A Discrete Particle Swarm Optimization Algorithm for Archipelago Berth Allocation Problem

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***Abstract*— According to the special circumstances of the archipelago berth allocation, this paper proposes a model of Archipelago Berth Allocation Problem(ABAP), which considers numerous constraints such as the adaptability of berths, the depth of channels and the characteristics of ships. The objective of the problem is to minimize the sum of the handling time, waiting time and the sailing time in the port area of every ship. We introduce a formulation for solving this problem. Next, we present a Discrete Particle Swarm Optimization (DPSO) to find an approximate solution for the problem. Some reasonable parameters of DPSO are determined through several tests. Finally, we set the Zhoushan Islands, China as an example. Computational experiments show that the algorithm is effective, and has achieved great results in terms of stability, convergence and running time.**

***Index Terms*— Berth allocation; Archipelago berth; Discrete Particle Swarm Optimization**

I. INTRODUCTION

The berth allocation problem plays an important role in the port management. A lot of factors should be taken into consideration when solving this problem, such as the adaptability of the berth, the depth of channels and the characteristics of ships, etc. In the practical operation, the berth allocation is mainly dependent on human experience, which means it is lack of scientific management. As a result, the scheduling decisions which are lack of scientific management will affect the working efficiency and service level of the whole berth operation and restrict the long-term development of the port and shipping industry.

This paper studies the archipelago berth allocation problem (ABAP). Compared to the ordinary BAP, ABAP has its own complexity and particularity. The distances between each berth and the ships' sailing time in the archipelago must be taken into consideration when solving ABAP. Take Zhoushan Islands, China, for example, in order to handle a wide variety of cargos such as oil, coal, ore, grain and container, the berths are diverse and scattered. This paper addresses the problem of determining the berthing position and order of each ship in the condition of numerous constraints. Through reasonable arrangements of the berthing position and the order of ships, it can contribute to improve the archipelago berth operation efficiency and service level.

The studies of BAP have become more and more popular. It can be modeled in different ways. Based on the arrival time of the ships, the BAP can be modeled as static or dynamic. Ref.[1] presented an efficient planning of berth allocation for container terminals in Asia from a static point of view. Ref.[2] discussed the problem of dynamic berth allocation in the public berth system. As for the spatial aspects of the berths, the BAP can be divided into discrete and continuous. Ref.[3] described a method based on a GA that can be used to directly solve the continuous BAP for container ports. Ref.[4] reviewed and described three main models of the discrete dynamic berth allocation problem, and compared all models from a computational perspective through extensive numerical tests. The discrete BAP has the advantage of easiness in scheduling but it is not fully efficient in terminal usage, and the continuous BAP exhibits the complete opposite characteristics [5]. Judging from the scope of the study, the BAP can be divided into the simple berth allocation problem, the integrated berth allocation and handling equipment assignment problem. Ref.[6] addressed an effective approach to solve the issue of berth allocation and quay crane assignment. Ref.[7] used a deep integration method to deal with the berth allocation and quay crane assignment problem. Ref.[8] presented an application of the Multi-Objective Evolutionary Algorithm to solve the BAP. Ref.[9] combined genetic algorithm (GA) with heuristic to find a hybrid evolutionary algorithm for the problem of berth and quay crane scheduling. Eduardo, Ref.[10] proposed a hybrid metaheuristic that combines Tabu Search (TS) with path relinking to solve the dynamic berth allocation problem.

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Ref.[11] is discovered through simulation of a simplified social and wide applications in a variety of fields. Ref.[12] proposed equations analogous to the classical PSO equations, then, presented a discrete particle swarm optimization algorithm for the problem of scheduling parallel machines. Ref.[13] proposed an improved version of the PSO approach to solve Traveling Salesman Problems (TSP). Ref.[14] introduced a new hybrid algorithmic nature inspired approach based on PSO for the vehicle routing problem. It is tested on a set of benchmark instances and produced very satisfactory results. Ref.[15] presented a meta-heuristic approach to portfolio optimization problem using PSO technique. The PSO model demonstrated high computational efficiency in constructing optimal risky portfolios. Ref. [16] studied the dynamic routing problems and proposed several effective algorithms. Ref. [17] proposed HPSO which adds particles neighbor information to diversify the particle swarm to enhance the convergence speed. Ref. [18] designed a modified PSO which can enhance the quality and speed of the particle evolution.

In summary, scholars have achieved a lot of useful researches on the BAP. But most of them focus on general port and consider only one type of berth such as container berth. In this paper, we study the archipelago berth allocation problem and consider the situation of multi-type berths. PSO is a very effective swarm intelligence algorithm which can be applied widely, so we present a Discrete Particle Swarm Optimization which combines Genetic Algorithm and PSO to solve the ABAP.

This paper is organized as follows. The next section gives the motivation for introducing an Archipelago Berth Allocation Problem (ABAP) model. In the third section, we present a suitable algorithm to solve the ABAP, the Discrete Particle Swarm Optimization (DPSO), and analyzed in detail. Computational experiments are presented and analyzed in the fourth section and the final section discusses conclusions and future research.

II. Mathematical formulation of Archipelago Berth Allocation Problem

A. Description of the Archipelago Berth Allocation Problem

Archipelago berth allocation problem can be specifically described as follows: in a scheduling period, n ships loaded with different types of cargos entering the archipelago area, they need to compete for m berths to moor and unload. Any ship can anchor at any berths as long as the ship meets certain conditions such as the varieties of cargos, berth depth and channel depth. The same berth can only serve one ship at the same time. The departure of ships is only allowed when the handling tasks are complete. ABAP generally sets the time span of the ships in port as optimization goals; the time span of ships in port consists of sailing time, handling time and waiting time once the ship enters into archipelago area. ABAP is a combinatorial optimization problem with complex constraints.

Compared with general BAP, ABAP has two prominent characteristics: firstly, ABAP has many types of berths, ships loaded with a specific type of cargo must unload on the berth subjected to corresponding type of cargo, and therefore archipelago berth allocation problem must be regarded as a problem with a strong type of cargo constraints. Secondly, in general BAP, berths are relatively centered. Therefore, the sailing time which ships need to arrive at each berth can be ignored. While in ABAP, berths disperse in the archipelago, the distance of each berth which a ship arrives at differs, thus it is necessary to consider the sailing time of ships in the archipelago. In addition, the conditions of berths and channels are more complex in ABAP.

Fig. 1 shows the model of ABAP. Assume that a coal ship arrives at the archipelago at a certain moment, and there is a vacant coal berth to allow the ship to moor and unload. An oil tanker has just finished unload. Another oil tanker waiting for service nearby immediately enters the berth as soon as the former leaves and new arrivals have to wait in the waiting area. Newly-arrived container ships can do nothing but wait because container berths are busy.

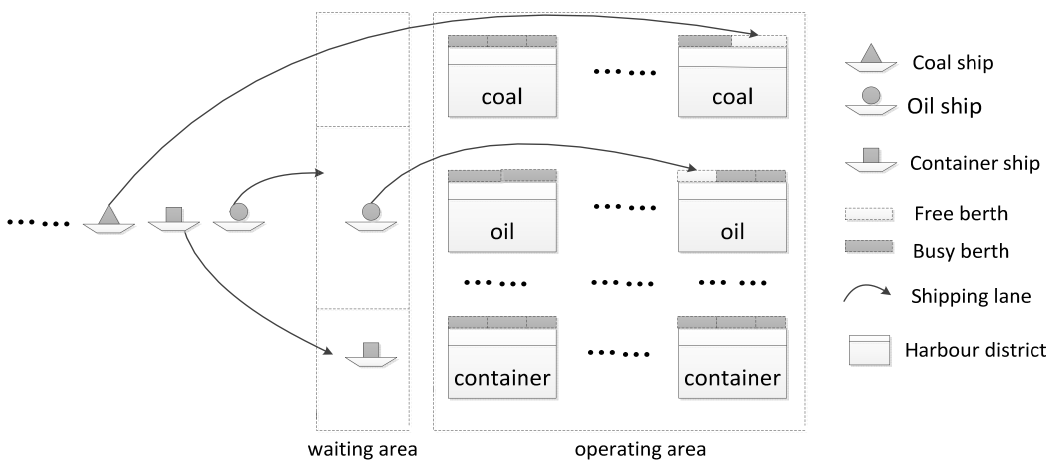

Figure 1. Model of ABAP

B. Design of The Archipelago Berth Allocation Problem Model

The following is assumed for the ABAP:
In a scheduling period, the time of arrival of each ship is available.

（i） The handling time is determined by the quantity of cargos and handling efficiency of berths.
（ii） Berth shifting is disregarded, each ship has to moor exactly once.
（iii） Service order of ships is in accordance with the principle of first come first serve and emergent ship takes priority of service.
（iv） Berths should meet the tonnage requirements of moored ships. Accordingly channels should meet the tonnage requirements of the passing ships.
（v） Every dock has sufficient inventory capacity.
（vi） Some unexpected conditions such as bad weather or equipment failure are not considered.

The notation used in this paper is summarized in the following:

Indices：
$i=(1,2,...,n)\in V$ set of ships;
$j=(1,2,...,m)\in B$ set of berths;
$k=(1,2,...,r)\in K$ set of the type of cargos;
Parameters：
A_i: arriving time of ship i;
L_i: leaving time of ship i;
S_i: sailing time of ship i;
O_i: handling time of ship i;
W_i: waiting time of ship i;
T_i: tonnage of ship i;
C_j: berthing capacity of berth j,
N_j: navigable ability of shipping lane leading to berth j;
D_j: the type of cargos of berth j；
G_i: the type of cargos of ship i；
Decision variables:

$$X_{ij}=\begin{cases}1, & if\ ship\ i\ is\ served\ at\ berth\ j; \\ 0, & otherwise.\end{cases}$$

We now present our model. The objective function is to minimize the total time of all ships spent in port, which is composed of sailing time, handling time and waiting time. The ABAP may be formulated as follows:

Minimize

$$Z=\sum_{i=1}^{n}(L_i-A_i)=\sum_{j=1}^{m}\sum_{i=1}^{n}(S_{ij}+O_{ij}+W_{ij})\cdot X_{ij} \tag{1}$$

Subject to

$$\sum_{j=1}^{m} X_{ij}=1 \ ; \ i\in V \tag{2}$$

$$\sum_{j=1}^{m}\sum_{i=1}^{n} X_{ij}=n \ ; \ i\in V,\ j\in B \tag{3}$$

$$(C_j-T_i)X_{ij}\geq 0 \ ; \ i\in V,\ j\in B \tag{4}$$

$$(N_j-T_i)X_{ij}\geq 0 \ ; \ i\in V,\ j\in B \tag{5}$$

$$if X_{ij}=1,\ D_j=G_i \ ; \ i\in V,\ j\in B \tag{6}$$

$$L_i-A_i\geq 0 \ ; \ i\in V \tag{7}$$

$$0\leq X_{ij}\leq 1 \ ; \ i\in V,\ j\in B \tag{8}$$

$$S_{ij}\geq 0, O_{ij}\geq 0, W_{ij}\geq 0, \ i\in V,\ j\in B \tag{9}$$

Where, the constraint (2) ensures ship i must be serviced at one berth in any order of service. Constraint (3) shows the sum of ships serviced on each berth equals total ships that arrive in port. Constraint (4) enforces if ship i moor at berth j, then the tonnage of ship i cannot surpass the approved berthing capacity of berth j. Constraint (5) indicates the tonnage of ship cannot surpass the navigation capacity. Constraint (6) means if ship i moor at berth j, then the cargo type of ship i should be within the range of cargos varieties that berth j is able to service.

III. Modeling the Discrete Particle Swarm Optimization

According to the characteristics of ABAP, this paper proposes a DPSO which is suitable for solving ABAP on the basis of the basic PSO.

A. Basic Particle Swarm Optimization

The Particle Swarm Optimization (PSO) proposed by American scholars [11] is an emerging swarm intelligence algorithm which is based on social influence and social learning of social psychological mode. A particle swarm optimization maintains a group of certain number of particles, and each particle represents a feasible solution. Particles fly in a multidimensional space, and their position adjustment depends on the experiences of their own and their neighbors'.

The velocity and position of each particle is adjusted by the following formula [16]:

$$x_i(t+1)=x_i(t)+v_i(t+1) \tag{10}$$

$$v_i(t+1)=v_i(t)+c_1r_1(t)[y_i(t)-x_i(t)] + c_2r_2(t)[y_{i}'(t)-x_i(t)] \tag{11}$$

Where i denotes the i-th particle in the swarm, t is the iteration number. $x_i(t)$ is the position vector of the i-th particle. $v_i(t)$ is the velocity vector of the i-th particle, it can be seen as the inertial term of the particle motion. c_1 and c_2 are two constant numbers, which are often called the cognitive confidence coefficients. $y_i(t)$ is the individual best position that particle i has reached, $c_1r_1(t)[y_i(t)-x_i(t)]$ can be seen as the cognitive term, which affects the particles to move toward optimal value in the individual search. $y_{i'}(t)$ is the global best position that all the particles has reached, $c_2r_2(t)[y\,'(t)-x_i(t)]$ can be seen as the social term, which affects the particles to move toward optimal value in the global search.

B. Discrete Particle Swarm Optimization

The basic PSO is easy to operate and implement, but it can not be used directly to solve discrete or combinatorial optimization problems. The nature of the particle swarm optimization is that particles obtain updated information from their individual extreme values and the group, whereas the way for the particles to obtain information from individuals and groups is not unique.

Therefore, based on the speed displacement formula proposed by reference [17], the paper designed a discrete particle swarm optimization suitable for solving ABAP. The algorithm introduces crossover and mutation in the genetic algorithm to search for the optimal solution by crossing the particle with individual extreme value and groups' extreme value, as well as the mutation of the particle itself.

The ABAP belongs to a kind of NP-hard problems, which is difficult to solve through mathematical analysis methods. Currently, relatively effective methods for approximate solution contains heuristic algorithm, Simulated Annealing (SA), Genetic Algorithm (GA), Ant Colony Optimization (ACO), etc. This paper resorts to a DPSO model with advantages of higher speed, better convergence and stronger robustness compared with other existing solving methods on BAP, which is suitable for solving ABAP. Computational experiments prove the effectiveness of the algorithm.

C. Code Design

In the paper, the encoding of the particles uses integers. Each particle represents a scheduling plan. The length of the particles is dependent on the number of ships. The dimension of a particle corresponds to serial number of the ship. Encoding refers to serial number of the berth. The serial number of ships follows the principle of first come first serve and emergent ship takes priority of service. Firstly number each ships according to their arrival order, then transfer the serial number of emergency ships to the top 30% of the all the numbers. In the actual operation, flexible adjustments should also be required to meet certain demands.

Fig. 2 shows an example of a coding scheme including 10 ships and 5 berths. The first dimension represents that ship 1 is mooring at berth 2; the second dimension represents that ship 2 is mooring at berth 4. If there exists several ships moor at one berth, like ship 1, ship 6 and ship 8 are all mooring at berth 2, then according to the rule of encoding order, the ship in previous number receives service first.

dimension	1	2	3	4	5	6	7	8	9	10
code	2	4	1	3	5	2	3	2	1	5

Figure 2. Encoding schematic diagram

In the practical berth allocation process, ships loaded with different cargos can only be moored at specific berths. We take this issue into consideration when encoding, and then come up with a segment encoding method based on constraints of the cargo types. The basic idea is to segment coding according to the types of cargos. Crossover and mutation are also processed segmentally. Particles encoding obeys the following principles: the particles are divided into several segments according to the type of cargos; the code of appropriative berths matches the specific particle dimension, while the code of general berths matches the dimension of all particles. The status update of particles abides by the following principles: a segment of code of particles are selected randomly to conduct crossover and mutation. Different segments can't do crossover or mutation mutually. This encoding cleverly solves the problem of constraint on the type of cargos, therefore it is particularly suitable for solving the model of ABAP.

Fig. 3 shows an example of a coding scheme including 5 iron ore ships, 5 coal ships, 3 iron ore berths and 3 coal berths. Ships 1 to 5 are iron ore ships, ship 6 to ship 10 are coal ships. Berths 1 to 3 are iron ore berths, berth 4 to 6 are coal berths. Given the above assumptions, ship 1 to ship 5 can be moored at berth 1 to berth 3, and ship 6 to ship 10 can be moored at berth 4 to berth 6. Crossover and mutation are operated in 1-5 dimensions or 6-10 dimensions of particles.

dimension	1	2	3	4	5	6	7	8	9	10
code	2	1	3	2	3	4	5	6	5	6

Figure . 3 Segmented encoding schematic diagram

D. Fitness Function

The objective function of ABAP is to minimize the total time of all ships spent in port, which is composed of sailing time, handling time and waiting time. The fitness function can be formulated as follows:

$$\mathrm{F} = \min\ Z = \sum_{\mathrm{i}=1}^{n} \left(L_i - A_i\right)$$

Sailing time $S_i = D_i/V_i$, where D_i is the distance between ship i and berth, V_i is the sailing speed of ship i.

Handling time $O_i = Q_i/E$, where Q_i is the weight of cargos in ship *i*, E is the handling efficiency of berth.

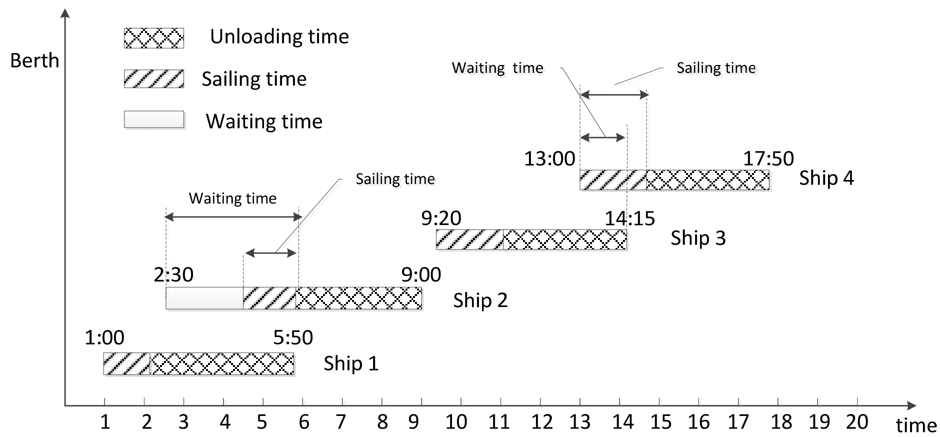

Figure. 4 The time of ships spent in port schematic diagram

Waiting time $W_i=L_j-A_i$ when $A_i<L_j$, otherwise $W_i=0$, where A_i is the arriving time of ship i, L_j is the leaving time of the previous ship j in the same berth.

Leaving time $L_i = \begin{cases} A_i + S_i + O_i\ , & if\ \ S_i \geq W_i; \\ A_i + W_i + O_i\ , & otherwise\ . \end{cases}$

Total time of ship spent in port $T_i=L_i-A_i$. Fig. 4 shows the time of ships spent in port.

Constraint (6) stands for the constraint of type of cargos, which can be solved through segment encoding method in 3.2.1. Constraints (4) and (5) are restrictions on berths and channels to ship tonnage, which can be resolved by the following method: examining whether the solution to particles can meet berth and channel restrictions before updating the particle state. If the restriction is violated, then replace the ineligible particles with random ones until they match the condition. This approach not only solves the constraints on berths and channels, but also increases the diversity of the particles to a certain extent, which can help to prevent the group into a local optimum. Other constraints are on variables themselves (limit of the domain of definition on variables), which can be addressed through the limitation of encoding range.

E. Particle Update Method

Based on the particle update method described by reference [17], this paper presents the particle update formula as follows:

$$X_{\mathrm{i}}^{k+1} = c_2 g(c_1 g(wf(X_i^k), pB_i^k), gB_i^k)\ ,\quad \mathrm{w}, c_1, c_2 \in [0,1] \tag{12}$$

Where X_{i}^{k+1} is the position vector of particle i, w is the inertia coefficient, c_1 is the cognitive coefficient, and c_2 is the social coefficient, pB_i^k is the individual best position that particle i has reached, gB_i^k is the global best position that the group of particles has reached. The formula (12) consists of three parts.

The first part is $wf(X_i^k)$. This part can be seen as the inertial term, which indicates the memories of the particle to the previous state. It can be achieved by the particle mutation in the model of DPSO. w is the probability of mutation.

$$wf(X_i^k) = \begin{cases} f(X_i^k), & \lambda < w; \\ X_i^k, & otherwise. \end{cases} \tag{13}$$

The particle mutation uses the method of exchanging two positions in the interior of the particles. Firstly, generate two positions randomly, and then exchange them.

The second part is $c_1 g(X_{\mathrm{i}}^k, pB_i^k)$. This part can be seen as the cognitive term, which indicates the particle is moving towards the optimal value in the individual search. It can be achieved by the particle crossover in the model of DPSO. c_1 is the probability of crossover.

$$\mathrm{c}_1 g(X_i^k, pB_i^k) = \begin{cases} g(X_i^k, pB_i^k), & \lambda < c_1; \\ X_i^k, & otherwise. \end{cases} \tag{14}$$

The particle crossover uses the method of multi-point crossover. Firstly, generate two positions randomly, and then cross the corresponding position of original particle and optimal particle. Figure 6 shows the procedure of particle crossover.

The third part is $c_1 g(X_{\mathrm{i}}^k, gB_i^k)$. This part can be seen as the social term, which indicates the particle is moving towards the optimal value in the global search. It can be achieved by the particle crossover in the model of DPSO. The method of crossover is similar to the second part. c_2 is the probability of crossover.

$$\mathrm{c}_1 g(X_i^k, gB_i^k) = \begin{cases} g(X_i^k, gB_i^k), & \lambda < c_2; \\ X_i^k, & otherwise. \end{cases} \tag{15}$$

Fig. 5 shows the procedure of the Discrete Particle Swarm Optimization Algorithm for Archipelago Berth Allocation Problem.

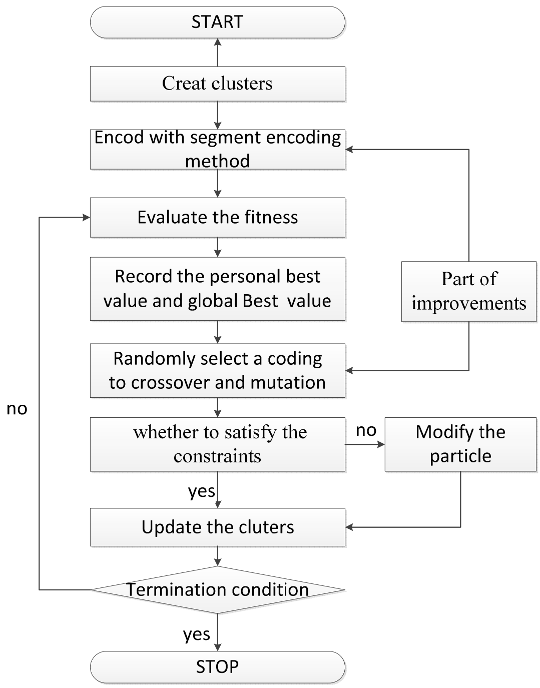

Figure . 5 The procedure of the DPSO

IV. Optimization Results and Analysis

A. Basic Data

Zhoushan Islands is the largest archipelago along the coast of China, they are located in the convergence zone of the north-south shipping channel and the Yangtze golden waterway. Facing the Pacific Ocean, Zhoushan Islands are close to the international routes, and have rich resources of deep-water coastline and superior natural conditions of port construction. All these reveal the prominent location advantage of the Zhoushan Islands.

In this paper, we set the Zhoushan Islands, China, as an example to study the ABAP of various bulk commodities. The data used are collected from actual conditions. The choice of berths follows such principles: the bulk commodities of Zhoushan Islands are basically divided into six categories, so we select six types of berths. Bulk commodity ships are generally in large scale, and therefore we only select large berths. We assume all berths are available and qualified, which are constructed after planning. 30 berths are selected in accordance with the above principles. Part of berth information is shown in Table 1.

TABLE 1.
PART OF BERTH INFORMATION

Berth Number	Type Of Berth	Berthing Capacity (Ton)	Handing Efficiency （Ton/hour）	Harbor District	Sailing Distance (Kilometer)	Remark
1	Oil	250000	12000	Dinghai	43	Existing
2	Oil	50000	4500	Dinghai	43	Existing
3	Oil	80000	6000	Dinghai	43	Existing
……	……	……	……	……	……	……
14	Ordinary Cargos	50000	3000	Laotangshan	58	Existing
15	Ordinary Cargos	200000	8000	Lvhua	128	Existing
16	Coal	50000	3000	Liuheng	12	Existing
……	……	……	……	……	……	……
28	Container	100000	6000	Jintang	55	Planning
29	Container	100000	6000	Jintang	55	Planning
30	Container	100000	6000	Jintang	55	Planning

TABLE 2.
PART OF SHIP INFORMATION

Ship Number	Type Of Cargos	Weight Of Cargos (Ton）	Arrive Time	Route Speed (Kilometer/Hour）	Tonnage (Ton)
1	Oil	50000	2.3	22	50000
2	Oil	150000	6.6	22	200000
3	Oil	180000	8.7	22	200000
……	……	……	……	……	……
50	Coal	40000	5.4	22	50000
51	Coal	50000	6.8	22	50000
52	Coal	120000	9.2	22	150000
……	……	……	……	……	……
98	Container	100000	61.4	22	100000
99	Container	50000	64.5	22	50000
100	Container	80000	68.7	22	100000

The data in the Table 1, such as the berths type, tonnage, operating efficiency, affiliation are actual data. The sailing distances of the ships entering the port are obtained by the following method: as most ships intending to enter the Zhoushan Islands must go pass the large lighthouse at the door of Xiazhi, this paper chooses the point of the lighthouse as the entrance of the archipelago. The sailing distance of each ship entering the area equals the distance from the point of entrance to the point of its berth.

On the choice of ship arrival frequency, according to the records of arrival and cargo throughput, we assume 100 ships arrive within 72 hours. The sailing speed of the ships accords with short distance speed of general cargo ships. Part of the arriving ships is shown in Table 2.

B. Parameter Setting

The main parameters of DPSO are as follows:

w: Inertia coefficient, the probability of mutation.

c_1: Cognitive coefficient, the probability of crossover.

c_2: Social coefficient, the probability of crossover.

P: Population size of particle.

N_{max}: Maximum number of generations.

c_1, c_2, P and N_{max} are determined by test. w is determined by the linear decreasing method, which is calculated as follows:

$$w = w_{\min} + (w_{\max} - w_{\min})(N_{\max} - N)/N_{\max}$$

Here, $w_{\max} = 0.9$, $w_{\min} = 0.6$.

Fig.6 shows the performance under population size of 40, crossover rate of 1, 2000 generations. We can learn from the curves that the values of objective function are not improved obviously after 1000 generations. So 1000 generations will be sufficient to acquire a near-optimal solution.

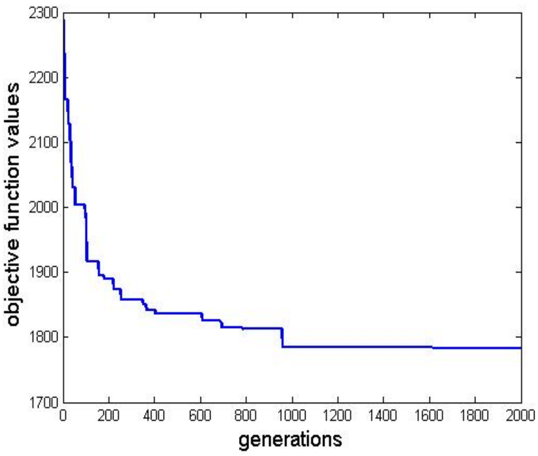

Figure 6. the performance of calculation

Table 3 shows how the different values of crossover rate affect the objective function with P= 40 and N_{max} = 1000. According to the optimal value, the one of c_1=c_2=1 outperforms the others.

TABLE 3.
PERFORMANCE COMPARISON OF DIFFERENT CROSSOVER RATE

Crossover rate	The number of optimal value		The average running time (s)
	1750-1800	1800-1850	
0.8	3	7	191.3
0.9	5	5	189.6
1	9	1	190.4

Table 4 shows how the different values of population size affect the objective function with c_1=c_2=1 and N_{max} = 1000. The optimal value with the population size of 40 is much better than the population size of 20 and 30. Moreover, the optimal values are close to each other with population size of 40, 50, and 60, so the population size is set to 40.

TABLE 4.
PERFORMANCE COMPARISON OF DIFFERENT POPULATION SIZES

Population sizes	The optimal value	The average running time (s)
20	1832.7	97.7
30	1859.3	144.5
40	1.7682	190.3
50	1.7974	233.5
60	1.7668	280.4

To sum up, P = 40, c_1=c_2=1 and N_{max} = 1000 are adopted.

C. Results and Analysis

Under the hardware environment of Intel(R)Core(TM) i3/3.07GHz/4.00GB and the software environment of Windows 7 operating system, the algorithm runs 20 times independently on MatlabR2012a, the results are given in Table 5.

From Table 5 we can see that all the optimal values are in the range of 1760-1800 in 20 running times. Moreover, when the scale of the example reaches 100 ships and 30 berths, all the running times are in the range of 221-230 seconds. It shows that the operation of algorithm is more stable, reliable and efficient.

We select the optimal scheduling program in history for further analysis. In ABAP, the total time each ship spent in port is determined by sailing time, handling time and waiting time once entering into the port, in which the waiting time is an important indicator to measure the level of port services. By computation, we come to the total time in port and the total wait time of the various types of ships, as shown in Table 6.

From Table 6, we can know that for ships serviced in Zhoushan Islands, the total waiting time takes up 18.93% of the total time spent in port. Overall, berths resources are generally scarce. As for coal ships, the proportion of waiting time to total time in port accounts for more than 20%, while the corresponding proportion of chemical material ships is only 0.40%. This result illustrates a wide gap of the utilization between various types of

TABLE 5.
OPERATION RESULTS

Number	The optimal value	Running time (s)	Number	The optimal value	Running time(s)
1	1766	223	11	1797	226
2	1772	227	12	1769	228
3	1777	225	13	1770	225
4	1782	224	14	1784	223
5	1793	223	15	1787	224
6	1798	226	16	1790	222
7	1759	225	17	1777	227
8	1765	227	18	1783	225
9	1777	223	19	1787	226
10	1783	224	20	1790	223

TABLE 6.
THE TOTAL TIME IN PORT AND WAITING TIME OF EACH TYPE OF SHIP

Type of ship	Total time in port	Total waiting time	Proportion of waiting time
Oil	283.2725	56.015	19.77%
Chemical Materials	60.7272	0.2424	0.40%
Iron Ore	196.2545	34.2696	17.46%
Ordinary Cargos	255.7697	48.3152	18.89%
Coal	574.8378	132.6255	23.07%
Container	396.3335	62.9999	15.90%
Total/Mean	1767.195	334.4676	18.93%

berths. The scarcest one is coal berth, which indicates efforts should be taken to increase the construction of such berths. Berth for chemical raw materials is relatively more adequate, its utilization can be increased through transferring so its functions can be broadened. In the future berth construction process, we should take both the demand and the balance of berth resources into consideration.

V. CONCLUSIONS

In this paper, we present a discrete particle swarm optimization (DPSO) that can be used to solve the Archipelago Berth Allocation Problem directly. The method was initially applied to Zhoushan Islands berth allocation. On model design in ABAP, we consider the geospatial distribution of each port and sailing time of ships in the port, and propose an algorithm to calculate the time span of ships in port. As for the design of DPSO, a coding scheme of segments and state update strategy of the particles is raised under the condition of many types of berths to better solve the problem with a strong type of cargo constraints. In empirical research, we collect and analyze the relevant information of the Zhoushan Islands, then establish a database of ABAP in Zhoushan Islands. Through an archipelago berth allocation experiment of 100 ships and 30 berths, it turns out that the algorithm is effective, and has achieved great results in terms of stability, convergence and running time. Finally, the utilization of various types of berths is calculated based on the analysis of the experimental results. Advice for improvement is put forward, which has some reference value for the actual work.

This DPSO model designed in the paper not only can be used to solve ABAP, but also can be used to solve the workshop scheduling and vehicle routing optimization problems. In the future research, the model is desired to be extended to other areas. In this paper, the research focus on the static ABAP model, the further study can be extended to the dynamic ABAP model. At the same time, DPSO can combine with other intelligent algorithms to improve the performance of the algorithm. As a result, the research and improvement of dynamic ABAP model is one of the directions of further research.

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REFERENCES

[1] Imai, A., Nagaiwa, K. and Chan, W. T. "Efficient planning of berth allocation for container terminals in Asia", Journal of Advanced Transportation, 1997, 31(1), pp.75-94.

[2] Imai, A., E. Nishimura and S. Papadimitriou. "The dynamic berth allocation problem for a container port." Transportation Research Part B: Methodological, 2001, 35(4), pp. 401-417.

[3] Ganji, S., A. Babazadeh and N. Arabshahi. "Analysis of the continuous berth allocation problem in container ports using a genetic algorithm." Journal of Marine Science and Technology, 2010, 15(4), pp. 408-416.

[4] Buhrkal, K., et al. "Models for the discrete berth allocation problem: A computational comparison." Transportation Research Part E, 2011, 47(4), pp. 461-473.

[5] Imai, A., Sun, X., Nishimura, E. and Papadimitriou, S. "Berth allocation in a container port: using a continuous location space approach." Transportation Research Part B: Methodological, 2005, 39(3), pp. 199-221.

[6] Birger, R., Wout, D. and Rowan V. S. "An enriched model for the integrated berth allocation and quay crane assignment problem," Expert Systems with Applications, 2011, 38(11), pp.14136-14147.

[7] Du, Y. Q., Chen, Q. S. and Ji, X. T. "Service-oriented berth allocation and quay crane assignment", Computer Integrated Manufacturing Systems, 2011, 17(9), pp. 2051-2060.

[8] Cheong, C. Y., Tan, K. C., Liu, D. K., and Lin, C. J. "Multi-objective and prioritized berth allocation in container ports", Annals of Operations Research, 2010, Vol.180, No.1, pp. 63-103.

[9] Liang, C., Huang Y., and Yang Y. "A quay crane dynamic scheduling problem by hybrid evolutionary algorithm for berth allocation planning", Computers and Industrial Engineering, 2009, Vol.56, No.3, pp.1021-1028.

[10] Eduardo, L., Belen, M. and Marcos M. J. "Artificial intelligence hybrid heuristic based on tabu search for the dynamic berth allocation problem", Engineering Applications of Artificial Intelligence, 2012, Vol.25, No.6, pp.1132-1141.

[11] Kennedy, J., Eberhart, R. "Particle swarm optimization", Proceedings of IEEE International Conference on Neural Networks, 1995, pp.1942-1948.

[12] Kashan, A. H., Karimi, B. "A discrete particle swarm optimization algorithm for scheduling parallel machines",

Computers & Industrial Engineering, 2009, Vol.56, No.1, pp.216-223.
[13] Liao, Y. F., Yau, D. H. and Chen, C. L. "Evolutionary algorithm to traveling salesman problems", Computers and Mathematics with Applications, 2012, Vol.65, No.5, pp.788-797.
[14] Marinakis, Y., Marinaki, M. and Dounias G. "A hybrid particle swarm optimization algorithm for the vehicle routing problem", Engineering Applications of Artificial Intelligence, 2012, Vol.23, No.4, pp. 463-472.
[15] Wang, J.,Wu, Z.,Wang, H. "A novel particle swarm algorithm for solving parameter identification problems on graphics hardware", International Journal of Computational Science and Engineering, 2011, Vol.6, No.1-2, pp.43-51.
[16] Li, J., Fu P.H. "Label correcting algorithm for dynamic tourist trip planning," Journal of Software, 2012, Vol.7, No.12, pp. 2899-2905.
[17] Zou, S. L., Li, J. and Li, X. Q. "A hybrid particle swarm optimization algorithm for multi-objective pickup and delivery problem with time windows," Journal of Computers, 2013, Vol.8, No.10, pp. 2583-2589.
[18] Yang, J. J., Li, J., Chen, Y. and Liu, X.T., et al. "Multi-Objective Distribution Model and Algorithm for Online Shopping Express Logistics," Journal of Computers, 2013, Vol.8, No.10, pp. 2558-2564.
[19] Andries, P. E. "Fundamentals of Computational Swarm Intelligence", 2006, Wiley, pp.65-68.
[20] Pan Quan-ke, Wang Wen-hong and Zhu Jian-yin. "Hybrid heuristics based on particle swarm optimization and variable neighborhood search for Job Shop scheduling", Computer Integrated Manufacturing Systems, 2007, 13(2), pp.323-328

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