Simulation-based Optimization on Quay Crane Scheduling of Container Terminals

Li Haoyuan, Sun Qi

Dalian Neusoft University of Information, Dalian 116023, China
E-mail: lihaoyuan@neusoft.edu.cn

Abstract: By applying the object-oriented simulation modeling method of discrete event system, this paper establishes an simulating model of container terminal operating system, including vessels, anchorages, berths, gantry cranes, internal and external container trucks and gate system. In order to solve the quay crane scheduling problem of container terminal, a lot of stochastic factors in the problem are taken into account. Simulation-based optimization (SBO) method is proposed to solve the problem. Genetic algorithm, particle swarm algorithm and simulated annealing algorithm are used respectively as the superior optimizer, and their application performance is compared and analyzed.

Key Words: Simulation-Based Optimization; Container Terminal; Quay Crane Scheduling

1 INTRODUCTION

In the container terminal operating system, quay crane is not only the most expensive and importantly handling machinery, but also a major bottleneck restricting the working efficiency of the entire marina. All container terminals hope quay cranes can conduct operations at best efficiency. Container managers pay more and more attentions to improve operational efficiency by optimizing quay crane scheduling.

For quay crane scheduling, Daganzo[1] divided ship handling tasks into several lifting area and established a mixed integer programming model to solve quay crane scheduling. By this method, the number of quay crane assigned to each lifting area is determined, with the objective of optimizing the shortest total delay time for all ships. Kim[2] established a single-ship quay crane scheduling model, using branch and bound method and greedy random search algorithm as the solution methods. Lee[3] established a quay crane scheduling integer programming model and used genetic algorithms as the solution method. Wang Huiqiu[4] considered the factor of non-crossing and safe distance, and established a mixed integer programming model of the quay crane scheduling, and solved the problem by genetic algorithm. Tan Shengqiang[5] established a multi-objective integer programming model based on ship service priority. Legato[6] considered the factors such as the average operating rate, the preparation time, the delivery time, the safety requirements and so on. Chung[7] established a model considering the task priority and non-interference factors, and used an improved genetic algorithm to solve.

These studies are based on the traditional analytic-based modeling method to solve the quay crane scheduling problem, mainly for the deterministic environment. However, many uncertainty factors (such as the operational efficiency of the quay crane, the operation of the external card in the yard) make the deterministic model cannot reflect the real system and affect the accuracy of the final decision-making scheme. In this paper, the influence of random factors of quayside operation is fully considered, and the quay crane scheduling problem is studied by simulation-based optimization method. Genetic algorithm, particle swarm algorithm and simulated annealing algorithm are used respectively as the superior optimizer, and their application performance is compared and analyzed.

2 SIMULATION MODEL

2.1 Container terminal layout

Container terminal operating system simulation model is established in this paper based on the actual layout of a domestic container ports, as shown in Fig.1. Quay consists of four berths, each berth assigned several quay cranes, each quay crane is equipped with 10 internal container trucks; The yard consists of 36 operating areas, each area can accommodate 50 × 6 × 4 standard containers, each area is equipped with one gantry crane to complete the internal and

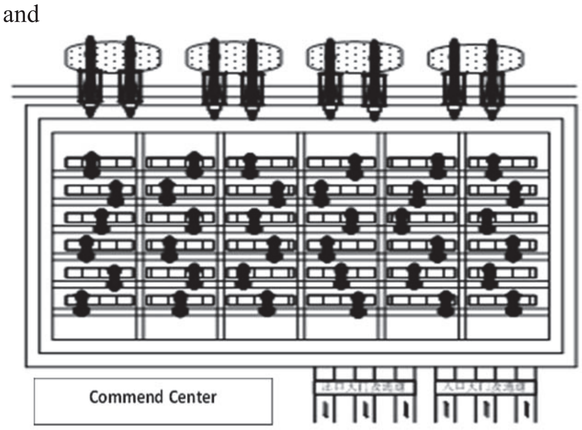

Fig.1 Layout of container terminal

external container truck loading and unloading operations, The gate of the yard is composed of 3 entrance channels and 3 exit channels. It is responsible for the procedures of handling external container trucks and the allocation of operating areas.

2.2 Quay Crane Scheduling Problem Description

When a container ship enters a berth, the ship will be allocated a certain number of quay cranes for loading and unloading operations. Figure 2 is a schematic diagram of quay crane scheduling. As shown in Figure 2, the ship is divided into several ship areas. The goal of dispatching is to assign the task vessel area for each quay crane and the sequence of operations in different areas. So that container ships can be completed as quickly as possible.

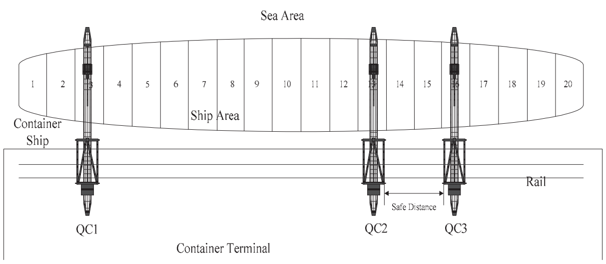

Fig. 2 A schematic diagram of quay crane scheduling

In the actual operation of the quay crane, some physical constraints must be taken into account.

Firstly, at any time during the operation, one ship area can be assigned to only one quay crane until it completes all operations in the area.

Secondly, quay cranes run on the same rail, so the quay cranes can not cross each other. This is also the most important constraint on the quay crane scheduling problem..

Thirdly, for safety reasons, any two quay cranes must maintain a certain distance to ensure the safety of the operation. in this chapter, it is assumed that the safety distance between the two quay cranes is more than two ship areas.

2.3 Simulation Parameters Setting

In this simulation model, considering only a single container ship unloading operation, and the container ship is divided into 20 areas, the unloading task of each area is (80,168,180,66,200,180,220,60,50,140,46,210,20,90,160, 110,250,50,200,160), unit: TEU. After the arrival of the ship, the allocation of three quay cranes involved in the operation. Each quay crane is equipped with 10 internal container trucks for horizontal transport. The travel time of the quay crane from one ship area to another is 60 seconds.The simulation time is set as the whole process of unloading the container ship. The simulation model simulates the operation of the quay cranes, the operation of the gantry cranes, the horizontal transport operations of the internal container trucks, and also includes the operation of the external container trucks in the yard. Among them, take full account of the operating efficiency of the gantry crane and gantry crane, the impact of external container trucks and other random factors. Each stochastic parameters are set as follows:

(1) The arrival time interval of external container truck is exponentially distributed, parameter $\lambda = 0.45$.

(2) Quay crane handling efficiency is normally distributed $N(34.6, 2.69)$.

(3) Yard gantry crane operating efficiency is normally distributed $N(60.2, 69)$.

(4) Processing time of external container truck at the gate, empty vehicles is normally distributed $N(40.43, 2.69)$, load vehicle is normally distributed $N(61.28, 2.69)$.

3 SIMULATION-BASED ALGORITHM

3.1 The algorithm principle

The principle of simulation-based genetic algorithm is as shown in Fig.3. At first, the simulating model of the real system needs to be built. By optimization algorithm, the initial parameters of the system performance are produced. Put the initial parameters into the system model, take the output as evaluation index and bring them back to optimization algorithm. Then the better performance parameters could be got by evolution searching. Put them as new input back to the system model, get the output, reevaluate and optimize again until the results meet the stopping criterion. In this way, the final system optimized parameter could be got.

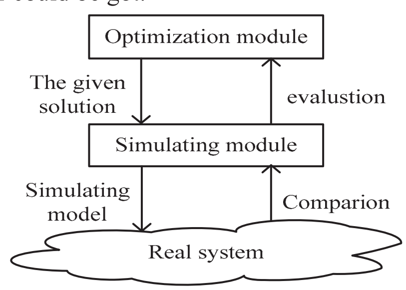

Fig.3 Principle of SBO algorithm

3.2 Genetic Algorithms Design

(1)Coding scheme

In the past, the sequence of operation of the quayside bridge has been used as the coding method. Previous studies has used the sequence of quay crane operation as the coding method. In this paper, the sequence of ship areas operation is used as the coding method. As shown in Figure 4, the gene in the chromosome represents the ship area number, and when the sequence of area operation is determined, the

Chromosome	11	18	20	15	5	13	2	10	3	4	17	14	7	9	1	6	12	16	19	8
Operating Sequence	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20

Fig. 4 Chromosome coding

sequence of the quay crane operation is determined accordingly.

Considering that the simulation-based optimization method is to run the simulation model rather than the mathematical model to obtain the evaluation value of the solution, the use of this encoding can take full advantage of the logic of the simulation program. In the simulation process, with the operation of the simulation program, the operating sequence of the quay crane is gradually acquired. The generation of the operation sequence of quay crane and the running process of the simulation program are realized perfectly. And this encoding method can meet the requirements of the non-crossing constraint and the safe distance constraint.

(2) The objective function

Select the container ship loading and unloading time span as the objective function value, as shown in Equation (1).

$$Fitness = \max_{b} F_b \tag{1}$$

(3) The genetic operator

Because this paper uses a sequence coding, the use of traditional single point cross or Double-cut point cross method will produce legal codes. In order to repair the infeasible codes, meanwhile, in order to better preserve the adjacent relationship between chromosomal genes, the sequential crossover method is chosen as the crossover operator.

The mutation is to select the number of genes in the population according to the mutation probability, and the mutation operator can make the population jump out of the bureau. In order to solve this problem, two genes in chromosome were randomly selected according to the probability, and the ship area number of the two genes were exchanged.

3.3 Particle swarm optimization (PSO) design

(1) Coding scheme

Similarly, the operation sequence of ship area is taken as the expression of particles, in sequential coding. The operation sequence of quay crane is same to 3.2(1).

(2) Objective function

Similar with 3.2(2), taking the time span of the container ship loading and unloading operation as the value of objective function.

(3) Velocity update equation

the location of particle i : $x_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$

the velocity of particle i : $v_i = (v_{i1}, v_{i2}, \cdots, V_{iD})$

the best point of particle i : $p_i = (p_{i1}, p_{i2}, \cdots, p_{iD})$

the best points of all particles in the group: $p_g = (p_{g1}, p_{g2}, \cdots, p_{gD})$

The velocity of the particle is initialized with $V_{\max}$, $V_{\max}$ equals 20.

The particle velocity is updated according to the following equation:

$$v_{iD}^{k+1} = v_{iD}^{k} + c_1 \xi (p_{iD}^{k} - x_{iD}^{k}) + c_2 \eta (p_{gD}^{k} - x_{iD}^{k}) \tag{2}$$

learning factors c_1 and c_2 both equal 2.

(4) Location updating

The velocity is set to the probability that the particle changes, and if the velocity is large, the particle changes to a new permutation sequence with greater probability. Here the velocity to be mapped to [0,1]. The position update process of the particles is described as follows: the particle velocity normalization is first performed. Suppose the range of particle bit value is n, and the velocity of particle is v_i^{k+1}, then

$$S(v_{id}^{k+1}) = \frac{\left|v_{id}^{k+1}\right|}{n} \tag{3}$$

Obviously, the range of $S(v_{id}^{k+1})$ is between 0 and 1. It determines whether the coding of particle i produces a swap. Once generating an exchange in this probability, the position d of particle i changes into the corresponding bit value of the best solutions for the group, as shown in Fig. 5

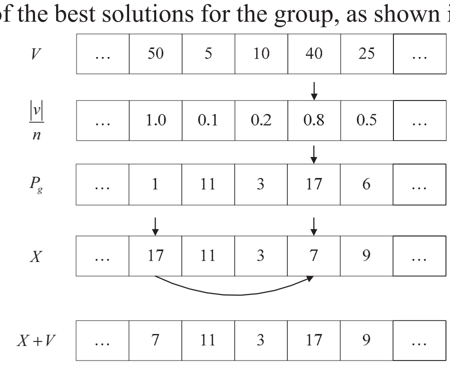

Fig.5 Schematic diagram for particle update

(5) Mutation operator

Since the particles converge at the same probability as the optimal solution of the population, if the particles are exactly the same as the population, they will not change. In order to avoid this, a mutation operator is introduced. When the particle and the population optimal solution are the same, two positions in the code are selected at random and the bit value is exchanged.

3.4 Simulated annealing (SA) algorithm design

(1) Coding scheme

Similarly, taking the operation sequence of container ship area as the expression of particles, in sequential coding. The operation sequence of quay crane is same to 3.2(1).

(2) Objective function

Similar with 3.2(2), taking the time span of the container ship loading and unloading operation as the value of objective function.

(3) Neighborhood definition

In accordance to the expression of the sequence coding used in this chapter, the neighborhood is defined as the set of the pairwise change of the operation sequence in the ship area. For example: from a current state [1, 2, 3, 4, ...], exchanging the operation sequence of two ship areas (exchanging 1 and 4), then get a new state [4, 2, 3, 1, ...]. This completes a neighborhood move.

(4) Temperature parameter setting

Set the initial temperature $T_0 = 10000$, the terminating temperature $T_f = 0$.

Annealing function $T_{k+1} = T_k - \Delta T$, $\Delta T = 100$.

Achieve thermal equilibrium by setting the inner-loop iteration $n(T_K)$, here set $n(T_K) = 50$.

4 EXPERIMENTAL ANALYSIS

4.1 Experimental result

(1) Simulation-based generic algorithms (GA) algorithm

Considering the influence of a series of random factors in the simulation model, the evaluation value of the same chromosome derived by running a simulation program will be different, and therefore, in the experiment, each chromosome runs five times simulation averagely, and the average of the five-time outputs is the evaluation value of the chromosome. Population size is 50, maximum iteration is 100, crossover probability is 0.9, and mutation probability is 0.1.

Through the simulation-based GA computation, the optimal ship area operation sequence is:

[9，12，15，8，19，4，18，1，6，2，14，20，3，11，13，7，17，5，10，16]

The total time range of container ship unloading operation is 65228s (18.12h) in this sequence, and the calculating time of the algorithm is 6762s (1.88h).

(2) Simulation-based particle swarm optimization (PSO) algorithm

Similarly, considering the random factors in the experiment, each chromosome runs five times simulation averagely, and the average of the five-time outputs is the evaluation value of the chromosome. Particle population size is 30, and maximum iteration is 100.

Through the simulation-based PSO computation, the optimal ship area operation sequence is

[18，2，6，15，3，9，17，8，11，14，1，13，4，19，16，7，12，20，5，10]

The total time range of container ship unloading operation is 61098s (16.97h) in this sequence, and the calculating time of the algorithm is 5275s (1.47h).

(3) Simulation-based simulated annealing (SA) algorithm

Similarly, considering the random factors in the experiment, each chromosome runs five times simulation averagely, and the average of the five-time outputs is the evaluation value of the chromosome. Initial temperature is 10000, and terminating temperature is 0. Each outer-loop iteration anneals 100, and the inner-loop time is 30.

Through the simulation-based SA computation, the optimal ship area operation sequence is

[19，15，4，6，14，18，13，20，5，10，17，9，2，1，8，16，11，3，7，12]

The total time range of container ship unloading operation is 62595s (17.39h) in this sequence, and the calculating time of the algorithm is 6075s (1.69h).

4.2 Performance comparison analysis

The main computational cost of the simulation-based optimization algorithm is spent on the evaluation of each solution. For the sake of fairness, from the parameter setting, it is guaranteed that the three simulation-based algorithms are equal in the number of times the simulation model is run.

(1) Experiment 1

GA: population size is 10, and the maximum iteration is 100.

PSO: particle population size is 10, and the iteration is 100

SA: initial temperature is 10000, terminating temperature is 0, annealing process $T_{k+1} = T_k - 100$, and the inner-loop time is 10.

The convergence of three algorithms is shown in Fig. 6.

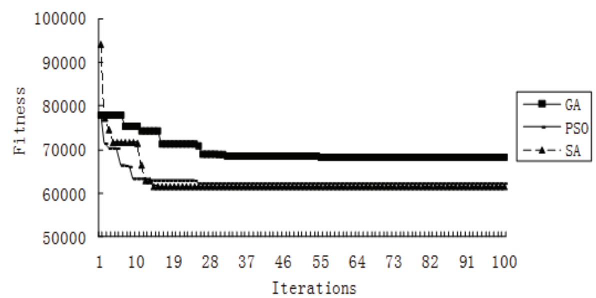

Fig. 6 the performance comparison of GA, PSO and SA in experiment 1

As it can be seen from Fig. 6, since the population size is small, GA has the worst performance, while SA and PSO have better optimization performance. This is because SA can accept poorer non-optimal solution at the beginning with a relatively high temperature. This feature enables SA to avoid the local optimum in a certain extent, with stronger local search capabilities and "climbing" capabilities. In the PSO algorithm, the particles have "memories": under one-way flow of information, the best solution from the history and current best solution together give information to other particles, the entire search process is to follow the optimal update process. Compared with GA algorithm, all the particles may be faster to converge to the optimal solution. The genetic algorithm can share the information with each other through the chromosomes, so the whole population moves more evenly to the optimal region. However, when the population size is small, it is easy to fall into the local optimum, and the convergence speed is slower compared with the other two algorithms.

(2) Experiment 2

GA: population size is 30, and the maximum iteration is 100.

PSO: particle population size is 30, and the iteration is 100

SA: initial temperature is 10000, terminating temperature is 0, annealing process $T_{k+1} = T_k - 100$, and the inner-loop time is 30.

The convergence of three algorithms is shown in Fig. 7.

As it can be seen from Fig. 7, the optimization performance of GA algorithm improves with the increase of population size, yet still poorer than the performance of SA and PSO algorithm.

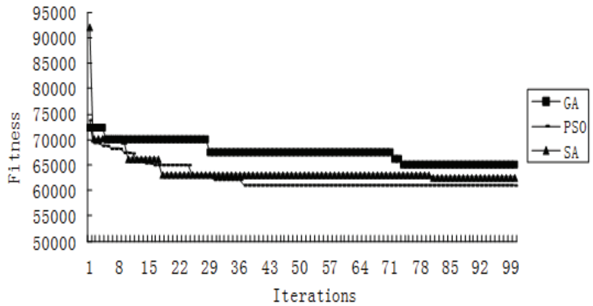

Fig. 7 the performance comparison of GA, PSO and SA in experiment 2

(3) Experiment 3

GA: population size is 50, and the maximum iteration is 100.

PSO: particle population size is 50, and the iteration is 100

SA: initial temperature is 10000, terminating temperature is 0, annealing process $T_{k+1} = T_k - 100$, and the inner-loop time is 50.

The convergence of three algorithms is shown in Fig. 8.

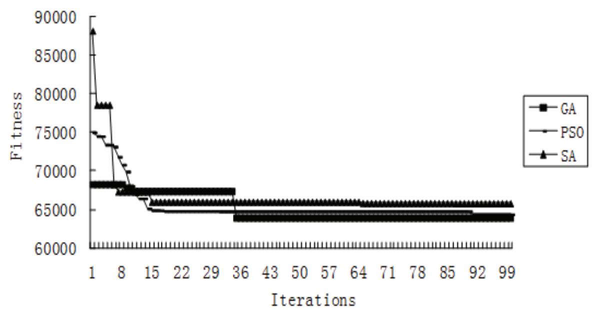

Fig. 8 the performance comparison of GA, PSO and SA in experiment 3

As it can be seen from Fig. 8, the optimization performance of GA algorithm is get fully enhanced. The strong global search ability of GA algorithm is fully reflected from the most outstanding performance in the three algorithms.

In summary, through the comparison of three algorithms in the performance of optimization, GA algorithm, due to its strong global search capability, can reach a better solution in the case of the larger population, but at the expense of long computation time. SA algorithm and PSO algorithm is more suitable for smaller population groups, giving full play to the features of strong local search ability, and quick convergence.

5 CONCLUSION

This paper solves the quay crane scheduling problem of container terminals by the simulation-based optimization (SBO) method. The method, fully considering the interference of random factors, applies GA algorithm, PSO algorithm and SA algorithm respectively as its superior optimizer, and compares the application performance of the three algorithms in simulation-based Evolutionary computation. Experimental results show that this method can obtain better solution to the container terminal quay crane scheduling problem, meanwhile provide effective analysis on the application performance of different algorithms.

EFERENCES

[1] C. F. Daganzo, The crane scheduling problem, Transportation Research Part B, Vol.23, No.3, 159-175, 1989.

[2] K. H. Kim, A crane scheduling method for port container terminals, European Journal of Operational Research, Vol.156, No. 3, 752-768,2004.

[3] D. H. Lee, Quay crane scheduling with non-interference constraints in port container terminals, Transportation Research Part E, Vol.44, No.1, 124-135, 2008.

[4] H. Q. Wang, Quay crane scheduling in port container terminals: mathematical model and solution algorithm, Beijing, Tsinghua University, 2006.

[5] S. Q. Tan, Study of multi-objective consecutive berth integrated scheduling of quay based on hybrid algorithm, Journal of Ningxia University, Vol.36, No.2, 131-139, 2015.

[6] P. Legato, Modeling and solving rich quay crane scheduling problems, Computers & Operations Research, Vol.39, No.9, 2063-2078, 2012.

[7] S. H. Chung, A modified genetic algorithm for quay crane scheduling operations, Expert Systems with Applications, Vol.39, No.4, 4213-4221, 2012.