-distance shipments [3]. When using sea and land transport, the container port is a vital transit station.

The efficiency of container loading and unloading at the transit station will directly affect the overall logistics efficiency, so how to improve the loading and unloading efficiency of the container port becomes an important part of improving the efficiency of multimodal logistics. Chen et al. [4] proposed a port performance assessment framework based on wharf container handling events.

The evaluation results showed that the framework could not only accurately estimate port performance indicators, but also effectively generate port comparison results such as port performance ranking and regional port comparison. Mei et al. [5] proposed a new integer programming model to solve the optimal scheduling problem of container wharf yard cranes from a low carbon perspective. They calculated the container volume in different blocks based on the actual operation data of Shanghai Yangshan deepwater port and solved the model to verify the effectiveness of the proposed method. Jin et al. [6] developed a multi-objective integer programming model with the objective function of minimizing the sum of container reloading, yard crane movement, and container counterweight difference in order to solve the intelligent optimization problem of single-space export container platform loading. Tests showed that the system could quickly solve load optimization problems with complex initial load data, thus demonstrating the applicability and effectiveness of the model.

This paper briefly introduces the container port and the berth-shore bridge allocation model of the container port and proposes using a genetic algorithm for the allocation model to perform the optimization calculation. The adaptive cross-variance probability was used to improve the traditional genetic algorithm to enhance the optimization capability of the algorithm. An example analysis was carried out with three wharves in Beibu Gulf port, Guangxi.

The improved algorithm was compared with the particle swarm optimization (PSO) algorithm.

2. Introduction to Container Ports

Container port is a transit station in the container sea-land multimodal transport mode [7], which mainly provides a centralized berthing point for container shipping vessels, as well as a workplace for the collection and distribution of a large number of containers: containers from the inland are concentrated in the port and loaded onto cargo ships; containers transported by cargo ships are discharged in the port and dispersed to various destinations inland by land transport.

The conventional container port contains berths [8], quay fronts, yards, container freight stations, check bridges, control rooms, and container maintenance workshops. The berth is a docking point for container cargo ships, usually 300 m in length and at least 11 m in water depth. The quay front is the place near the berth where the container bridge crane is configured for the loading and unloading of containers, the specifications of which depend on the specifications of the crane and handling machinery. The yard is the place where containers are stored centrally [9], and the area is divided into front and back yards. The front yard is between the quay front and the back yard, where the storage of containers is temporary. The back yard is the place for long-term container storage. The container freight station is the place where containers are received, shipped, loaded, and distributed, usually near the road or railroad outside the wharf. The check bridge is the entrance and exit of the wharf. The control room is the scheduling center of the entire container port. The container port has the basic functions of cargo storage, distribution, loading, unloading, etc. The characteristics of its production operation include no interruption, benefit paradoxicality, multi-sectoral cooperation, and unbalanced operation.

In terms of definition, container has the following characteristics: ① strong and reusable; ② easy to load and unload as well as handling; ③ easy loading and unloading of goods; ④ able to adapt to a variety of modes of transport; ⑤ large enough volume, at least 1 m3.

3. Optimization Algorithm for Port Logistics Efficiency

3.1 Berth-shore bridge allocation model for container ports

When loading and unloading cargoes in container ports, it is necessary to first allocate berths in the port and then allocate equipment for loading and unloading cargoes to the cargo ships in the berths [10]. The solution to the above allocation problem is the port loading and unloading operation process, which belongs to linear programming, i.e., the linear objective function is made optimal, or as optimal as possible, under the complex linear constraints. In this paper, the optimization of the container port loading and unloading problem aims to improve the loading and unloading efficiency, i.e., to reduce the loading and unloading service time as much as possible under the premise of guaranteeing the loading and unloading service. In order to facilitate the calculation of the optimization algorithm, it is necessary to establish a mathematical model of the berth-bridge allocation of the port first.

In addition, if the mathematical model is completely considered in establishing the mathematical model, there are too many factors affecting targets, not only difficult to count but also increase the amount of calculation. Therefore, in order to make some simplification, the corresponding assumptions will be set for the mathematical model [11]: (1) the arrival time of the cargo ship is known, and the time when the shore bridge corresponding to the berth of the cargo ship starts working later than the arrival time of the cargo ship; (2) the shoreline and the time are divided by a fixed-length; (3) the cargo ship is not allowed to move until the and unloading work is completed at the berth; (4) the port berth is continuous along the shoreline, and the berth can accommodate anyone arriving cargo ship; (5) the loading and unloading efficiency of the shore bridge for the cargo ship is the same; (6) there are maximum and minimum limits on the number of shore bridges for loading and unloading of a single cargo vessel.

Objective function:

$$\min Z = \sum_{i \in V} [\mu(e_i - s_i) + (1-\mu)(s_i - a_i)] \tag{1}$$

Conditional functions:

$$\sum_{i \in V} \sum_{q \in R_i} q \cdot r_{itq} + \sum_{i \in V} w_{it} \le Q \quad \forall t \in T_1 \tag{2}$$

$$\sum_{i \in V} \sum_{q \in R_i} q \cdot r_{i(H-1)q} \le Q \tag{3}$$

$$\sum_{q \in R_i} r_{itq} = r_{it} \quad \forall i \in V, t \in T \tag{4}$$

$$M(1-u_{it}) + \left| \sum_{q \in R_i} q \cdot r_{i(t+1)q} - \sum_{q \in R_i} q \cdot r_{itq} \right| \ge 1 \quad \forall i \in V, t \in T \tag{5}$$

$$M \cdot u_{it} - \left| \sum_{q \in R_i} q \cdot r_{i(t+1)q} - \sum_{q \in R_i} q \cdot r_{itq} \right| \ge 0 \quad \forall i \in V, t \in T \tag{6}$$

$$M(1-u_{it}) + w_{it} \ge \sum_{q \in R_i} q \cdot r_{i(t+1)q} - \sum_{q \in R_i} q \cdot r_{itq} \quad \forall i \in V, t \in T \tag{7}$$

$$-M \cdot u_{it} + w_{it} \le 0 \quad \forall i \in V, t \in T \tag{8}$$

$$\sum_{t \in T} r_{it} = e_i - s_i \quad \forall i \in V \tag{9}$$

$$(1+t) r_{it} \le e_i \quad \forall i \in V, t \in T \tag{10}$$

$$t \cdot r_{it} + H(1 - r_{it}) \geq s_i \quad \forall i \in V, t \in T \tag{11}$$

$$\Delta b_i \geq b_i - b_i^0 \quad \forall i \in V \tag{12}$$

$$\Delta b_i \geq b_i^0 - b_i \quad \forall i \in V \tag{13}$$

$$b_j + M(1 - y_{ij}) \geq b_i + l_i \quad \forall i, j \in V, i \neq j \tag{14}$$

$$s_j + M(1 - z_{ij}) \geq e_i \quad \forall i, j \in V, i \neq j \tag{15}$$

$$y_{ij} + y_{ji} + z_{ij} + z_{ji} \geq 1 \quad \forall i, j \in V, i \neq j \tag{16}$$

The parameter meanings of the relevant symbols of the berth-shore bridge allocation model for the container port described above are shown in Table 1.

Table 1. Relevant parameters of the berth-shore bridge allocation model for container ports

Symbols	Parameters	Symbols	Parameters
V	The set of vessels receiving loading and unloading services in the port	β	Berth deviation factor
Q	Number of shore bridges that can work simultaneously	M	A large positive number
L	Port shoreline length, every 10 m a berth section	b_i	The berth of vessel i
T	The set of time periods in one-hour increments	s_i	Work start time of vessel i
T_1	The subset of T, without the last time period compared to T	e_i	Work end time of vessel i
T'	The set of time periods affected by uncertainties during the loading and unloading work of the shore bridge	r_{it}	1 if there is at least one shore bridge working on vessel i at the time $t \in T$, 0 for the rest
l_i	Length of vessel i, 10 m in one unit	r_{itq}	1 if there is exactly $q \in R_i$ shore bridges working on the vessel i at time $t \in T$, 0 for the rest
b_i^0	Ideal berth for vessel i	Δb_i	The deviation between the ideal and actual berths of vessel i
m_i	Shore bridge demand for vessel i	w_{it}	The number of shore bridges ready to be assigned to vessel i at time $t \in T_1$
$r_i^{\min}$	Minimum number of shore bridges that can serve vessel i at the same time	u_{it}	1 when there is at least one shore bridge ready for distribution to the vessel i at time $t \in T_1$, 0 for the rest
$r_i^{\max}$	Maximum number of shore bridges that can serve vessel i at the same time	y_{ij}	1 if vessel i is moored in front of vessel j, 0 for the rest
R_i	Range of the number of shore bridges available to vessel i	z_{ij}	1 if the end time of vessel i is not later than the starting time of vessel j, 0 for the rest
a_i	Arrival time of vessel i		
μ	Weighting factor		
α	Shore bridge efficiency interference index		

3.2 Optimization of port Logistics Efficiency based on Genetic Algorithm and Improvement of Genetic Algorithm

Genetic algorithms mimic selecting the superior and eliminating the inferior in nature [12]. It first randomly generates chromosomes representing alternative solutions, swaps or mutates the segments in different chromosomes in the iterative process, keeps the superior segments, and removes the inferior ones under the guidance of the adaptation function to achieve the superiority search. However, traditional genetic algorithms still have defects in practical applications, which affect the performance of optimization [13].

In the face of different kinds of optimization problems, the settings of crossover and mutation probabilities are different; therefore, it is usually necessary to set an approximate range by experience and determine the appropriate value by orthogonal experiments.

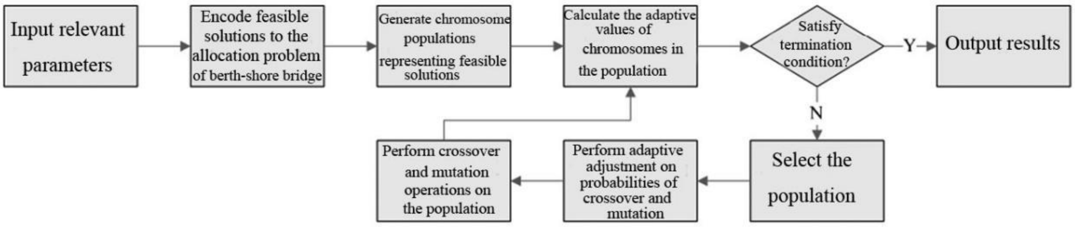

Figure 1: The improved optimization process

To address the defects of the crossover and mutation probabilities in the above traditional genetic algorithm, this paper improved it with adaptive crossover and mutation probabilities, so that the crossover and mutation probabilities in the genetic algorithm can be adjusted autonomously with the iteration of the algorithm to avoid the degradation of the optimization performance caused by too large or too small probability in the late iteration. The optimization process of the improved genetic algorithm for the berth-shore bridge allocation problem is shown in Figure 1.

①First, the relevant parameters are input, referring to Table 1 above.

②Chromosome encoding was performed on feasible solutions to the berth-shore bridge allocation problem. In this paper, the feasible solutions are encoded in the form of non-negative real numbers [14]. The length of the chromosome depends on the number of vessels to be assigned. Here is an example of five vessels to be assigned, and the encoding of one of the feasible solutions is shown in Figure 2. The first row is the arrangement order of vessels, and the number is the vessel number; the second row is the berth of the vessel, and the number is the berth number; the third row is the limit of the number of shore bridges at the berth, and the number is the minimum number of shore bridges required for the corresponding berth to serve the loading and unloading of the corresponding vessel. The arrangement order of the vessel is determined first, and then the number of berths and shore bridges is assigned according to the arrangement order. The first chromosome segment in Figure 2 can be interpreted as "Vessel No. 5 receives the loading and unloading services of at least three bridges at berth No. 4", and the other segments are decoded in the same way.

$$\begin{array}{r} \text{Vessel arrangement} \\ \text{Vessel berth} \\ \text{Shore-bridge limits} \end{array} \begin{bmatrix} 5 & 4 & 1 & 3 & 2 \\ 4 & 8 & 11 & 6 & 7 \\ 3 & 1 & 2 & 2 & 3 \end{bmatrix}$$

Figure 2: Encoding example

③ The population is randomly generated according to the coding form described above. Firstly the vessels are randomly arranged without repeating numbers; then, non-repetitive vessel berths are randomly assigned to each numbered vessel, and a minimum number of shore bridges (r_i) is set randomly for each berth, and this value needs to be within $[r_i^{\min}, r_i^{\max}]$.

④ The adaptive value of each chromosome in the population is calculated, the adaptive value function used in the genetic algorithm is the objective function in the allocation model above. In order to calculate the adaptive value of chromosomes, it can be seen from the objective function of the allocation model that the work start time, work end time, and arrival time of the vessel corresponding to each gene in the chromosome and the corresponding weights are known, while the effective work start time and end time need to be obtained by decoding the chromosomes under the conditional constraints of the allocation model. The decoding rules are as follows. The gene segments of chromosomes are accessed in left-to-right order, and then whether vessel i corresponding to the accessed gene segment can use r_i shore bridges in the time period of $[s_i - 1, e_i - 1)$ is determined. If there is vessel i idling on the assigned berth b_i in the time period of $[s_i, e_i)$, the work start time of vessel i is s_i; otherwise, s_i is pushed back one time unit as the new s_i. Determination of the number of shore bridges used in the time period is repeated until the work start time is confirmed. After decoding, each vessel confirms its own effective start time, and the effective end time is calculated based on the number of shore bridges and work efficiency and substituted into the objective function to calculate the adaptive value of chromosomes [15].

⑤ The chromosomes in the population are selected; the individuals are ranked in descending order of adaptive value, and the top 10% of them are selected as the offspring of this iteration directly. The missing 10% of individuals are randomly generated and participate in the crossover variation with the remaining 90% to the subsequent crossover and mutation. The individuals that are directly used as the offspring and the first 90% of individuals ranked by adaptive value after the crossover and mutation are combined to form the offspring generated by this iteration.

⑥Adaptive adjustment was performed on the probabilities of crossover and mutation before crossover and mutation of the population, this step is an improvement of the traditional genetic algorithm in this paper, and the adaptive probability calculation formula is:

$$\begin{cases} P_c = \begin{cases} P_{c1} - \dfrac{(P_{c1}-P_{c2})(Z'_{\max}-Z'')}{Z_{\max}-Z_{avg}} & Z' \geq Z'_{avg} \\ P_{c1} & Z' < Z'_{avg} \end{cases} \\ P_m = \begin{cases} P_{m1} - \dfrac{(P_{m1}-P_{m2})(Z'_{\max}-Z'')}{Z'_{\max}-Z'_{avg}} & Z' \geq Z'_{avg} \\ P_{m1} & Z' < Z'_{avg} \end{cases} \end{cases} \quad (17)$$

where P_c and P_m are the crossover and mutation probabilities after adaptive adjustment, P_{c1} and P_{c2} are the initial crossover probabilities, P_{m1} and P_{m2} are the initial mutation probabilities, Z' is the adaptive value of an individual, $Z'_{\max}$ is the maximum adaptive value of the current generation of population, Z'' is the greater adaptive value of the individuals in which crossover or mutation occurs, and Z'_{avg} is the average adaptive value of the current generation of population.

⑦ After the adaptive probability is calculated, the crossover and mutation operations are performed on the chromosomes according to the probability. In this paper, sequential crossover is used for the crossover operation of chromosomes to avoid illegal offspring. The mutation operation for chromosomes then uses multi-level mutation. The first row of chromosomes is the sorting of vessels, and the number refers to the number of vessels, which cannot be changed at will, i.e., random mutation cannot be used, so the number is exchanged with the number of other mutated gene loci; the number of berths in the second row and the number of shore bridges in the third row are randomly mutated within their respective limits.

⑧ Steps ④, ⑤, ⑥, and ⑦ are repeated until the termination condition is reached. The termination condition includes reaching the set maximum number of iterations and the convergence of the adaptive value of the population to stability. The iteration can be terminated if either of the two conditions is met.

4. Example Analysis

4.1 Port Introduction

Beibu Gulf port integrated three major ports, Qinzhou bonded port, Beihai port, and Fangcheng port, in February 2007. Relying on policy advantages, location advantages, and hinterland economic characteristics, it gradually developed the layout of three industries, including the heavy chemical industry based on petrochemicals, forest pulp paper, iron and steel, energy, grain, oil and food processing, the high-tech industry based on electronic information, biopharmaceuticals, and marine industry, and the special industry based on port logistics, coastal tourism, and commerce. The port takes the initiative to serve the national strategy, expand port functions, improve port capacity, and is committed to being an international gateway, a trunk port, and a regional international shipping center.

Figure 3: Guangxi Beibu Gulf port

4.2 Experimental Environment

In this study, the improved genetic algorithm was simulated and analyzed by MATLAB software [15]. The experiments were conducted on a laboratory server with Windows 7 operating system, Core I7 CPU, and 16 G memory size.

4.3 Experimental Parameters

The example data used for the simulation experiments came from the data of Guangxi Beibu Gulf port within one week. In this paper, the logistics data of three wharves in two days were selected as the example data. The length of the shoreline of the three wharves was 1500 m, then $L = 150$, i.e., there were 150 berth segments. Fifteen shore bridges in the wharves could work at the time, i.e., $Q = 15$. Wharf 1 served 30 cargo ships in two days, Wharf 2 served 40 cargo ships in two days, and Wharf 3 served 50 cargo ships in two days, of which 50% were small cargo ships, 30% were medium cargo ships, and 20% were large cargo ships. In addition, the relevant parameters required to optimize the logistics using the allocation model include weighting factor ($\mu = 0.5$), interference index to shore bridge work ($\alpha = 0.8$), and berth deviation factor ($\beta = 0.01$). The set of time periods affected by uncertainties in shore bridge loading and unloading operations is $T' = \{0,1,2,\cdots,9\}$.

The relevant parameters required to optimize the allocation model using the genetic algorithm are as follows. The initial size of the population is 50, and the maximum number of iterations is 500. After the orthogonal test, the crossover probability is 0.8, and the mutation probability is 0.1. The crossover and mutation probabilities in the traditional genetic algorithm were improved so that they could be adjusted adaptively according to the adaptive value of the population. The initial size of the population and the maximum number of iterations in the improved algorithm was the same as that in the traditional genetic algorithm. The initial crossover probabilities used for crossover probability adjustment are $P_{c1} = 0.8$ and $P_{c2} = 0.75$, and the initial mutation probabilities used for mutation probability adjustment are $P_{m1} = 0.1$ and $P_{m2} = 0.05$.

In addition to further verify the effectiveness of the improved genetic algorithm, the PSO algorithm, which is an imitation of bird foraging in nature, was used for comparison. Its relevant parameters are as follows: the population size was 50, the maximum number of iterations was 500, the inertia weight was 0.5, and the learning factors were all 2.

4.4 Experimental Results

This study used the PSO, traditional genetic algorithm, and improved genetic algorithm to optimize the berth-shore bridge allocation model for three wharves respectively, and the average adaptive value convergence curves of the three wharves in this process are shown in Figure 4. It was seen from Figure 4 that the adaptive values of the populations converged to stability gradually as the iterations proceeded, regardless of the kind of optimization algorithm. The comparison of the convergence curves between the three optimization algorithms demonstrated that the PSO algorithm converged the slowest and had the largest adaptive value at stabilization, the traditional genetic algorithm converged faster than PSO and had a lower adaptive value at stabilization, and the improved genetic algorithm converged the fastest, converged to stabilization in about 150 iterations, and had the smallest adaptive value at stabilization.

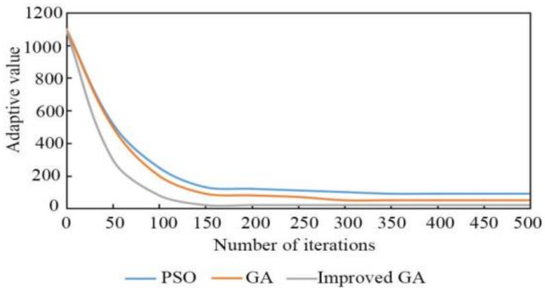

Figure 4: Convergence curves of the three algorithms when optimizing the allocation model

The shore-bridge loading and unloading schemes for the three wharves within two days were optimized by three optimization algorithms, and the total time consumed for the shore-bridge loading and unloading operations at the three terminals after optimization is shown in Figure 5. It was seen from Figure 5 that the total time consumed for the shore-bridge loading and unloading at Wharf 1 was 2145 min under the optimization scheme of the PSO algorithm, 1759 min under the optimization scheme of the genetic algorithm, and 1521 min under the optimization scheme of the improved genetic algorithm; the total time consumed for the loading and unloading at Wharf 2 was 2358 min under the optimization scheme of the PSO algorithm, 1986 min under the optimization scheme of the genetic algorithm, and 1742 min under the optimization scheme of the improved genetic algorithm; the total time consumed for the loading and unloading at Wharf 3 is 2569 min under the optimization scheme of the PSO algorithm, 2159 min under the genetic algorithm, and 1977 min under the optimization scheme of the improved genetic algorithm. The comparison in Figure 5 suggested that the total loading and unloading time of the optimization scheme of the improved genetic algorithm was the least and the total time of the optimization scheme of the PSO algorithm was the most. The horizontal comparison of the total loading and unloading time of different wharves under the scheme of the same algorithm showed that the total loading and unloading time of different wharves increased as the number of cargo ships to be served increased.

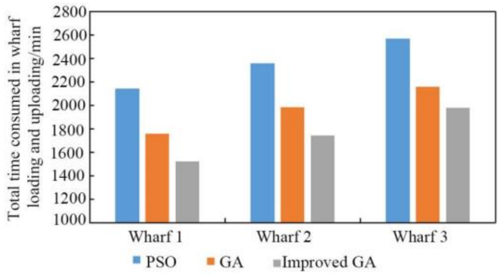

Figure 5: Total loading and unloading time of the three wharves under the allocation schemes of the three algorithms

As shown in Figure 6, the PSO algorithm spent 21 min in optimizing the allocation scheme for Wharf 1, 23 min in optimizing the allocation scheme for Wharf 2, and 25 min in optimizing the allocation scheme for Wharf 3; the traditional genetic algorithm spent 17 min in optimizing the allocation scheme for Wharf 1, 19 min in optimizing the allocation scheme for Wharf 2, and 21 min in optimizing the allocation scheme for Wharf 3; the improved genetic algorithm spent 15 min in optimizing the allocation scheme for Wharf 1, 17 min in optimizing the allocation scheme for Wharf 2, and 19 min in optimizing the allocation scheme for Wharf 3. The improved genetic algorithm took the least time to optimize the scheme regardless of which wharf was being optimized, while the PSO algorithm took the most time to optimize the scheme. The horizontal comparison demonstrated that the optimization time increased regardless of the algorithm as the number of vessels to be optimized increased.

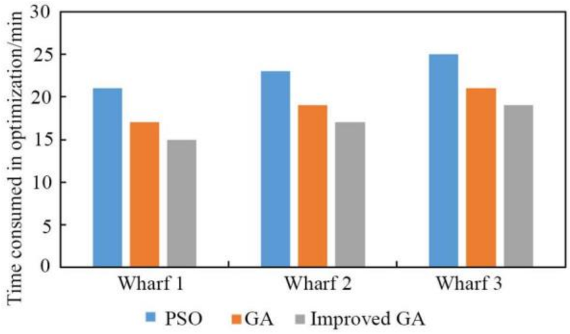

Figure 6: Time of three algorithms spent in optimizing the allocation schemes of three wharves

5. Conclusions

This paper briefly introduces the container port and the berth-shore bridge allocation model of the container port and proposes using a genetic algorithm for the optimization calculation of the allocation model. The traditional genetic algorithm was improved by the adaptive crossover and mutation probabilities in order to improve its optimization capability. Three wharves in Guangxi Beibu Gulf port were used as the subjects for example analysis. The improved genetic algorithm was compared with the PSO algorithm.

The results are as follows. (1) The improved genetic algorithm converged the fastest among the three algorithms in the process of optimization, and the adaptive value was the smallest when it converged to stable. (2) When the number of vessels requiring loading and unloading services increased, the total loading and unloading time of the optimized scheme increased regardless of the optimization algorithm; the total loading and unloading time of the optimized scheme of the improved genetic algorithm was the shortest and that of the PSO algorithm was the longest. (3)

The time spent in the optimization process of the three optimization algorithms increased with the increase of the number of vessels to be served at the wharf, while the improved genetic algorithm took the least time in optimization and the PSO algorithm took the most time.

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