Research on Yard Cranes Scheduling under Uncertainty Based on Improved Simulated Annealing Algorithm

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Abstract

Aiming at the problem of multi-yard cranes scheduling in multiple blocks of container terminals under uncertain conditions, this paper considers two kinds of predictable uncertain factors: the arrival time of task group and handling volumes , a mixed-integer programming model based on the framework of proactive response structure was developed to minimize the sum of the expected and variance total delays of all task groups. The improved simulated annealing genetic algorithm (ISAGA) is used to solve the problem. The simulation experiment considers 8 different situations in 5 different scenarios to compare the quality of the solutions of the two algorithms. The experimental results show that the total delay of the proposed improved simulated annealing genetic algorithm is reduced by 27.42% on average compared with that of the simulated annealing algorithm, which verifies the effectiveness of the improved algorithm.

Keywords

Container Terminal; Uncertain Environment; Simulated Annealing Algorithm; Genetic Algorithm; Yard Cranes Scheduling.

1. Introduction

In recent decades, with the increasing prosperity of maritime trade, the number of container terminals has continued to increase. The competition between the terminals is becoming more and more fierce, container transport has become an important logistics mode in international trade. As an important node connecting the sea and land in the process of container transportation, the throughput of a terminal increases rapidly every year. The crane in the yard is one of the important pieces of equipment of the container terminal. It is responsible for the storage and extraction of containers in the yard. Therefore, the yard cranes scheduling operations play a vital role in the entire operation of the terminal. A fast and effective yard cranes scheduling program can not only improve the efficiency of the terminal's operation but also enhance its competitiveness.

This paper mainly studies the improved simulated annealing genetic algorithm to solve the field bridge scheduling problem under an uncertain environment. The simulated annealing genetic algorithm is widely used in solving the scheduling problem. Zhou Xin [1] et al. mainly studied the Jobshop scheduling problem. In order to overcome the limitations of the traditional genetic algorithm, a hybrid simulated annealing algorithm was proposed to improve the efficiency of the Jobshop schedule, which verified the high efficiency of the proposed GASA algorithm and its effectiveness. Sung Ho Jung et al. [2] mainly studied the scheduling problem of multiple yard cranes in the same block. The goal was to minimize the time to complete the operation of all yard cranes in the block, taking into account the loading and unloading time of containers, travel time, and waiting time of yard cranes. The model is solved by using the genetic algorithm and simulated annealing algorithm, and the operation of the genetic algorithm is mainly added into the Boltzmann function of the simulated annealing algorithm. The experimental results show that the simulated annealing genetic algorithm is superior to the genetic algorithm in calculation time and average target value. Fan Houming et al. [3] established a collaborative optimization model for container yard space allocation and multi-yard cranes scheduling by minimizing the sum of the moving cost and idle cost of yard cranes. The simulated annealing algorithm is used to solve the problem, and the simulated annealing algorithm is mainly added after genetic algorithm mutation operations. To increase the global search capability of the algorithm. The experimental results show that the algorithm has a faster convergence rate and better results than the genetic algorithm. Yao Qian et al. [4] studied the problem of yard cranes scheduling and storage space allocation in the yard storage space and established a mathematical model to minimize the total waiting time of the truck and the energy consumption of all the operations on the yard cranes. The idea of the simulated annealing algorithm is introduced into fitness function, crossover probability, and mutation probability in genetic algorithm operation. Kong Liang et al. [5] studied the collaborative optimization of multiple resources in the export yard and established a two-level programming model in which the upper model minimizes the total operation time of the in-outlet operation system in the export yard, while the lower model minimizes the storage time of the export containers.

The above research is the application of the simulated genetic algorithm in the field cranes scheduling in a certain environment. This is an ideal environment, and there are many uncertain factors in the reality of container terminals. Yard cranes scheduling are easily affected by these uncertain factors.

Yiqin Lu [6] et al. considered the comprehensive scheduling optimization problem of the vehicles in the yard, the running speed of yard cranes, and the time uncertainty of the yard crane's lifting and unloading tasks. The goal is to complete all the tasks in the yard in the least amount of time for all the yard cranes .The particle swarm algorithm is used to solve the problem model and verify the effectiveness of the proposed model. The disadvantage is that the consideration is small. Lu Yiqin [7] et al. mainly studied the uncertain yard cranes scheduling problem when the external trucks arrive randomly. The goal is to minimize the time for completing the task yard cranes scheduling model is established and set trucks also consider using reward function, using particle swarm optimization algorithm solving the model, and random variables set trucks randomly to time is to meet the Poisson distribution. The experimental results show that the convergence effect of the function under uncertain conditions is better than that under certain conditions, which verifies the effectiveness of the algorithm. Wenqian Liu et al. [8] established a stochastic programming model from the perspective of prediction strategy by considering two uncertain factors, namely the uncertain arrival time of the external truck and the uncertain loading capacity of the yard crane. Particle Swarm Optimization Algorithm and Genetic Algorithm are used to solve the problem. The experimental results show that the balanced distribution of the loading and unloading capacity of yard cranes can improve the operation efficiency of the container terminal. Junliang He [9] et al. studied the arrival time of the yard container that needs to be handled by yard cranes and the scheduling problem of the uncertain number of handling. To minimize the delay cost of crane scheduling under certain conditions and the expected value of the additional loss cost under uncertainty, a multi-objective programming model is established, and a three-stage algorithm based on the genetic algorithm is used to solve the model. Finally, this algorithm is used to solve the problem to verify the effectiveness and practicability of the model.

The above researches are considered a bridge scheduling problem under the uncertain environment, but not in combination with simulated annealing algorithm and genetic algorithm to solve the model. Therefore, this paper takes the multi-yard cranes scheduling in the multi-blocks as the object. The influence of the uncertain arrival time and the handling volumes of task groups to be processed on the yard cranes scheduling is considered. A mathematical model based on the proactive reaction decision-making framework is proposed and the corresponding improved simulated annealing genetic algorithm is designed to solve it.

2. Problem description

The yard cranes scheduling problem specifically refers to the container terminal operator according to the information such as the arrival time of the container trucks and the container storage location during a certain planning period, the loading and unloading operations of containers are assigned to the corresponding cranes in the yard according to certain rules.

There are many uncertain factors in the reality of container terminals. For example,the arrival time of task groups is uncertain because the truck is earlier or later than the specified time for some reason. Since the ship may load/unload more or less than its planned processing capacity, and the number of storage/extraction containers may be more or less than its planned processing capacity, the amount of task group processing is also uncertain. In order to reduce the complexity of calculation, the scheduling object is not each container but a task group. The construction method of the task group mainly refers to the method proposed by He[10] et al. The task of containers from the same ship or adjacent bays in the same container area and loaded and unloaded in the same batch is defined as a task group. In this paper, by referring to the scenario analysis method proposed by Yamashita D S[11] et al., the enumeration method is used to list all kinds of situations that may occur in a limited number of scenarios, so as to establish the corresponding uncertain yard cranes scheduling model.

3. Model formulation

This paper considers the uncertainty of the arrival time of task groups and handling volumes and establishes the scheduling model according to the influence of these two predictable uncertainties on the yard cranes scheduling. A robust scheduling scheme with anti-jamming capability is developed without considering the sudden interference of random arrival of new task groups.

(1) The container specifications in each container area are uniform;

(2) The unloading task time of any container in the yard is a fixed constant, and the loading and unloading time is known. The processing time for each task group is determined by the number of container tasks contained respectively.

(3) At the same time, any yard crane can only handle one task group and the one-yard crane can only handle one task group;

(4) At the initial moment, the initial positions of all cranes are known. At the initial moment of scheduling, each crane is in an idle state and can be scheduled to its respective target task group position for loading and unloading operations;

(5) It is stipulated that the loading and unloading efficiency and moving speed of each yard crane are the same;

(6) The position of the task group to be processed is determined;

(7) The arrival time of each task group and the number of containers in the initial scheduling plan is uncertain;

(8) The location of other containers is unchanged except those requiring operations.

3.1 Model parameters are defined as follows:

P The handling efficiency of a yard crane;

V_h The horizontal moving speed of each crane in the yard;

W_{block} The width of each block in the yard;

L_{block} The length of each block in the yard;

S_x The horizontal distance between two horizontally adjacent blocks;

S_y The longitudinal distance between two vertical adjacent blocks;

T_r The time required for the yard crane to complete a turn;

lb The length of a bay;

Bl The number of bays in each block in the storage yard;

N The total number of task groups;

Y The total number of cranes in the yard;

NT The set of task groups to be processed, $NT = \{0,1,2,\dots,N\}$, where 0 represents a virtual task before the first processing task, representing the initial position of the crane in the yard;

NY The set of cranes in the yard, $NY \in \{1,2,\dots,Y\}$;

Ω The set of all scenarios in the scheduling plan;

i,j,m The number of the task group, $i,j,m \in NT$;

k The number of the bridge in the yard, $k \in NY$;

ω The index of scenarios, $\omega \in \Omega$;

P_ω The probability of Scenario, $\sum_{\omega\in\Omega} p_\omega = 1, \omega \in \Omega$;

d_i The estimated completion time of task groups, where $d_0 = 0$;

x_i The column corresponding to the block where task group i is located;

y_i The row corresponding to the block where task group i is located;

z_i The bay corresponding to the block where task group i is located;

M A large positive number;

$V_{i(\omega)}$ The number of containers in task group i in Scenario ω, where $V_{0(\omega)} = 0$;

$H_{i(\omega)}$ The needed handling time of task group i in Scenario ω, Since the various handling volume of task group i is uncertain, $H_{i(\omega)}$ is a parameter that varies with ω, $H_{i(\omega)} = V_{i(\omega)}P$, $H_{0(\omega)} = 0$

$r_{i(\omega)}$ The actual arriving time of task group i in Scenario ω, where $r_{0(\omega)} = 0$;

t_{ij} The moving time between task group i and j;

rt_i The actual arriving time of task group i;

The decision variables are defined as follows:

$\mu_{i(\omega)}$ The start served time of task group i in Scenario ω;

$\varepsilon_{i(\omega)}$ The actual completion time of the task group i in Scenario ω;

$\pi_{i(\omega)}$ The amount of delay in completion time of the task group i in Scenario ω;

$\varphi^k_{i,j(\omega)}$ $\varphi^k_{i,j(\omega)} = 1$, If both task group i and task group j are allocated to the k yard crane for processing, the processing sequence is to process task group i first, then task group j in Scenario;

$\varphi^k_{i,j(\omega)} = 0$, otherwise;

$\varphi^k_{0,j(\omega)} = 1$ represents the task group i is the first task group to be processed in the k yard crane;

3.2 Proactive-reactive scheduling model

$$min\, z = \sum_{\omega\in\Omega} p_\omega \sum_{i\in NT, i\neq 0} \pi_{i(\omega)} + \sum_{\omega\in\Omega} p_\omega \Big(\sum_{i\in NT, i\neq 0} \pi_{i(\omega)} - \sum_{\omega\in\Omega} p_\omega \sum_{i\in NT, i\neq 0} \pi_{i(\omega)}\Big)^2 \quad (1)$$

The objective function (1) to minimize the sum of the expected delay and the variance delay of the total completion delay of all task groups.

Eq. (2) express that the calculation formula of the delay amount of the completion time of task groups; Eq. (3) express that the calculation formula of the task group processing time of the task group i in Scenario ω; Eq. (4) express that the calculation formula for the actual completion time of task group i in Scenario ω; Eq. (5) defines the formula for calculating the travel time of the yard crane from task group i to task group j. Since the environment of the yard crane is three-dimensional, considering the above specific situation. Eq. (6) ensure that the start time of each yard crane is not earlier than the arrival time of the task group; Eq. (7) express that that if the task group i to be processed by the yard crane is adjacent to the task group j, and it is assumed that the yard crane processes the task group i first. Then the time when task group j is served cannot be earlier than the sum of the completion time of task group i and the moving time of the yard crane from task group i to task group j; Eq. (8) and Eq. (9) defines that each task group is only allocated to a one-yard crane for processing, and the yard crane is processed only once; Eq. (10) and Eq. (11) express that to ensure the balance of the operation of yard cranes, each yard crane is assigned to a corresponding task group; Eq. (12) is referred to that the yard crane operation is unidirectional; Eq. (13) guarantees the continuity of yard cranes operation, stipulating that the yard crane must move to the next task group when completing the current task group's operations; Constraint (14) and (15) defines the decision variables.

$$\pi_{i(\omega)} = max\left(\varepsilon_{i(\omega)} - d_i, 0\right), i \in NT, i \neq 0, \omega \in \Omega \tag{2}$$

$$H_{i(\omega)} = V_{i(\omega)} \cdot P, i \in NT, i \neq 0, \omega \in \Omega \tag{3}$$

$$\varepsilon_{i(\omega)} = \mu_{i(\omega)} + H_{i(\omega)}, i \in NT, i \neq 0, \omega \in \Omega \tag{4}$$

$$\mathrm{t}_{ij} = \begin{cases} \dfrac{(x_i - x_j)\cdot S_x + (x_i - x_j - 1)\cdot L_{block} + (z_i + Bl - z_j)\cdot lb}{V_h}, if\ y_i = y_j, x_i \geq x_j \\ \dfrac{(x_j - x_i)\cdot S_x + (x_j - x_i - 1)\cdot L_{block} + (z_j + Bl - z_i)\cdot lb}{V_h},\ if\ y_i = y_j, x_i < x_j \\ 2\cdot T_r + \dfrac{|y_j - y_i|\cdot S_y + (|y_j - y_i| - 1)\cdot W_{block} + \min\left\{z_i + z_j - 1, 2\cdot Bl - (z_i + z_j - 1)\right\}\cdot lb}{V_h},\ if\ y_i \neq y_j, x_i = x_j \\ 2\cdot T_r + \dfrac{|y_j - y_i|\cdot S_y + (|y_j - y_i| - 1)\cdot W_{block} + (z_i + Bl - z_j)\cdot lb + S_x}{V_h},\ if\ y_i \neq y_j, x_i - x_j = 1 \\ 2\cdot T_r + \dfrac{|y_j - y_i|\cdot S_y + (|y_j - y_i| - 1)\cdot W_{block} + (z_j + Bl - z_i)\cdot lb + S_x}{V_h},\ if\ y_i \neq y_j, x_j - x_i = 1 \\ 2\cdot T_r + \dfrac{|y_j - y_i|\cdot S_y + (|y_j - y_i| - 1)\cdot W_{block} + (z_i + Bl - z_j)\cdot lb + (|x_i - x_j| - 1)\cdot L_{block} + |x_i - x_j|\cdot S_x}{V_h},\ if\ y_i \neq y_j, x_i - x_j > 1 \\ 2\cdot T_r + \dfrac{|y_j - y_i|\cdot S_y + (|y_j - y_i| - 1)\cdot W_{block} + (z_j + Bl - z_i)\cdot lb + (|x_i - x_j| - 1)\cdot L_{block} + |x_i - x_j|\cdot S_x}{V_h},\ if\ y_i \neq y_j, x_j - x_i > 1 \end{cases} \tag{5}$$

$$\mu_{i(\omega)} \geq r_{i(\omega)}, i \in NT, i \neq 0, \omega \in \Omega \tag{6}$$

$$\mu_{j(\omega)} \geq \varepsilon_{i(\omega)} + t_{i,j} - M \cdot (1 - \varphi_{i,j(\omega)}^k), i, j \in NT, j \neq 0, k \in NY, \omega \in \Omega \tag{7}$$

$$\textstyle\sum_{k\in NY} \sum_{i\in NT, i\neq j, i\neq 0} \varphi_{i,j(\omega)}^k = 1, \forall j \in NT, j \neq 0, \omega \in \Omega \tag{8}$$

$$\textstyle\sum_{k\in NY} \sum_{j\in NT, j\neq i, j\neq 0} \varphi_{i,j(\omega)}^k = 1, \forall i \in NT, i \neq 0, \omega \in \Omega \tag{9}$$

$$\textstyle\sum_{k\in NY} \varphi_{0,j(\omega)}^k \leq 1, \forall j \in NT, j \neq 0, \omega \in \Omega \tag{10}$$

$$\textstyle\sum_{j\in NT, j\neq 0} \varphi_{0,j(\omega)}^k = 1, \forall k \in NY, \omega \in \Omega \tag{11}$$

$$\varphi_{i,j(\omega)}^k + \varphi_{j,i(\omega)}^k \leq 1, \forall i, j \in NT, i \neq j, i, j \neq 0, \forall k \in NY, \omega \in \Omega \tag{12}$$

$$\textstyle\sum_{i\in NT, i\neq j} \varphi_{i,j(\omega)}^k = \sum_{m\in NT, j\neq m, m\neq 0} \varphi_{j,m(\omega)}^k, \forall j \in NT, j \neq 0, \forall k \in NY, \omega \in \Omega \tag{13}$$

$$\mu_{i(\omega)}, \varepsilon_{i(\omega)}, \pi_{i(\omega)} \in Z^+, i \in NT, i \neq 0, \omega \in \Omega \tag{14}$$

$$\varphi_{i,j(\omega)}^k \in \{0,1\}, \forall i, j \in NT, i \neq j, j \neq 0, \forall k \in NY, \omega \in \Omega \tag{15}$$

4. Improved simulated annealing algorithm

Many heuristic algorithms have been used to solve the yard cranes scheduling problem. The yard cranes scheduling problem has been proved to be an NP-hard problem. The method of yard cranes uncertain dispatching is to transform multiple uncertainties into single uncertainties and single uncertainties into certainty. The Simulated Annealing algorithm was first proposed by Metropolis et al. in 1953. This paper improves on the traditional simulated annealing algorithm and introduces the operation of genetic algorithm to improve the global search ability of the algorithm and considers two domain transformation strategies to generate new populations.

4.1 Initial solution generation strategy

The first part shows the sequence of Y yard cranes handling N task groups, where the service sequence of N task groups is randomly disrupted. The second part represents the handling volumes corresponding to Y yard cranes, and N task groups are randomly assigned to Y yard cranes. The details are shown in Figure1.

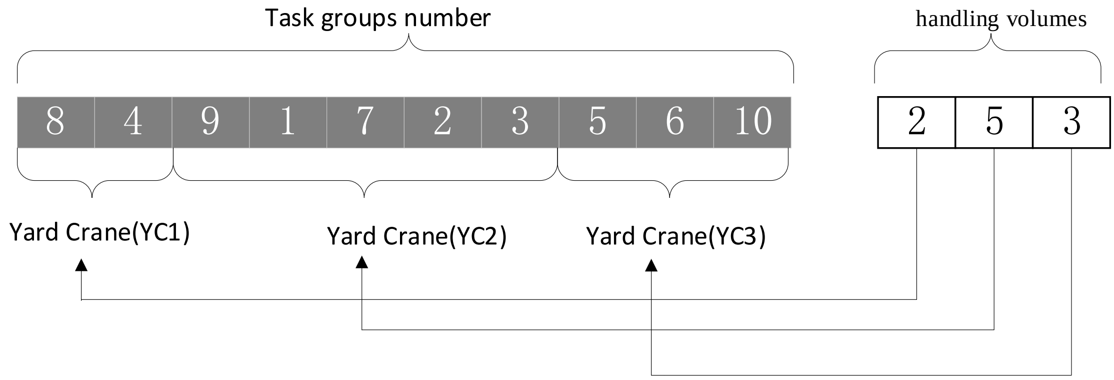

Figure 1. Representation of the solution

Figure 2 shows the situation where 3-yard cranes handle 10 task groups. The first part represents the random arrangement of task groups numbered, and the second part represents the handling volumes of task groups corresponding to the 3-yard cranes. In the figure, the handling volumes of the yard crane 1($YC1$) is 2, and the numbering sequence of the task box group served by the yard crane 1 is $8 \rightarrow 4$; the handling volumes of the yard crane 2($YC2$) is 5, and the service sequence is $9 \rightarrow 1 \rightarrow 7 \rightarrow 2 \rightarrow 3$; the handling volumes of the yard crane 3($YC3$) is 3, and the service sequence is $5 \rightarrow 6 \rightarrow 9$.

4.2 Generation of domain solutions

To improve the efficiency of the simulated annealing algorithm, two domain transformation strategies are designed to generate new individuals.

4.2.1 Reverse order operation

Combined with the coding method of solution in this paper, the two parts are operated respectively. It is assumed that there are Y-yard cranes to deal with N task groups.

Step1:Randomly select two numbers $P1$ and $P2$, and $P1, P2 \in [1, Y]$,$P1 \neq P2$.

Reverse the number of task box groups in $P1$and $P2$;

Step2: Randomly select two numbers $P3$ and $P4$,and $P3, P4 \in [1, N]$,$P3 \neq P4$. Reverse the number of task box groups in $P3$ and $P4$;

Step 3: Combine the new individuals corresponding to the two parts to generate a new individual.

4.2.2 Disturbance and interchange operations

Step 1: For the operation of the first part, a random number R ($R \in N$)is generated at random, and R gene locations are extracted from the original individual task groups coding in the first part, the sequence of which is randomly disrupted, and then put back.

Step 2: For the operation of the second part, a random number M($M \in Y$) is generated at random, and M gene sites are extracted from the number of task groups corresponding to the yard cranes in the second part, the order of the sequence is randomly disrupted, and then put back.

Step 3: Combine the new individuals corresponding to the two parts to generate a total of new individuals.

4.3 Genetic algorithm operation

Since the genetic algorithm in the global search ability is more outstanding, so this paper will combine the simulated annealing algorithm and genetic algorithm, solve the model together. Here is the operation of the genetic algorithm.

4.3.1 Cross operation

Combined with the chromosome coding method in this paper, the two parts are intersected in different ways. To make sure you get more diverse populations.

The specific steps for the cross method of the task groups number in the first part are as follows.

Step1: Set up m task groups, randomly select two individuals as parent 1 and parent 2, and randomly generate a random number R between [1, m];

Step2: Compare the task groups codes in parent generation 1 and child generation 2 with R, reserve the codes less than or equal to R in parent generation to child generation 1 and child generation 2, and set all other positions to 0;

Step3: Compare parent generation 2 and child generation 1, reserve the codes in parent generation 2 that are greater than R to set 0 in child generation 1 under the principle of sequence;

Step4: Compare the parent generation 1 with the child generation 2, following the same steps as Step 3.

The second part is the crossover mode of yard cranes processing capacity: a crossover bit is randomly selected from the parent generation, a single point crossover is carried out first, and then the parent generation is operated in reverse order according to the crossover bit so as to obtain their own offspring. Figure2 is part of the code for the cross operation

```
new_sx=zeros(1,N+Y);
new_sy=zeros(1,N+Y);
R=unidrnd(N);
YX=unidrnd(Y);
YY=unidrnd(Y);

remainx=[];
remainy=[];
for i=1:N
if(sx(i)<=R)
new_sx(i)=sx(i);
else
remainx=[remainx sx(i)];
end
if(sy(i)<=R)
new_sy(i)=sy(i);
else
remainy=[remainy sy(i)];
end
end
k=1;
for j=1:N
if(new_sx(j)==0)
new_sx(j)=remainy(k);
k=k+1;
end
end
m=1;
for j=1:N
if(new_sy(j)==0)
new_sy(j)=remainx(m);
m=m+1;
end
end
new_sx(N+1:N+Y-YX)=sx(N+YX+1:N+Y);
new_sx(N+Y-YX+1:N+Y)=fliplr(sx(N+1:N+YX));
new_sy(N+1:N+Y-YY)=sy(N+YY+1:N+Y);
new_sy(N+Y-YY+1:N+Y)=fliplr(sy(N+1:N+YY));
```

Figure 2. Cross operation

4.3.2 Cross operation

The first part randomly exchanges the number sequence of the two task groups to perform mutation operations, and the second part randomly exchanges two-yard cranes processing tasks to ensure that more populations are generated. Figure3. is part of the code for mutation operation.

```
a) a=1:size(s,2);
b) P1=a(unidrnd(size(a,2)));
c) a=setdiff(a,P1,'stable');
d) P2=a(unidrnd(size(a,2)));
e) b=s(P1);
f) s(P1)=s(P2);
g) s(P2)=b;
h) new_s=s;
```

Figure 3. Mutation operation

4.4 Solving steps of improved simulated annealing genetic algorithm

(1) Set the parameters of the two algorithms, the initial temperature T_0, cut-off temperature T_f, and cooling coefficient $\alpha$of the simulated annealing algorithm; the crossover probability P_c and mutation probability P_m of the genetic algorithm;

(2) A population is randomly generated through the initial solution generation strategy and the population size is N;

(3) Randomly select two chromosomes as parents 1 and 2 in the initial population;

(4) Perform crossover and mutation operations in the genetic algorithm on the chromosomes of parent 1 and parent 2 to produce new individual child 1 and child 2;

(5) Calculate the value of the objective function z of parent 1, parent 2, and generating new individual child 1 and child 2, mainly calculate the total delay $\pi_{i(\omega)}$ of all task groups in ω scenarios to complete the handling volumes. The main steps are as follows.

Step1. Calculate the actual starting service time T from NY yard cranes to the first task group, and compare the time when the yard crane arrives at the first task group to be processed (TY) with the actual arrival time of the task group (TT). If $TY \geq TT$, then $T = TY$, otherwise $T = TT$;

Step2. Calculate the completion time ST of the first task group for NY yard cranes;

$$ST = \text{The completion time of the first task group(T)} + \\ \text{Yard cranes handling efficiency(P)} \times \\ \text{The handling volumes of task group i under scene } \omega\left(V_{i(\omega)}\right)$$

Step3.Calculate the delay amount of the completion time of the first task group for each yard crane, that is, TT minus the planned completion time of the first task group;

Step 4. Calculate the total delay $\pi_{i(\omega)}$ for all task groups in scenario ω. First, calculate the actual time U when other task groups of each yard crane start to be served and compare the arrival time of the task group to be served by the current yard crane with the completion time (TC) of the previous task group plus the movement time of the yard crane(TY) according to the coding sequence. If $TC + TY \geq TT$, then $U = TC + TT$, otherwise $U = TT$. Then calculate the completion time of each task group according to the number of containers contained in each task group until all task groups have been calculated. Then calculate the delay time for each yard crane to complete all task groups according to Step2 and Step3. $\pi_{i(\omega)}$ is the sum of all delay times of NY yard cranes in ω scenarios.

Step5. Calculate the objective function of each individual according to Formula (1);

(6) Compare the original individual objective function z_2 with the new individual's objective function z_2. If $z_1 - z_2 < 0$, keep the original individual, if $z_1 - z_2 \geq 0$, the Metropolis criterion function determines whether to accept the new individual; Metropolis rule function:

$$P_t(x_{old} \Rightarrow x_{new}) = \begin{cases} 1 \ , \quad E(x_{new}) \leq E(x_{old}) \\ exp\left(\frac{E(x_{new})-E(x_{old})}{T}\right) \quad , E(x_{new}) > E(x_{old}) \end{cases} \tag{16}$$

In the formula, P_t represents the probability of receiving new individuals, $E(x_{old})$ represents the objective function value of the original individuals, $E(x_{new})$ represents the objective function value of the new individuals after the crossover and mutation operations of the two domain transformation strategies and the genetic algorithm, and T represents the temperature control parameters in the simulated annealing algorithm. As can be seen from Equation (16), when the value of T is large, the probability of the original individual being replaced by the new individual is high. However, with the continuous iteration, the value of T becomes smaller and smaller, and the probability of the original individual being replaced by the new individual is very low, so as to obtain the global optimal result.

(7) Whether the solution output by Metropolis criterion satisfies the stopping condition, if it is satisfied, jump out of the total calculation, obtain the optimal solution and output the optimal result, if not satisfied, change the temperature control parameter value T, return to (2), and then loop Until

the optimal solution is obtained. The following figure4 is the specific flow chart of the proposed improved simulated annealing genetic algorithm.

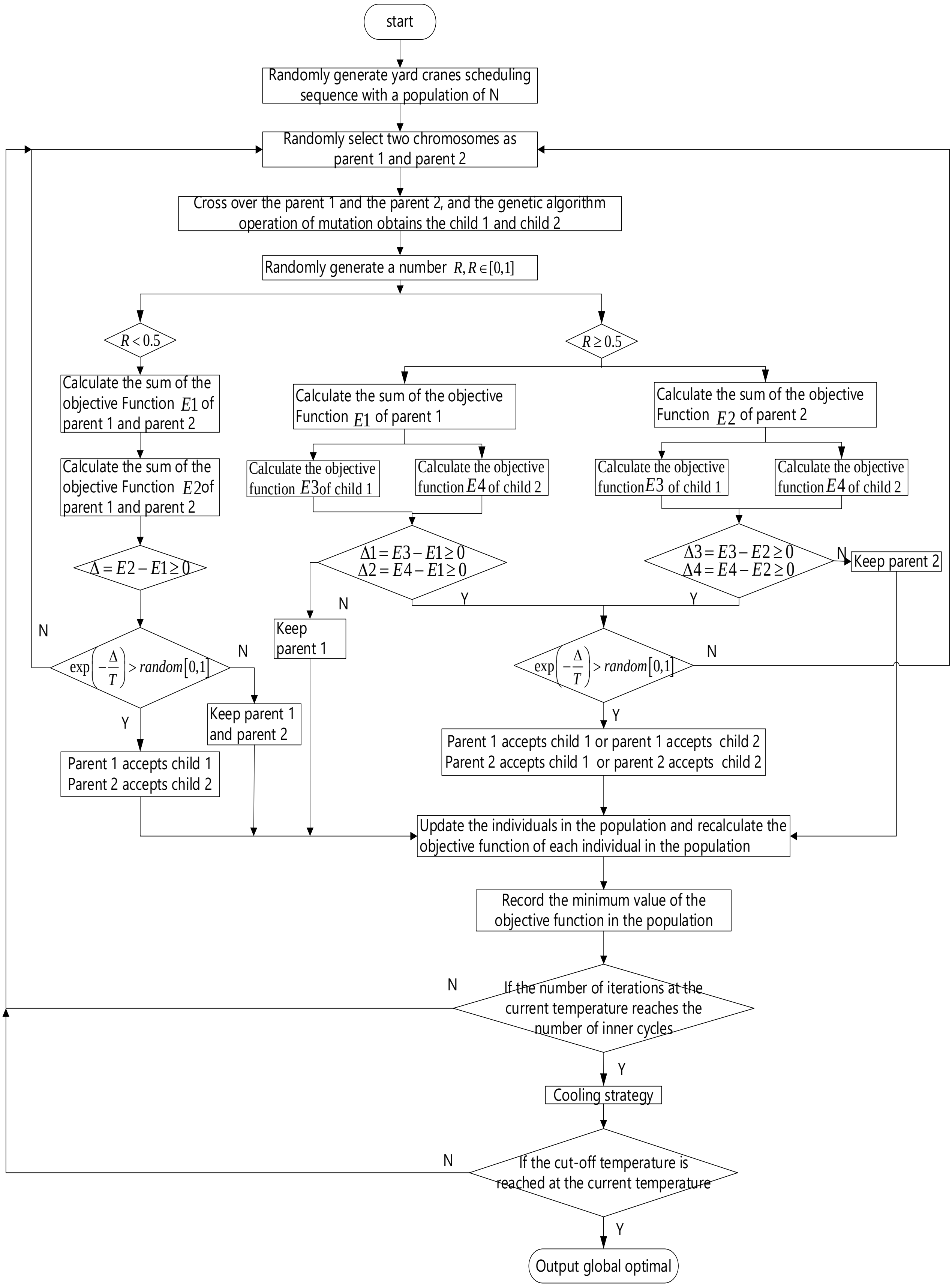

Figure 4. Improved simulated annealing genetic algorithm flow chart

5. Numerical experiment

To verify the validity of the mathematical model proposed in this paper and the performance of the improved simulated annealing genetic algorithm (ISAGA), this paper designs a series of numerical experiments and compares it with the simulated annealing algorithm (SA). Using MATLAB R2016A program, run on Intel Core i51.60 GHz CPU, 12GB memory computer.

The research object of this experiment is a container terminal, which studies the yard cranes scheduling in a certain planned period (2H).The layout of the container terminal is shown in Figure 1.There are 40 bays in each block in the figure. At the same time, the direction of the yard is defined as the x-axis and the vertical direction is the y-axis. position. Table 1 illustrates the processing efficiency of each yard crane, the operating speed and the relevant parameters in the container terminal blocks.

Table 1. Experimental parameter values

parameter	$p/(task \cdot min^{-1})$	$V_h/(m \cdot min^{-1})$	W_{block}/m	L_{block}/m	S_x/m	S_y/m	T_r/min	lb/m	Bl
Numerical value	1	1	5	40	4	2	3	1	40

5.1 Multi-yard cranes scheduling experiment in different scenarios

To verify the effectiveness of the method designed in this paper in dealing with two predictable uncertain factors (that is, the uncertainty of the arrival time of task groups and the uncertainty of task groups to be processed), the classical scheduling method under certain conditions and the stochastic programming method in reference [13] are used to solve 15 task sets with 6 field bridges under 5 scenarios, which are compared with the methods presented in this paper, the results of the experiment are shown in Table 2. Considering that the uncertainty of the arrival time of task groups and the number of task groups to be processed was also studied in the literature [9], the information of task groups and yard cranes was referred to Table1 and Table2 in literature [9], and the information of the arrival time of task groups and the amount of the task groups to be processed under five scenarios was referred to Table 3.

The classical scheduling scheme under certain conditions is generated based on Scenario 1. However, in actual production scheduling, the arrival time and processing capacity of task groups are often unable to be determined in advance. The classical scheduling method under certain conditions can only obtain the optimal solution under a certain situation, and the robustness of the scheduling scheme is poor. As shown in Table 2, the target value of the proposed method in the other four scenarios is far better than that of the classical scheduling method under certain conditions. The stochastic planning method takes the expected performance of the system as the optimization goal and considers the influence of uncertain factors at a certain level, but it is too one-sided and does not comprehensively consider the target performance in each scenario, but only pursues the expected performance. It can be seen from Table 2 that, except for scenario 4, the total delay time of task groups proposed in this paper is shorter than that of the random programming method in the other four scenarios. The convergence effect of the method proposed in this paper for solving the robust solutions under five scenarios is shown in Figure 5.

Table 2. Comparison of experimental results in 5 scenarios

	Determine environmental	Stochastic programming	Uncertain environmental
Scenario 1	571	662	522
Scenario 2	563	573	557
Scenario 3	665	769	627
Scenario 4	467	594	570
Scenario 5	632	653	466

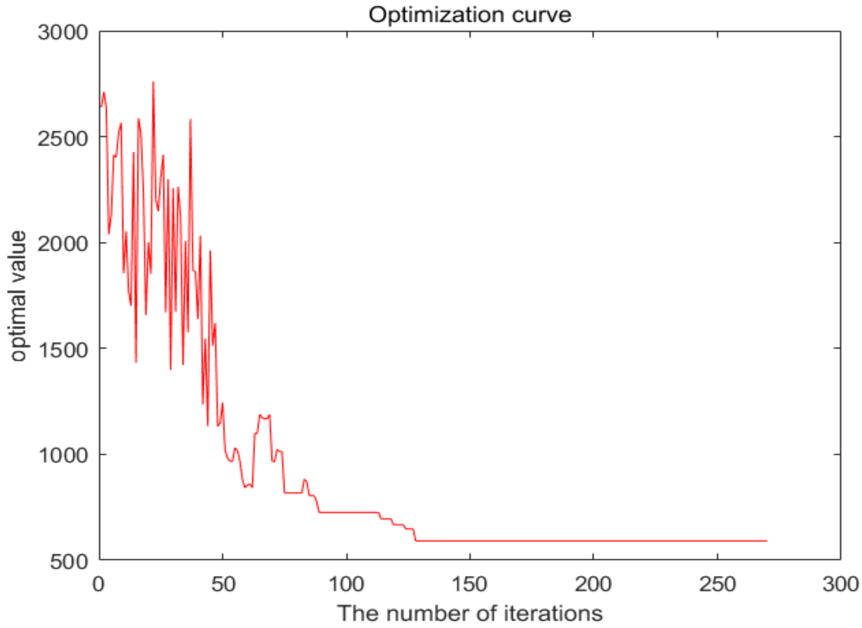

Figure 5. Convergence graph

5.2 Experimental comparison and analysis of two algorithms

In the experiment, a total of two algorithms are considered to solve this model. Improved Simulated Annealing Genetic Algorithm (ISAGA) and Simulated Annealing Algorithm (SA) are used to solve this model. Table 3 shows the respective parameter settings of these two algorithms. Table 4 shows the mean and standard deviation of the objective function obtained by the SA and ISAGA algorithms. A total of 8 groups of experiments were designed. Due to the probability convergence property of the algorithm, the same algorithm would get different solutions when solving the same example each time. Therefore, each experiment was conducted 10 times and the average value was taken as the final result.

Table 3. Solving algorithm parameter settings

algorithm	SA			GA	
parameter	T_0	T_f	λ	P_c	P_m
Value	1000	0.001	0.95	0.9	0.15

Table 4. Comparison of experimental results

No.	Size (YCs*TGs)	SA		ISAGA	
		mean	standard deviation	mean	standard deviation
1	3*5	93.76	0	93.76	0
2	4*6	756.2	0	756.2	0
3	5*9	156.192	8.26	99.584	60.58
4	6*15	1020.75	403.23	698.61	102.22
5	7*20	943.34	126.22	435.21	187.35
6	7*25	2001.81	677.01	1049.04	347.75
7	8*20	594.36	62.73	374.14	116.69
8	8*30	3033.62	1025.25	2636.22	860.82

Table 4 and Figure 6 show that when 3-yard cranes deal with 5 task groups and 4-yard cranes deal with 6 task groups, the objective function values obtained by the SA algorithm and ISAGA algorithm are the same, so the standard deviation of both groups is 0. As the scale of the experiment continues to increase, the total delay in solving task groups continues to increase. With the increase in the number of yard cranes and the number of task groups, there is an obvious difference between the solutions of SA and ISAGA. As can be seen from Table 4 and Figure 6, the approximate optimal solution obtained by the improved simulated annealing genetic algorithm (ISAGA) is superior to the simulated annealing algorithm (SA), and the total delay of task groups is 27.42% lower than that of SA on average. The ISAGA algorithm proposed in this paper is also significantly better than the SA algorithm in solving the optimal solution of these 8 groups of experiments, which verifies the superiority and effectiveness of the ISAGA algorithm in solving the yard cranes scheduling problems with these two uncertain factors.

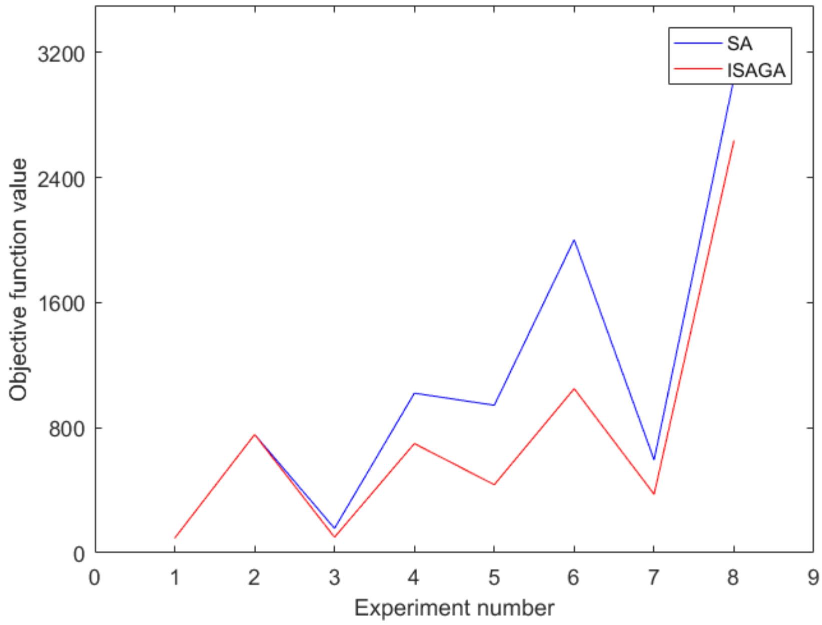

Figure 6. Comparison of experimental results

6. Conclusion

In this paper, a mixed-integer programming model for multi-yard cranes scheduling in multi-blocks under uncertain environments is established. Considering the uncertainty of the arrival time of task groups and the handling volumes to be processed, minimize the sum of the expected total delay and the total variance total delay of the completion time of all task groups. In this paper, an improved simulated annealing genetic algorithm (ISAGA) is used to solve the problem. The crossover and mutation operations of the genetic algorithm (GA) are considered in the simulated annealing algorithm (SA), and two domain transformation strategies for generating new individuals are considered. The experimental results show that the total delay calculated by the ISAGA algorithm is reduced by 27.42% on average compared to the SA algorithm. This paper does not use an accurate algorithm to solve the model, the next step can consider using a precise algorithm solver such as CPLEX to solve the model.

Acknowledgements

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