ISSN: 2414-1895 DOI: 10.6919/ICJE.202108_7(8).0010

Integrated Scheduling for Berth and Quay Crane in Automated Container Terminals based on Proactive-reactive Method

Enjie Wu, Jin Zhu

Shanghai Maritime University, Shanghai 201306, China.

enjietg@126.com

Abstract

In this paper, the integrated scheduling problem for berth and quay crane in automated container terminals under uncertain conditions is studied, in other words, aiming at the ship arrival time and the sudden failure of the quay bridge are two different types of uncertainty factors. A decision framework combining proactive scheduling strategy with response scheduling strategy is proposed, the problem is decomposed into two sub-problems: proactive and reactive scheduling. Aiming at the uncertainty of the actual arrival time of ships, a robust proactive scheduling scheme is generated by increasing the buffer time. For quay crane fault uncertain, in scheduling phase reaction, the loss caused by sudden fault for quay crane, considering the reality of different interests preference, based on prospect theory analysis, terminal operators and ship operators are given in the face of the quay crane fault decision-making behavior, set up to restore target cost minimizing mixed integer programming model. An improved adaptive genetic algorithm was proposed to solve the model, and three groups of simulation experiments were designed. By comparing the performance of the proactive-reactive scheduling strategy with other scheduling strategies, the effectiveness of the proactive-reactive scheduling strategy was verified.

Keywords

Uncertainty; Berth and Quay Crane; Proactive-Reactive; Integrated Scheduling.

1. Introduction

In the actual production scheduling, the operation of the automated wharf will be affected by a variety of complex uncertain factors, such as the uncertain time of ship arrival at the port and the unexpected failure of the quay crane. Therefore, the study of berth quay crane integrated scheduling problem under uncertain conditions is closer to the actual situation.In general, the sources of uncertainty in the shore production of automated wharves are mainly divided into three categories [1]: the uncertainty outside the system, the uncertainty in the normal production process and the anomaly of dispersion. Most literature was studied considering from outside the system uncertainty berth and quay crane integrated scheduling problem, such as peng-fei zhou [2] for the uncertainty of ship arrival time and handling time, discrete berth layout was built based on chance constrained dynamic berth and quay crane joint distribution 0-1 uncertain programming model, ships to minimize the average waiting time, An improved genetic algorithm was designed to solve the problem. Tan, etc. [3] to study the ship time of arrival and container cart empirical berth and quay crane integrated scheduling problem, proactive response scheduling strategy is put forward, a stochastic programming model is established, and a two-phase heuristic algorithm based on genetic algorithm framework, through the numerical experiment and scene analysis verify the validity of the proposed model and solving method. Wang [4] established an integer programming model aiming at minimizing the total time cost and location deviation, and proposed a combination of SWO algorithm and PGA algorithm to solve the model,

ISSN: 2414-1895 DOI: 10.6919/ICJE.202108_7(8).0010

aiming at the impact of the uncertainties of ship arrival time and container loading amount on the integrated scheduling of berth and quay crane e. Liang Chengji etc. [5] on ship's arrival time and handling time random berth quay crane joint scheduling problem, by adding a buffer time method to solve the impact of uncertainty factors, set up to ship in the port of the total time of berth, deviating from the preference punishment, customer satisfaction, and delay the time the goal of minimizing the sum of mixed integer programming model, An improved genetic algorithm is proposed to solve the problem. As for the study of uncertainty in normal production process, Rodriguez-Molins et al. [6] consider the dynamics and uncertainty of the operating environment, and for the joint allocation of continuous berths and quay crane, in order to absorb the impact of delayed arrival of ships and the fluctuation of equipment operation efficiency, A mixed integer linear programming model was built to minimize the ship service time and maximize the robustness or buffer time, and a genetic algorithm was designed to solve the model. Shang et al. [7], aiming at the uncertainty of quay bridge operation efficiency, established a robust optimization model for the joint allocation of continuous berths and quay crane with the aim of minimizing the ship waiting time and the weighted sum of working time, and solved the problem by using genetic algorithm and insertion heuristic algorithm. As for the study of dispersion anomaly, Yang Chunxia [8] established a berth-quay rescheduling mathematical model aiming at minimizing the additional cost caused by the deviation of ship berthing position and time in view of bad weather and wharf production accidents, and used Memetic algorithm to solve the problem. Yang et al. [9], when considering the interruption of port operation for some reason, used the means of simulation to reproduce the scene and used the mixed integer linear programming model to allocate the berth quay crane. Li et al. [10], aiming at the impact of quay bridge failure and dispatch of ships and other emergencies on berth and quay crane allocation, built a disturbance recovery model for berth and quay crane allocation plan with the objective of minimizing the deviation of ship's time in port and time of departure as well as the recovery cost, and solved it by using heuristic algorithm based on SWO.

To sum up, the current uncertainty environment integrated scheduling berth and quay crane most studies only consider the influence of uncertainty factors, or not at the same time to consider a variety of different types of uncertain factors influence on integrated scheduling berth and quay crane, can not accurately reflect the reality and the requirement of port operation management, and more than most scheduling policy can only deal with the same type of uncertainty Therefore, it is necessary to systematically study the berth and quay bridge integrated scheduling problem under different types of uncertainty factors Berth of automation in uncertain conditions and quay crane integrated scheduling problem, this paper adopts a proactive response strategies to deal with two different types of typical uncertainty, the uncertainty of the shipping time of arrival (predictable) and quay crane the uncertainty of fault (predictable) problems, in the heart of the proactive scheduling predictable uncertainty factors into consideration, tong A proactive scheduling scheme with robustness is generated by scheduling too reasonably. In the case of unexpected and uncertain disturbance, the reaction submodel is used to adjust it so as to obtain the optimal scheduling scheme Considering the actual schedule usually involves the different interests of preference needs, so in the response phase, this article considers terminal and ship two decision makers approach uncertain losses, based on prospect theory analysis and code are given and under the condition of the ship in the face of uncertain decision-making behavior, and adjust to minimize loss cost, obtain the optimal scheduling schemeIn order to make the calculation result more accurate and avoid entering the local optimum in advance, this paper designs an improved adaptive genetic algorithm to solve the model, which can effectively reduce the search area of the algorithm and reduce the calculation time of the algorithm, so as to get the approximate optimal solution.

2. Problem statement

2.1 Sub-section Headings

In the proactive stage, the uncertain factors of ship arrival time are treated as predictable ones in this paper, It is assumed that the ship's actual arrival time obeys the uniform distribution $[C_i - \Delta C_i, C_i + \Delta C_i]$

ISSN: 2414-1895
DOI: 10.6919/ICJE.202108_7(8).0010

with the planned arrival time C_i as the mean value, ΔC_i represents the variation range of the ship's arrival time, this is shown in Figure 1. In order to reduce the interference of vessel arrival time uncertainty, set up some buffer time for each ship, buffer for each ship's maximum time, set the ship buffer time still occupies the corresponding berth and shore bridge resources, and the other on the ship and the ship do not have the time and space of the conflict, that is one of the optimization goal is to maximize the buffer time, Taking minimizing the penalty cost of delayed departure, the increased port transportation cost when the ship deviates from its preferred docking location, and the quayside bridge operation cost as the objective of performance optimization, a proactive scheduling model can be obtained. Considering the uncertain situation of unexpected sudden failure of quay bridge in the process of implementing proactive scheduling scheme, decision-makers must make timely decisions on whether to carry out response scheduling of berth quay bridge resources and how to carry out response scheduling to reduce the loss caused by unpredictable events in the response stage. For automation terminal, when you meet the emergency shore bridge needs to perform scheduling scheme reaction, and reaction scheduling may affect the terminal and the corresponding interest demand, so the ship and terminal is the most sensitive reaction scheduling policy makers, to consider their attitude to response scheduling is necessary, in order to solve this problem, based on the reaction stage uses the prospect theory, In order to improve the comprehensive adaptability of the berthing quays integrated scheduling plan.

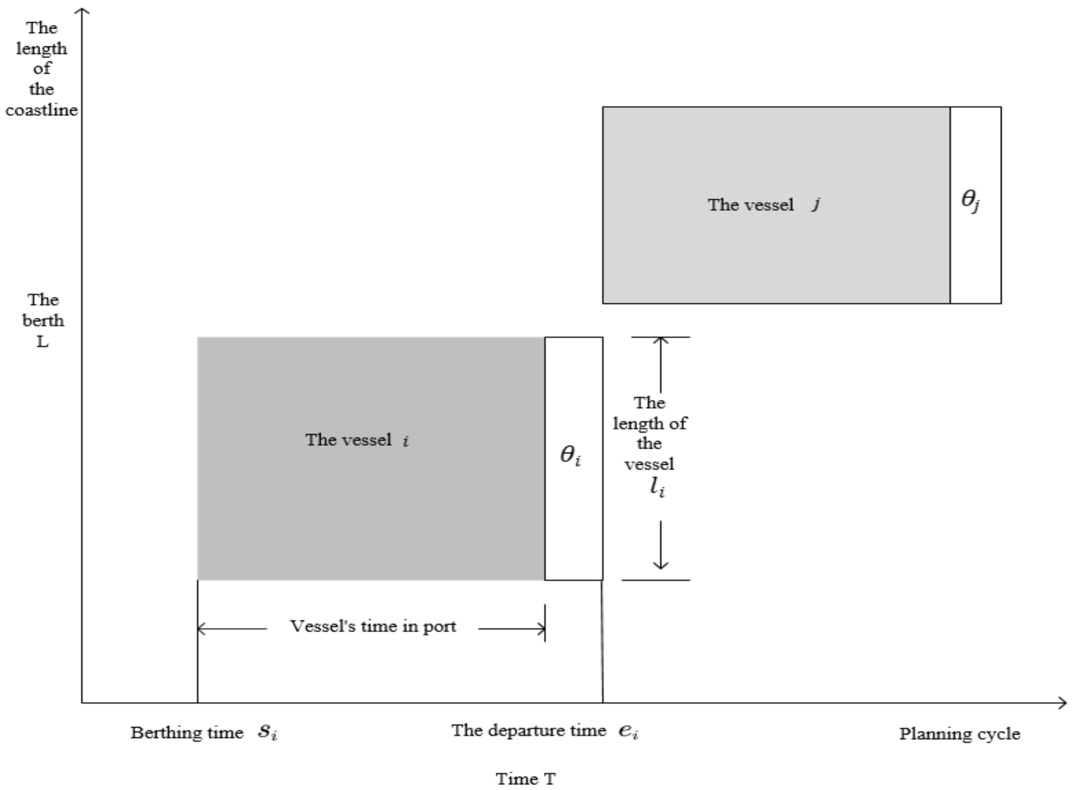

Fig. 1 Example of BACAP

3. Model formulation

3.1 Mathematical model of proactive stage

Parameters:

V Set of vessels, $V = \{1, \ldots, i, \ldots, S\}$, which is indexed by i;

Q Set of QCs, $Q = \{1, \ldots, k, \ldots, W\}$, which is indexed by k;

q Total number of QCs;

L Total length of quay shoreline;

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T Set of planning periods, $T = \{1, \ldots, t, \ldots, H\}$, which is indexed by t;

S Total number of vessels arriving at port during the plan period;

W Total number of available QCs at quay;

H Length of the planning period;

w_i The number of tasks for the vessel i;

l_i Length of vessels i including horizontal safe distance;

A_i The arriving time of vessel i;

r_i^{max} The maximum number of QCs simultaneously serving vessel i;

r_i^{min} The minimum number of QCs simultaneously serving vessel i;

D_i The planned departure time of the vessel i;

B_i The maximum buffer time allocated by the vessel i;

p_i Preferred berthing location of the vessel i;

c_1 Penalty cost per unit time for vessel i to depart port later than D_i;

c_2 Transportation cost per unit distance when vessel i is berthed away from the preferred location;

c_3 QC operation cost per unit time;

γ The weight of the objective function;

M A large positive number;

The decision variables:

e_i Berthing end time (time when the handling ends) of vessel i;

b_i Berthing position of vesse i;

s_i Berthingstart time of vessel i;

r_{it} The number of QCs assigned to vessel i in time period t;

q_{it} 1; if vessel i has loading and unloading operations in time period t, 0 otherwise;

y_{ij} 1; if vessel i is berthed below vessel j in berth area, 0 otherwise;

z_{ij} 1; if handling of vessel i ends no later than handling of vessel j starts in berth area, 0 otherwise;

r_{it}^k 1; if vessel i is served by QC k in time period t,0 otherwise;

θ_i Buffer time of the vessel i;

θ_{itq} 1; if vessel i has q QCs in service and the buffer time is t, 0 otherwise;

$$minf = \sum_{i \in V}\{c_1(e_i - D_i)^+ + c_2|b_i - p_i| + c_3 \sum_{t \in T} r_{it}\} + \gamma \sum_{i \in V} - \theta_i \quad (1)$$

$$\sum_{i \in V}\sum_{k \in Q} r_{it}^k \leq W, \forall t \in T \quad (2)$$

$$q_{it} \leq \sum_{k \in Q} r_{it}^k \leq M \cdot q_{it}, \forall i \in V, t \in T \quad (3)$$

$$t \cdot q_{it} \geq s_i + M \cdot (q_{it} - 1), \forall i \in V, t \in T \quad (4)$$

$$e_i \geq q_{it} \cdot (t+1), \forall i \in V, t \in T \quad (5)$$

$$r_i^{min} \leq \sum_{k \in Q} r_{it}^k \leq r_i^{max}, \forall i \in V, t \in T \quad (6)$$

$$\sum_{t \in T} q_{it} = e_i - s_i, \forall i \in V \quad (7)$$

$$r_{it} = \sum_{k \in Q} r_{it}^k, \forall i \in V, t \in T \quad (8)$$

$$v \cdot \sum_{t \in T}\sum_{k \in Q} r_{it}^k \geq w_i, \forall i \in V \quad (9)$$

$$b_i + l_i \leq L, \forall i \in V \quad (10)$$

$$b_i + l_i \leq b_j + M(1 - y_{ij}), \forall i, j \in V, i \neq j \quad (11)$$

$$e_i + \theta_i \leq s_j + M(1 - z_{ij}), \forall i, j \in V, i \neq j \quad (12)$$

$$y_{ij} + y_{ji} + z_{ij} + z_{ji} \geq 1, \forall i, j \in V, i \neq j \quad (13)$$

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$$r_{it}^{k+1} + r_{it}^{k-1} - r_{it}^{k} \in \{-1,0,1\}, \forall i \in V, t \in T, k \in Q \tag{14}$$

$$\sum_{i \in V} r_{it}^{k} \leq 1, \forall t \in T, k \in Q \tag{15}$$

$$\sum_{t \in T} \sum_{q \in Q} \theta_{itq} = 1, \forall i \in V \tag{16}$$

$$\theta_i = \sum_{t \in T} \sum_{q \in Q} \theta_{itq} \cdot t, \forall i \in V \tag{17}$$

$$\sum_{t \in T} \sum_{k \in Q} r_{it}^{k} = \sum_{t \in T} \sum_{q \in Q} \theta_{itq} \cdot q, \forall i \in V, k, q \in Q \tag{18}$$

$$v \sum_{t \in T} \sum_{k \in Q} r_{it}^{k} \geq w_i + v \sum_{t \in T} \sum_{q \in Q} \theta_{itq} \cdot t, \forall i \in V \tag{19}$$

$$A_i \leq s_i \leq H, \forall i \in V \tag{20}$$

$$0 \leq \theta_i \leq B_i, \forall i \in V \tag{21}$$

$$q_{it}, y_{ij}, z_{ij}, \theta_{itq}, r_{it}^{k} \epsilon \{0,1\}, \forall i, j \in V, t \in T, k \in Q, i \neq j \tag{22}$$

The objective function (1) takes the penalty cost of minimizing the delayed departure of a ship, the increased terminal transport cost when a ship deviates from its preferred docking location, and takes it as the performance optimization objective, and takes the buffer time as the robust performance index.Constraint (2) To ensure that the number of quay Bridges for service vessels in any period of time does not exceed the total number of available quay Bridges; Restraint (3), (4) and (5) to ensure that there is no shore bridge to serve the vessel before and after berthing; Constraint (6) denotes the specific range of quay Bridges serving a ship; Constraint (7) to ensure that there is a quay bridge to serve the vessel after berthing;Constraint (8) represents the relationship between decision variables and; Constraint (9) Ensure that the number of quay Bridges provided can complete the loading and unloading tasks of the ship; (10) Guarantee that the berthing position of all vessels must be within the shoreline of the wharf; Constraint (11) represents the berthing position relationship between the two ships; Constraint (12) represents the berthing time relationship between two ships; Constraint (13) ensures that there will be no conflict between any two vessels in berthing position and time; Constraint (14) Guaranteed that the quay Bridges serving the same ship must be continuous and cannot cross and cross between the quay Bridges; Constraint (15) ensures that each quay bridge can only serve one ship at a time; Constraints (16) and (17) define the domain and interrelationship of decision variables; Constraint (18) means that the number of shore Bridges in the buffer time remains constant; Constraint (19) ensures that the vessel's task quantity can be met and that the vessel still occupies berths and quay bridge resources within the delay time; Constraints (20) and (21) define the value range of relevant decision variables; Constraint (22) defines 0-1 variables.

3.2 Mathematical model of reaction stage

Assume that the baseline scheduling result of the proactive phase is s_i^*, e_i^*, b_i^* and r_{it}^*, The new scheduling after response scheduling is s_i, e_i, b_i and r_{it}. The total cost of the base schedule and the new schedule can be expressed in the following two expressions:

$$TC^o = \sum_{i \in V} \{c_1 (e_i^* - D_i)^+ + c_2 |b_i^* - p_i| + c_3 \sum_{t \in T} r_{it}^*\} \tag{23}$$

$$TC^n = \sum_{i \in V} \{c_1 (e_i - D_i)^+ + c_2 |b_i - p_i| + c_3 \sum_{t \in T} r_{it}\} \tag{24}$$

So the increment of the total cost :

$$\Delta TC = TC^n - TC^o \tag{25}$$

For the vessels, the time deviation of each ship's baseline dispatch and the time deviation of the new dispatch can be expressed by the following two formulas:

$$TD_i^o = (e_i^* - D_i)^+, TD_i^n = (e_i - D_i)^+ \tag{26}$$

Then the incremental time deviation of vessel i delayed departure from port :

$$\Delta TD_i = TD_i^n - TD_i^o \tag{27}$$

we can obtain the negative deviation cost caused by deviating from the originally planned schedule in consideration of the port planner and vessel owners' perspectives.

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For the port planner

$$\mu(TC^n) = \begin{cases} 1 & \Delta TC \geq \left(1/\sigma_1\right)^{1/\tau_1} \\ \sigma_1(\Delta TC)^{\tau_1} & 0 \leq \Delta TC < \left(1/\sigma_1\right)^{1/\tau_1} \\ 0 & \Delta TC < 0 \end{cases} \tag{28}$$

For the owner of vessel i

$$\mu(TD_i^n) = \begin{cases} 1 & \Delta TD_i \geq \left(1/\sigma_2\right)^{1/\tau_2} \\ \sigma_2(\Delta TD_i)^{\tau_2} & 0 \leq \Delta TD_i < \left(1/\sigma_2\right)^{1/\tau_2} \\ 0 & \Delta TD_i < 0 \end{cases} \tag{29}$$

The objective is to minimize the weighted average sum of membership function of deviation cost caused by deviation from proactive dispatching, taking into account the decision-making attitudes of ports and vessels.

$$\min f(x) = \lambda * \mu(TC^n) + (1-\lambda) * \frac{\sum_{i=1}^{V} \mu(TD_i^n)}{V} \tag{30}$$

Where x is the decision vector, and λ is the tradeoff coefficient between the port and the vessel.

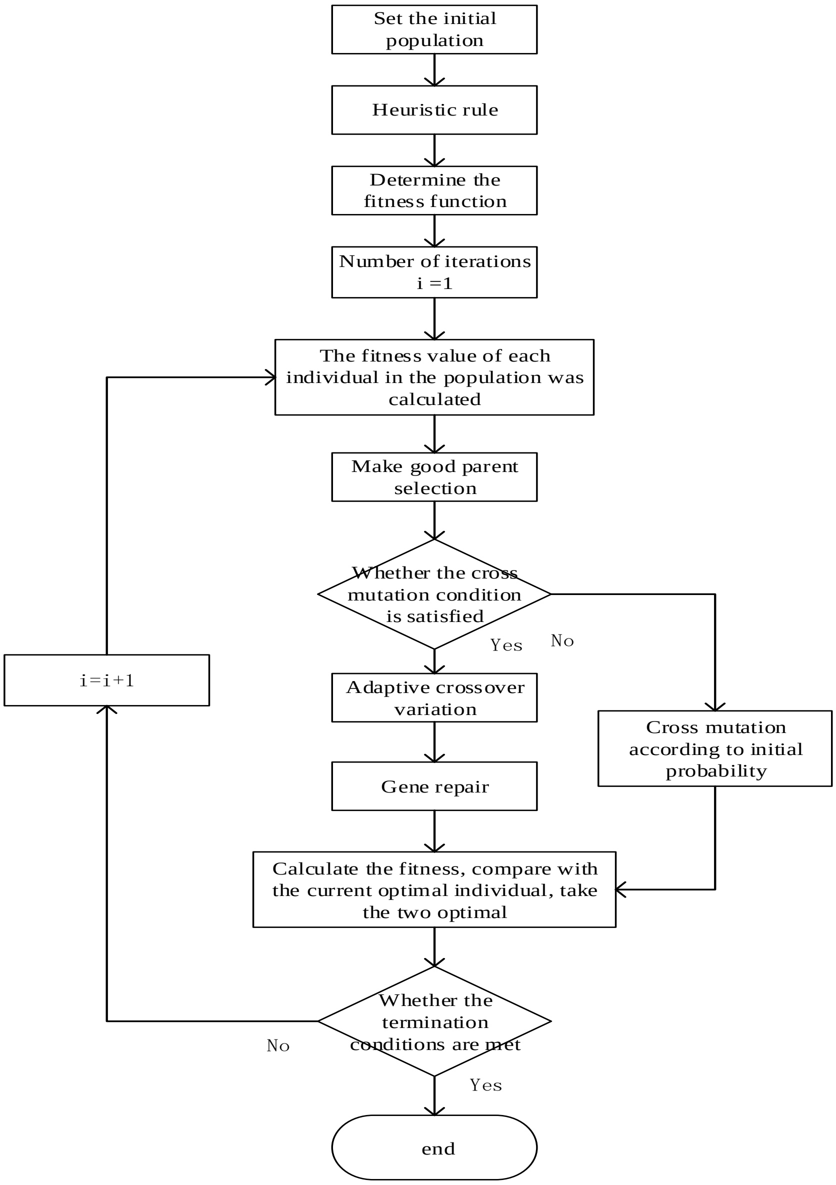

Fig. 2 Structure diagram of the improved adaptive genetic algorithm

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4. Solution algorithm

Since the integrated scheduling problem of berth quay bridge belongs to NP problem [11], an improved genetic algorithm combining adaptive genetic algorithm and heuristic method is proposed to solve the model. The algorithm flow chart is shown in Figure 2.

4.1 Chromosome encoding

Based on the characteristics of the model, the matrix encoding method of natural number is adopted. The chromosome is composed of a two-dimensional array, which contains five parts: the ship's berthing order, the berthing time, the berthing position, the number of shore Bridges allocated by the ship and the buffer time added by the ship. An example of the encoding of a chromosome is shown in Table 1.

Table 1. Chromosome

attribute	gene 1	gene 2	gene 3	gene 4	gene 5
Order of arrival	1	2	3	4	5
Time of arrival	12	37	41	61	72
Berthing position	847	21	531	70	232
QC number	4	5	3	2	4
Buffer time	2	1	2	1	3

4.2 Population initialization

Vessels are arranged in the port arrival order according to the plan, and the part of the berthing position of the ship in the chromosome is randomly generated within the range of $[0, L-l_i]$, The assigned code of the number of quay Bridges is based on the number of quay Bridges required by each vessel. Random between $[r_i^{min}, r_i^{max}]$. The actual arrival time of the ship is uniformly distributed $[C_i - \Delta C_i, C_i + \Delta C_i]$ with the mean value of the planned arrival time, and the added buffer time is generated randomly. Confined by the actual arrival time of the ship, the upper limit of the initial buffer time is $\theta_0 = 3.5$.

4.3 Fitness function

According to the characteristics of the objective function solved by the model, the following formula is used to calculate the individual fitness value in the population, where $Fit(x)$ is the individual fitness value in the population, and $f(x)$ is the objective function to be solved. α is a parameter related to the size of the problem, and its value will be determined during the parameter test of the genetic algorithm.

$$Fit(x) = \{1 + exp[f(x)/\alpha]\}^{-1} \tag{31}$$

4.4 Genetic manipulation

The improved adaptive genetic algorithm adopts adaptive crossover and mutation, and the probability of crossover and mutation is reduced to protect the survival of superior individuals when the applicable value of the population is relatively dispersed. When the individual fitness values of the population tend to be the same or the local optimal, the crossover and mutation probabilities increase to escape the local optimal solution. The formula of crossover probability and mutation probability is

$$P_c = \begin{cases} P_{c1} - (P_{c1} - P_{c2})(f_{avg} - f)/f_{avg} - f_{min}, & f \le f_{avg} \\ P_{c1}, & f > f_{avg} \end{cases} \tag{32}$$

$$P_m = \begin{cases} P_{m1} - (P_{c1} - P_{c2})(f_{avg} - f)/f_{avg} - f_{min}, & f' \le f_{avg} \\ P_{m1}, & f' > f_{avg} \end{cases} \tag{33}$$

Where P_{c1}, P_{c2}, P_{m1}, P_{m2} are the predefined parameters, f_{min}, f_{avg} are the minimum and average fitness values respectively, and f, f' are the fitness values of the larger fitness values and the mutant individuals in the two crossover individuals respectively.

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4.5 Algorithm comparison

In the algorithm, parameters are set as follows: population size 300, iteration times 600, $P_{c1} = 0.7$, $P_{c2} = 0.3$, $P_{m1} = 0.25$, $P_{m1} = 0.18$, Weight coefficient $\gamma = 0.33$, According to the improved adaptive genetic algorithm, the optimal convergence graph is calculated and drawn, as shown in Fig. 3. Experimental data was generated by the rules in Table 2. It can be seen from the convergence graph of algorithm optimization that the convergence result of the improved adaptive genetic algorithm is better than that of the standard adaptive genetic algorithm for the same number of iterations. In terms of convergence value, the convergence value of the improved adaptive genetic algorithm is 348.17, while that of the standard adaptive genetic algorithm is 360.41, and the improved adaptive genetic algorithm is better than the standard adaptive genetic algorithm in terms of convergence speed.

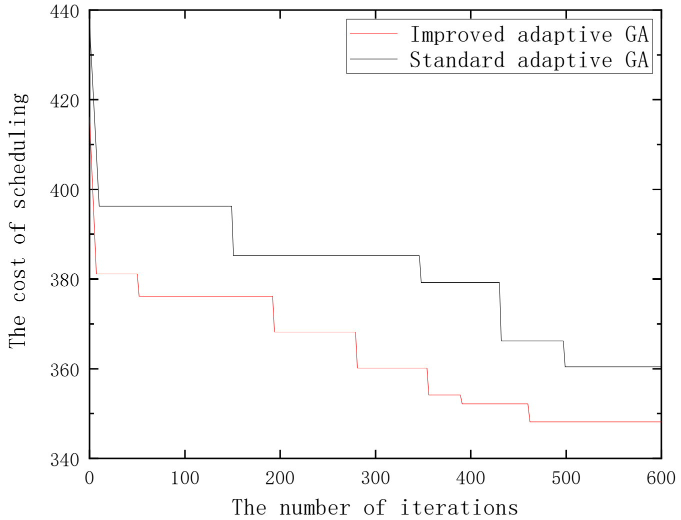

Fig. 3 The algorithm optimizes the convergence graph

5. Computational experiment

A automation in domestic terminal as the background, the automation terminal's coastline is 1200 m, a total of 15 configuration, gantry cranes, and assume that shore bridge uniform distribution of the initial position from left to right in a range of $[0,1200]$, according to the integrated scheduling berth shore bridge planning cycle is 96 h, a plan within the term of a total of 15 to the port of shipping, to test and verify the effectiveness of the proposed model and algorithm, Use the [12] such as Xiang berth gantry cranes scheduling problem in the research of random examples, case parameters generated rules as shown in table 1, 5 groups example rules generated by table 2, The actual arrival time of A_i ship follows the distribution of $[C_i - 2, C_i + 2]$.

Table 2. Parameter generation rule

Parameter	Settings
l_i	$U(70,\ 340)$
w_i	$U(200,\ 3400)$
r_i^{max}	$[l_i/50]$
r_i^{min}	$r_i^{max} \times 0.3 + 1$

5.1 Selection of weight coefficient γ

The weight coefficient γ is a key parameter to optimize the objective function. Before comparing the model results, a reasonable weight coefficient should be determined. Therefore, in order to avoid the

ISSN: 2414-1895 DOI: 10.6919/ICJE.202108_7(8).0010

occurrence of accidental errors, 5 groups of examples generated by the rule in Table 2 were selected for experimental analysis, including 1, 1/3, 1/5, 1/7 and 1/9 respectively. The total scheduling cost changes under different weight coefficients are obtained, as shown in Fig. 4. It can be seen from the figure that the optimal scheduling cost corresponds to the weight coefficient in the range of approximately 1 to 1/3. Therefore, 1/3 of the weight coefficient was selected in this experiment.

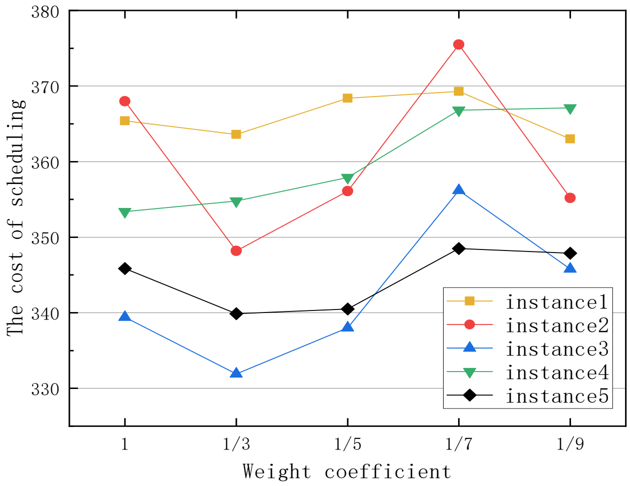

Fig. 4 Selection of weight coefficient

5.2 Performance analysis of scheduling strategy

This section evaluates the performance of the model by comparing it with other scheduling policies.

Rescheduling strategy (RP): Right-shift strategy ($Right\ Pushing$) is one of the most common methods used to schedule the system under uncertain conditions [12], and it basically follows the initial scheduling plan. However, when uncertainty occurs, subsequent scheduling is delayed until the effect of uncertainty is over.

In order to evaluate the performance of method ($PRSM$) in this paper and the above scheduling strategy, the following four performance comparisons are made.

Total dispatching cost (TC): This index reflects the overall dispatching performance of the terminal and also represents the interests of the port side;

Mean time deviation (TD_a): This indicator reflects the average dispatch performance of ships and also represents the interests of ships;

Maximum time deviation (TD_m): This indicator reflects the extent of the ship's time deviation;

Quay axle configuration cost(QC_s): This indicator reflects the performance of quay axle scheduling.

According to the rule in Table 2, we designed 5 groups of calculation examples, and the number of ships arriving at the port within the planning period is 15.

We compared the performance of the two scheduling strategies in the following two scenarios. According to the frame diagram of the proactive response scheduling model ($PRSM$) in Figure 1 and the actual dock operation scenario, this experiment can be divided into two scenarios:

Scenario 1: Only the ship arrival time is uncertain, but there is no uncertainty of sudden failure of quay bridge.

Scenario 2: Uncertainty of ship arrival time and sudden failure of quay bridge occurs

Table 4 shows the two scheduling strategies RP and $PRSM$ scheduling performance under Scenario 1. The mean value of the total scheduling cost under the two scheduling strategies and is 404.38 and 348.20 respectively, which increases by 38.1% and 18.9% respectively compared with the initial scheduling model, and the mean value of the time deviation obtained by the method in this paper is

ISSN: 2414-1895 DOI: 10.6919/ICJE.202108_7(8).0010

optimized by 43.4% compared with the strategy RP. In addition, the time deviation degree of the strategy RP is large. It shows that some ships deviate seriously from the original planned sailing date, and the time deviation degree of the method in this paper does not change much compared with the initial scheduling model, which reflects the applicability of the method in this paper when only the ship arrival time is uncertain.

Table 4. Comparisons between two different reschedule policies for Scenario I

instance	OSM				RP				$PRSM$			
	TC	TD_a	TD_m	QC_s	TC	TD_a	TD_m	QC_s	TC	TD_a	TD_m	QC_s
1	304.30	1.72	3.24	74.51	408.14	5.04	7.27	112.87	348.17	3.39	4.24	87.52
2	322.17	2.91	3.80	79.12	415.53	6.13	7.95	97.90	363.63	3.58	5.27	83.67
3	274.61	2.55	4.23	59.70	412.40	5.71	8.12	95.16	354.82	3.23	4.73	76.30
4	297.85	1.58	3.91	83.27	387.11	4.23	7.43	109.81	331.85	2.71	4.58	91.15
5	265.52	1.49	3.35	63.14	398.21	5.48	7.85	104.54	342.52	2.15	4.67	85.13
Avg	292.89	2.05	3.70	71.95	404.28	5.32	7.72	104.06	348.20	3.01	4.94	84.75

Table 5 shows the scheduling performance of the two scheduling policies under Scenario 2. It can be seen that the scheduling costs of the two scheduling strategies increase significantly when the ship arrival time is uncertain and the quakeshop sudden failure is uncertain at the same time. The average scheduling costs of the two strategies are 438.39 and 388.13, respectively. Compared with the RP strategy, the scheduling costs obtained by the proposed method PRSM are optimized by 11.5%. The average time deviation of the PRSM strategy was optimized by 40.9% compared with the RP strategy. It shows that the proposed method can effectively reduce the profit loss of port and ship when facing two kinds of uncertainty problems simultaneously. Compared with the RP strategy, the distribution of maximum time deviation and quay axle configuration cost under the PRSM strategy is optimized by 37.3% and 27.1%, which indicates that the proposed method can reduce the ship date variation and improve the quay axle scheduling performance.

Table 5. Comparisons between two different reschedule policies for Scenario II

instance	OSM				RP				$PRSM$			
	TC	TD_a	TD_m	QC_s	TC	TD_a	TD_m	QC_s	TC	TD_a	TD_m	QC_s
1	304.30	1.72	3.24	74.51	434.73	6.07	9.27	169.70	395.84	3.57	5.82	113.79
2	322.17	2.91	3.80	79.12	456.20	5.41	8.95	189.43	409.31	3.85	6.03	122.08
3	274.61	2.55	4.23	59.70	432.57	5.63	9.32	154.72	378.04	3.91	5.63	121.95
4	297.85	1.58	3.91	83.27	447.82	6.25	8.73	162.08	384.50	3.14	5.14	139.71
5	265.52	1.49	3.35	63.14	420.64	5.87	8.53	158.56	372.98	2.85	5.46	110.83
Avg	292.89	2.05	3.70	71.95	438.39	5.85	8.96	166.90	388.13	3.46	5.62	121.67

Combines two experimental analysis, the main reason is that heavy scheduling policy RP need and in view of the existing in the experiment to time of arrival of the ship and shore bridge abrupt failure of two different types of uncertainty scheduling schemes, and the proactive response scheduling policy through proactive stage can effectively deal with the issue of vessel arrival time uncertainty, reaction stages and combined with prospect theory model, In the face of sudden uncertainty problems, it is easier to deal with, and can provide a better scheduling scheme. Obviously, the proactive response strategy is more suitable for the real operation scene of the dock. It has the adaptability to the influence of various uncertain factors and can bring more benefits to the port and the ship.

6. Conclusion

For automation terminal in the actual operation in the process of the typical uncertain problems, that is, at the same time for shipping to port of time and land bridge fault the two different types of uncertain disturbance, and proactive scheduling strategy is proposed in this matching response strategy of combining the decision-making framework, view of the problem of uncertainty in ship's

ISSN: 2414-1895 DOI: 10.6919/ICJE.202108_7(8).0010

actual arrival time, Consider when making proactive scheduling plan is to build a robust plan and a certain amount of time can be set for each ship buffer, use of redundant time strategy to deal with random scene, actively considering uncertain factors, robust proactive scheduling model is established, considering proactive scheduling scheme in the implementation process, Shore bridge due to unpredictable failures, uncertainty, quantitative, to the cost of land bridge before and after the fault based on prospect theory analysis in the face of uncertain conditions scheduling policy, at the same time, considering the interests of the terminal and ship's preference, taken before scheduling plan as a benchmark reference points, to handle the land bridge sudden fault and to restore its interference minimizing cost targets, The corresponding response scheduling model is established. At the same time, compared with other scheduling strategies, it is proved that the proposed proactive response strategy can effectively reduce the cost of terminal scheduling and ship time deviation for uncertain disturbances such as ship arrival time and quay bridge sudden failure. In addition, through the experimental analysis of quay axle fault number, the results show that the interest preferences of different decision makers will also lead to different scheduling costs and time deviations, which can bring reference value to the actual operation of the automated terminals.

Acknowledgments

This research was supported by the Shanghai Pujiang Program (16PJC043).

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