

# Optimization Approach for Yard Crane Scheduling Problem using genetic algorithm in Container Terminals

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**Abstract.** *As the core operational issue in container terminals, yard crane scheduling problem directly affects the overall operation efficiency of port connecting highway or railway transportation and sea transportation. In practice, the scheduling of yard cranes is subject to many uncertain factors, so the scheme may be inapplicable and needs to be adjusted. From the perspective of proactive strategy, considering fluctuations in arrival time of external trucks as well as varied handling volume of yard cranes, a stochastic programming model is established in this paper to obtain a fixed scheme with the minimum expected value of yard crane makespan and total task waiting time over all the scenarios. The scheme does not require rescheduling when facing different situations. Subsequently, two algorithms based on certain rules are proposed to obtain the yard crane operation scheme in the deterministic environment, which are taken as the basic solution in the uncertain conditions, and then a tailored genetic algorithm is adopted to find the optimal solution with good adaptability to the uncertain scenarios. Finally, we use small-scale examples to compare the performance of algorithms in the deterministic and uncertain environment and then analyze the relationship between different yard crane configurations and the number of tasks. Large-scale experiments are performed to study the operation efficiency of the storage yard with different handling volumes assigned to each yard crane.*

## 1. Introduction

Accompanied with the development of the world economy and the increasing degree of global integration, container transportation has become an important logistics mode in international trade. As an important node connecting sea and land in the process of container transportation, the ports' throughputs have increased rapidly year by year. The configuration of the container terminals mainly consists of the intelligent gate, the container yard, and the quayside, as shown in Figure 1, where the container yard is the operation area to store the imported containers and exported containers. Yard crane is one of the key equipment and

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important resources in container yard, the operation efficiency of which may directly affect the scale and operation process of the whole port [1]. Yard crane scheduling scheme plays a crucial part in the operation process of containers in the port, including the handling sequences of tasks, the access time of each task, and the number of tasks assigned to yard cranes. Each task corresponds to a specific container, which is transported horizontally by trucks to or from one side of container blocks.

In reality, the actual arrival time of trucks loading exported containers or retrieving imported containers can be earlier or later than their appointed time. Any changes may have an impact on the suitability of the existing plan, which will lead to an increase of extra cost due to scheme adjustment. In this paper, we adopt two rule-based algorithms to generate an initial scheduling scheme with determined environment, then we deal with the uncertain situations by many scenarios, and a proactive scheduling plan is produced with minimum expected value of the sum of yard crane makespan and total task waiting time over all the scenarios through a tailored genetic algorithm.

The rest of this paper is organized as follows. After summarizing the related literatures in Section 2, the detailed description of the problem and the mathematical model with fundamental constraints are presented in Section 3. Subsequently, Section 4 puts forward the solution methods. Section 5 includes a series of experiments and the results are discussed, following with concluding remarks and future research topics in Section 6.

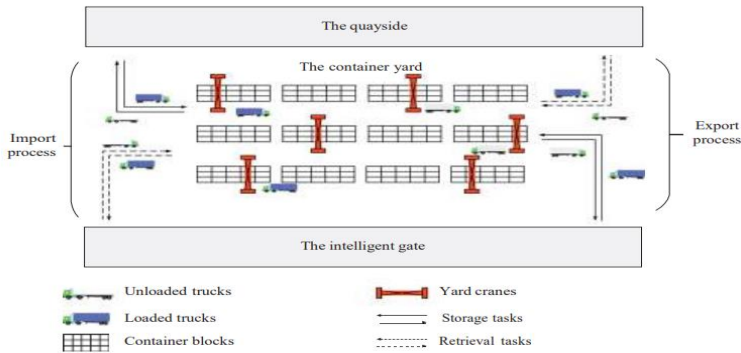


Fig 1: Configuration of the container terminal.

## 2. Literature Review

With the increasing importance of container transportation, scholars from various countries have been exploring effective methods to promote the container operation efficiency in the ports.

### 3.1. In the Deterministic Environment.

For the scheduling problem of a single yard crane, Kim et al. [2] are the first scholars to put forward the integer programming model to address the path problem and loading sequence of export containers. Narasimhan and Palekar [3] referred to the problem of minimizing the time needed for containers to be carried from the yard to the ship as the transtainer routing problem, proving that this problem is NP-complete. Ng and Mak [4] added storage containers based on the research in [2] to deliberate the scheduling problem of single yard crane to process loading/unloading tasks with different job ready times. For the scheduling problem of multiple yard cranes, Zhang et al. [5] considered the problem of deployment of multiple yard

cranes in a container yard with the aim of finding out the number and route of yard cranes moving between different blocks. However, the handling sequence of containers is not considered. Li et al. [6] extended the previous problem by solving scheduling problems for multiple yard cranes considering both storage and retrieval jobs, and some constraints in realistic operations, such as the interference and safe distance between cranes, are also put forward. Furthermore, Chang et al. [7] applied genetic algorithm to the similar scheduling problem of yard crane based on the idea of rolling horizon. Guo et al. [8] are also interested in yard crane dynamic scheduling problem. On the basis of predicting the arrival time of the vehicles, a YC management scheme with the shortest average waiting time of vehicles is proposed. Moreover, in the work of He et al. [9] and Sha et al. [10], the optimization of energy consumption is further added to the traditional yard crane scheduling problem. Wu et al. [11] addressed the yard crane scheduling problem based on continuous time. A clustering redistribution algorithm is proposed and its robustness and stability are verified by simulation. Galle et al. [12] not only considered the yard crane scheduling problem but also studied the container relocation problem. They simultaneously solved the handling sequence of containers and the location decisions of storage and turnover containers. Zhang et al. [13] studied the similar problem of gantry cranes scheduling for containers transhipped from highway to railway based on improved TSP.

### **3.2. In the Uncertain Environment**

The research on the uncertainty of port operations started late, and most references focus on the quayside [14–20] and resource allocation problem [21–23], whereas the uncertain yard crane scheduling is involved less. In the work of [24], the cycle operation of a yard crane is divided into different basic movements, of which the expectation and variance formulas are analyzed and deduced. Lu and Le [25] came up with a comprehensive scheduling optimization method for equipment in container terminals under uncertainty based on particle swarm optimization, aiming to minimize the operation time of yard cranes while coordinating quay cranes and truck operations. Considering uncertain friction, Yang et al. [26] developed a new output feedback control method for tower cranes to accomplish rapid jib and trolley positioning and payload sway suppression. Yang et al. [27] addressed the control problem for a class of multi-input and multi-output underactuated systems subject to plant uncertainties and actuator dead zones. The proposed method is verified by two kinds of cranes. He et al. [28] handled uncertainty based on uncertain scenario and employed VRP to formulate the yard crane scheduling problem, aiming to reduce the extra loss of adjusting schedule. Zhou et al. [1] addressed an approach of rolling-horizon strategy to deal with the interference factors on the retrieval operation of external trucks. They mainly optimized the task delay penalty cost and yard crane movement cost. Zheng et al. [29] studied the scheduling problem of a single yard crane with fixed operation area in a single block and formulated a two-stage stochastic programming model considering the uncertain release time of retrieval containers. A processing schedule is produced over all the uncertain scenarios. Lu [30] put forward a joint scheduling optimization model of automated guided vehicle and auto yard crane and handled uncertain variables with given distributions. The literatures closely related to the problem studied in this paper are summarized in Table 1. As stated above, it can be summarized that reactive strategy [1, 28] and proactive strategy [29, 30] are the two main methods on yard crane scheduling problem to deal with uncertain factors. This paper is oriented around the scheduling of multiple yard cranes under multiple uncertainties. Different from other studies, we produce a fix scheme adaptable to most uncertain cases for yard crane scheduling problem under uncertainties for the purpose of avoiding additional adjustment costs caused by rescheduling. The main contributions of this work are as follows: (1) a stochastic expected value model with uncertain parameters is presented for minimizing the

expected value of yard crane makespan and total task waiting time, (2) two rule-based heuristic algorithms and a tailored genetic algorithm are developed to obtain the baseline schedule based on proactive strategy, and (3) the influence of different yard crane configurations and varied handling volume is measured.

### 3.3. Problem Description

The growing volume of containers has brought pressure to the management of storage yard in port, which involves different resources such as yard trucks, yard cranes, and container blocks [31]. An efficient control method of cranes plays an important role in various fields of modern industry [32]. In many studies of yard crane scheduling problem, each yard crane is responsible for the designated container blocks, in which case the problem can be simplified, but the flexibility of yardcranes and some schemes with better results may be missed. In this paper, the yard cranes would not be restricted in a fixed container block, but the same row. The YC scheduling scheme may significantly impact the operation efficiency of container terminal, but in reality, the scheme may not always be appropriate due to uncertain factors. For example, Figure 2 shows a small example of yard crane scheduling, where the arriving sequence of tasks is assumed to be 1-3-2-4-8-6-7-9-5. The task sequence of YC1 is 4-6-9, the task sequence of YC2 is 2-8-5, and the task sequence of YC3 is 1-3-7. If task 2 arrives late, there will be a cross when YC1 accesses task 9 after handling task 6 while YC2 is to travel from task 2 to task 8. Besides, task 8 and task 9 may interfere with each other and one of them is forced to wait until the other finishes because the yard cranes could not be adjacent to each other for reasons of safety, in which case the subsequent tasks would be delayed. However, the schemes YC1: 2-4-6, YC2: 3-8-9, and YC3: 1-7-5 can deal with this situation better. Thus, it is necessary to develop a model to consider the interference of uncertain scenarios. In each scenario, the actual arrival times of tasks fluctuate randomly around the planned arrival time, and the handling volume of tasks assigned to each yard crane is also uncertain. Thus, a proactive scheduling scheme is produced with minimum expected value of two objectives over all the scenarios. Generally, the optimization goal of yard crane scheduling problem is to minimize the finish time of all tasks. However, the equipment scheduling schemes with close makespan may have a large gap in the corresponding total waiting time of the tasks. We randomly generate 1000 sets of feasible operation sequences of 30 tasks processed by 3 yard cranes and calculate the makespan of yard cranes and the total waiting time of tasks corresponding to each sequence. The results are shown in Figure 3, in which the sequences are sorted according to the value of makespan. It can be seen that the makespan of yard cranes and the total waiting time of tasks have the same change trend on the whole. However, for the similar results of makespan, there are many schemes in which the total waiting time of tasks varies greatly. The long waiting time of the task will affect the delivery of the container and the turnaround time of trucks. Therefore, the minimum mathematical expectation of the sum of yard crane makespan and task waiting time over all the scenarios is taken as the objective function in this paper.

### 3.4. Assumptions.

To ensure that the model can reasonably describe the problem above, several assumptions are given. Assumption 1. All the containers are located on the top of the stacks and accessible.

Assumption 2. The traveling speed of each yard crane is the same, without considering the additional time consumption caused by equipment starting and turning.

Assumption 3. The locations of containers are known beforehand.

Parameters and Variables.

The above problem can be described as a stochastic programming model using the following parameters and variables.

Parameters and sets: N: The set of all tasks

Table1: Comparison of research on similar yard crane scheduling problem

Literature	Subject	Outcome	Uncertainties				Approach
			Arrival time of trucks	Speed of trucks	Handling volume of yard cranes	Speed of yard cranes	
He et al. [28]	Multiple yard cranes	Readjusted scheme	✓		✓		Three-stage GA-based algorithm
Zhou et al. [1]	Multiple yard cranes	Readjusted scheme	✓				Genetic algorithm
Zheng et al. [29]	Single yard crane	Fixed scheme	✓				Simulated annealing algorithm, genetic algorithm
Lu [30]	Automated yard cranes	Fixed scheme		✓		✓	Particle swarm algorithm
This paper	Multiple yard cranes	Fixed scheme	✓		✓		Rule-based heuristic algorithm, tailored GA

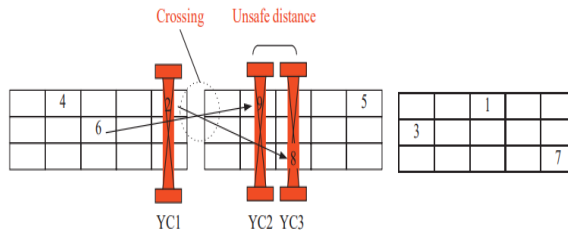


Fig 2: A sample of yard crane crossing and interference

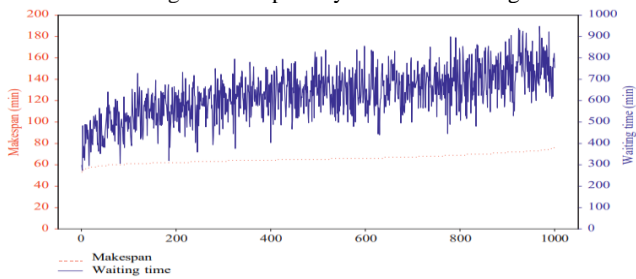


Fig 3: The experiment results of random generated sequences.

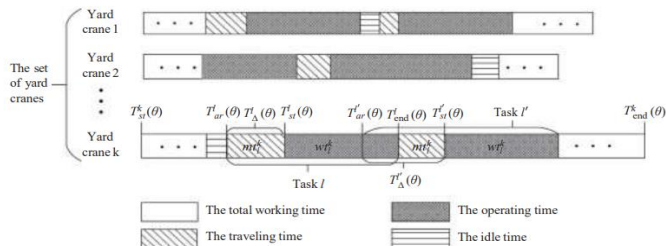


Fig 4: The time axis of yard cranes in scenario  $\theta$ .

the scenarios. Constraint (2) ensures that all the tasks should be handled. Constraint (3) defines the handling volume of each yard crane. Constraint (4) expresses the finish time of yard crane  $k$ . Similarly, constraint (5) defines the finish time of task  $l$ . Constraint (6) ensures

that the start time of any task should not be earlier than its arrival time. Constraint (7) and constraint (8) are used to determine the time relationship between two consecutive tasks. The latter task starts after the end time of the previous task with the addition of traveling time of the yard crane. Constraint (9) defines the waiting time of tasks. Constraint (10) shows the operation requirement of yard cranes. The distance between any two yard cranes at the same time must meet the safe limit. Constraint (11) ensures that yard cranes cannot cross each other. Constraint (12) is sub-tour elimination constraint. Constraints (13)–(16) guarantee the continuity of tasks and the balance of container flow. Constraints (17) and (18) indicate the first task and the last task of yard crane  $k$ . Constraint (19) ensures that each task should only be visited once by one yard crane. Constraints (20) and (21) express that each yard crane must start from and back to initial position. Constraints (22)–(24) are the restriction on the decision variables.

### 3.1. Problem Description and Mathematical Model

Many heuristic algorithms have been used to solve the scheduling problems (e.g., [33]). He et al. [28] and Zhou et al. [1] mainly used genetic algorithm to obtain a baseline schedule and then generated recovery schedules for different scenarios. In this paper, we propose rule-based heuristic algorithms to obtain a basic operation scheme in the deterministic environment, according to which the initial population in uncertain environment is generated, so as to achieve the purpose of improving the solving efficiency of the algorithm. A tailored genetic algorithm is designed for solving the problem with uncertain scenarios to obtain one well-adapted fixed scheme.

### 3.2. Rule-Based Heuristic Algorithm.

The main idea of the rule-based heuristic algorithm is to use two intuitive rules: the principle of proximity and first come first served basis. Two rule-based heuristic algorithms are designed to, respectively, produce operating sequences of tasks. Among the two solutions, the one with the best objective value is selected as the final scheduling scheme of yard cranes in the deterministic environment. The details of the rule-based heuristic algorithms are depicted below.

#### 4.2.1. The Principle of Proximity (POP)

The tasks are completed by the nearest available yard crane in order of arrival time. The candidate sets of yard cranes of the earliest task in the list are determined in turn. All the feasible yard cranes in sets  $Y1$  and  $Y2$  meet the safety distance and no crossing constraints, where idle yard cranes belong to the set  $Y1$  while working yard cranes belong to the set  $Y2$ . The set  $Y3$  contains two infeasible yard cranes locating on both sides of the task's position, in which case each of them is unable to travel to the task because the safety distance to another one is not met. The algorithm process of the principle of proximity rule is shown in Figure 5.

#### 4.2.2. First Come First Served Basis (FCFS)

The algorithm of first come first served basis is based on the work area division. Each yard crane is responsible for all tasks within a fixed area, where the number of tasks in each area is approximately the same. The corresponding schedules of yard cranes generated by the order of task arrival time are denoted by  $\alpha_1, \dots, \alpha_Y$ . On the other hand, other schedules  $\beta_1', \dots, \beta_{Y'}$  are obtained according to the shortest travel distance, taking half an hour for a period. Each yard crane operation sequence is determined in turn by comparing the value of objective

function. The specific steps of the Algorithm 1 are as follows.

### 3.3. Genetic Algorithm.

In this paper, a tailored genetic algorithm is designed where the update strategies in particle swarm algorithm is introduced. Based on the basic scheme obtained through two rules above, this algorithm uses random method to generate the initial feasible individuals. The main details of the algorithm are described as follows:

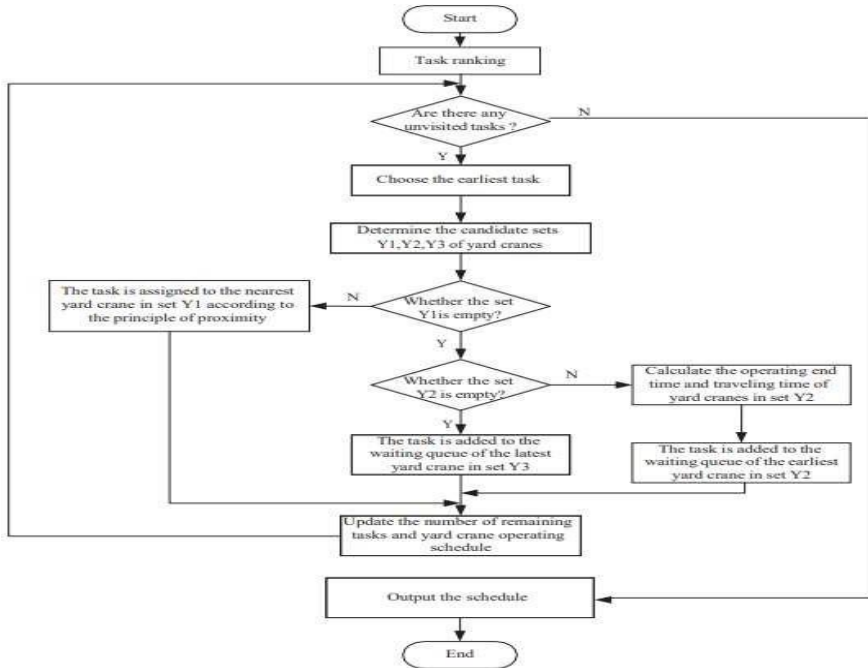


Fig5: The algorithm process of the principle of proximity rule.

- (1) *Chromosome Coding.* In this paper, the integer sequential encoding method is adopted and each code is divided into two sections, where the first section of code represents the operation order of all tasks named by numbers and the second section of code represents the handling volume of each yard cranes. Therefore, the total length of code indicates the sum of the number of tasks and the number of yard cranes (Figure 6).
- (2) *Population Initialization.* We make random changes to the sequence in the deterministic environment obtained through the rule-based heuristic algorithms introduced in Section 4.1 and retain the feasible changed sequences.
- (3) *Feasibility Judgment.* The feasibility of individuals is mainly affected by yard cranes. Yard crane operation constraints such as the prohibition of yard crane to cross each other and the limitation of safe distance are taken as conditions to judge the feasibility of each individual. To be specific, we record the change of relative position of the yard cranes by sorting their coordinates every moment.

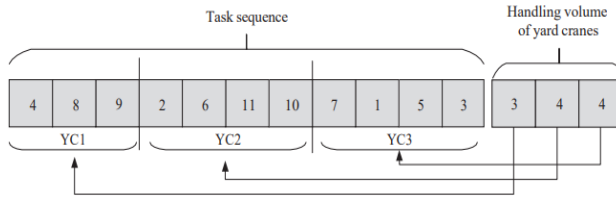


Fig 6: Coding schematic diagram.

- (1) *Fitness Calculation.* The fitness value is calculated for all individuals in the initial population, which is the reciprocal of the objective function.
- (2) *Update Strategies.* In this paper, a tailored individual update method is designed inspired by particle swarm optimization algorithm. We use the historical individual optimal solution and global optimal solution to update the chromosomes to avoid algorithm falling into the local optimal and to find the best solution along the optimal direction.  $\chi_t$

**Step 1. Crossover operation:** The coding of chromosomes contains the operation sequence of multiple yard cranes, and a large number of infeasible solutions will be generated when random exchange is due to the interference between yard cranes. Therefore, we randomly select a segment from the first section of one parent' code, which represents the operation sequence of a yard crane. The segment and the second section of the code will both be passed on to a child. The codes in other positions of the child are matched and determined in turn in order of another parent's code. An example is shown in Figure 7

**Step 2. Mutation operation:** The operation order mutation is adopted to obtain  $Z_1$  by changing the order of any two tasks in the first section. The handling volume mutation is performed by randomly interchanging the code of two sites in the second section, and the information in the first part needs to be adjusted accordingly, in which case  $Z_2$  is gained. Besides, each mutation method is accompanied by feasibility judgment, and once infeasible individual is produced, the mutation operation will be re-performed until successful. Figure 8 shows the detailed mutation operation process of an example.

**Step 3. Individual update:** The fitness values of the new individuals  $X_1, X_2, Y_1, Y_2, Z_1, Z_2$  are calculated, respectively, and the historical individual and global optimal states of the population are updated. The process of the tailored genetic algorithm is shown in Figure 9.

## 4. Computational Results and Discussion

### 4.1. Weight Experiments.

The optimal value of weight  $\phi$  in objective function is determined through small-scale experiments, where 30 tasks are handled by 3 yard cranes with 10 uncertain scenarios. It is clear that it makes no sense for  $\phi$  to be 0 or 1, and thus the weight value in experiments gradually increases from 0.1 to 0.9 with the step size of 0.1. Considering the characteristics of probabilistic convergence of the algorithm, different schemes can be obtained when the same parameters are used to solve the same example repeatedly. Therefore, each experiment is conducted 10 times and the mean value is taken as the final result



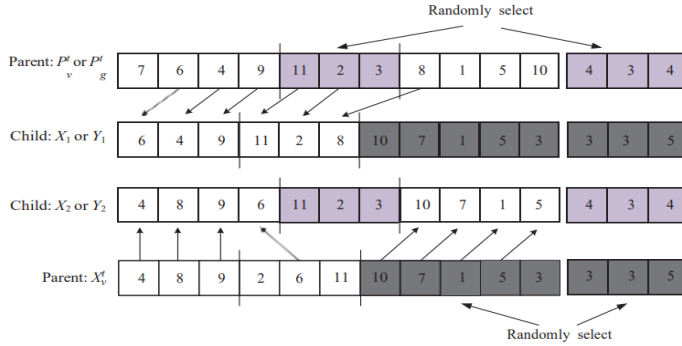


Fig 7: Crossover operation schematic diagram.

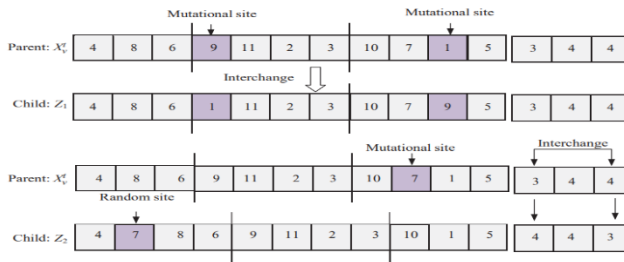


Fig 8: Mutation operation diagram.

## 4.2. Small-Scale Experiments

Through a series of experiments with different data scales, we firstly compare the performance of proposed algorithm and then analyze the sensitivity of certain parameters.

### 4.2.1. Algorithm Performance Analysis.

In the experiments, we consider a container block with 30 bays and 5 rows, where the number of tasks is 30 and the number of available yard time units. Each experiment is conducted 10 times and the mean value is taken as the final result. The results are shown in Table 3.

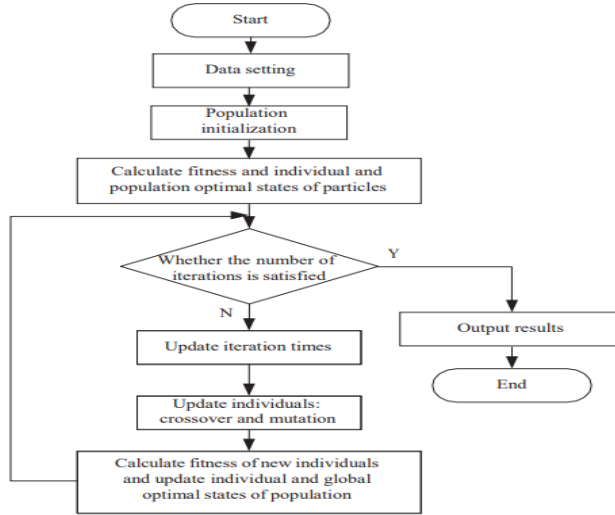


Fig 9. Process of tailored genetic algorithm.

When there are fewer tasks and fewer yard cranes, the total waiting time of tasks could be high due to the long travel distance between scattered tasks. It can be seen from Table 3 that the results of tailored genetic algorithm are optimal when the number of tasks is not more than 20 and the number of yard cranes is not more than 3. With the increasing number of tasks and yard cranes, the algorithm based on FCFS rule in the deterministic environment shows better performance compared with POP rule. However, the division of working areas of yard cranes is required ahead in this algorithm, leading to the loss of diversity and flexibility, and some schemes with better results may be missed. Meanwhile, the tailored genetic algorithm is of high complexity under uncertainty and can be time consuming, but the performance of optimizing is stable.

Table 2: The given information of tasks.

Task	Type	From	To	arrival time
1	1	0; 8	4; 8	1
2	1	0; 9	3; 9	2
3	1	0; 16	3; 16	3
4	2	1; 11	0; 11	3
5	1	0; 2	2; 2	4
6	2	1; 21	0; 21	6
7	1	0; 4	5; 4	8
8	1	0; 18	5; 18	8
9	2	2; 5	0; 5	10
10	1	0; 17	4; 17	10
11	1	0; 25	3; 25	12
12	1	0; 28	1; 28	14
13	2	3; 16	0; 16	15
14	2	4; 25	0; 25	16
15	1	0; 4	2; 4	16
16	2	2; 10	0; 10	16
17	1	0; 13	2; 13	18
18	1	0; 26	2; 26	21
19	1	0; 8	4; 8	21
20	2	5; 3	0; 3	23
21	1	0; 15	3; 15	23
22	1	0; 29	1; 29	25
23	2	5; 17	0; 17	26
24	1	0; 17	2; 17	27
25	2	3; 29	0; 29	28
26	1	0; 7	5; 7	29
27	1	0; 1	4; 1	35
28	1	0; 14	3; 14	38
29	1	0; 22	3; 22	40
30	2	2; 9	0; 9	42

#### 4.2.2. Sensitivity Analysis.

In this paper, 10 sets of experiments are carried out to analyze the influence of varying parameters on operation efficiency in terms of makespan of yard cranes and total waiting time of tasks in container terminals. Each set of experiment is repeated for 10 times and the optimal

result among them is adopted, as shown in Table 4.

It can be observed that with the same number of yard cranes, the more tasks there are, the longer the makespan of yard cranes and the longer the total waiting time of tasks it takes. When the number of tasks keeps unchanged, deploying more yard cranes can shorten the makespan and improve the operation efficiency. Moreover, the result of “30–3” shows little gap compared with results of “30–4,” which indicates that the number of yard cranes is enough to process the tasks and there is no need for another equipment. In practice, it is necessary to determine the optimal configuration of equipment considering the requirement of the balance between the equipment cost and the operation efficiency.

### 4.3. Large-Scale Experiments.

In the yard crane scheduling problem studied in this paper, the handling volume of each yard crane is uncertain, which plays a key role in operation efficiency of container terminals. A series of large-scale experiments are carried out to analyze the relationship between different handling volume assignment of yard cranes and the operation efficiency. The experiments involve 20 uncertain scenarios and 200 tasks processed by 6 yard cranes. The arrival intervals of tasks obey the exponential distribution. The container yard is of size with 30 bays and 15 rows. These specific results of experiments are shown in Table 5.

Table 3: The experiment result comparison of algorithms.

Number of tasks	Number of YCs	Deterministic environment				Uncertain environment with 20 scenarios	
		POP rule		FCFS rule		GAPSO	
		Obj	CT (s)	Obj	CT (s)	Obj	CT (s)
10	1	78.6	0.01	65.6	0.42	39.4	57.76
10	2	31.6	0.01	14.0	0.28	11.4	63.01
20	2	78.0	0.02	34.4	0.40	31.6	89.37
20	3	24.6	0.02	19.4	0.46	18.6	105.09
30	3	36.2	0.03	30.2	0.55	31.4	151.16
30	4	27.4	0.03	27.0	0.63	28.2	182.87

Note: “Obj” represents the objective function value and “CT” represents computational time.

Table 4: Sensitivity analysis of key parameters.

Number of tasks	Number of YCs	Makespan	Waiting time
10	1	23	64
15	1	35	150
20	1	51	228
15	2	21	17
20	2	26	40
25	2	47	50
20	3	25	9
25	3	29	9
30	3	43	14
30	4	43	6

Table 5: The experiment results of different handling volume assignment of yard cranes

No.	Handling volume	Makespan	Waiting time	Obj
1	35; 36; 42; 35; 29; 23	262	98	196.4
2	33; 34; 36; 31; 32; 34	260	48	175.2
3	33; 34; 34; 33; 32; 34	260	35	170
4	30; 37; 36; 31; 32; 34	260	43	173.2
5	36; 31; 33; 34; 28; 38	260	48	175.2
6	38; 29; 31; 36; 34; 32	260	60	180

It is clear that the varied handling volume of yard cranes has a noticeable impact on the operation time in the container yard when the total number of tasks keeps unchanged. When

there is a large gap between handling volume of yard cranes, the operation completion time of each yard crane is unbalanced, in which case the makespan depends on the yard crane with the largest handling volume. The busy yard crane is also responsible for the task delays, while the situation is that the yard cranes with a small amount of tasks are often idle, whose abilities are not fully used. On the contrary, the makespan of yard cranes and the total waiting time of tasks both reach the minimum when the assignment of handling volume is more balanced, which is conducive to improving the operating efficiency in container terminal and achieving the optimality of the system.

## 5. Conclusion

With the expansion of global economy, container throughput keeps the upward trend, in which case the effective management and scheduling of resources in container terminals is a necessary guarantee for the smooth circulation of container flow. The problem of yard crane scheduling with uncertain factors studied in this paper can not only adapt to the realistic situation but also reduce the extra cost of scheme adjustment due to uncertain situation. We fully consider the characteristics of dynamics, uncertainty, and complexity of the yard crane scheduling problem in the uncertain environment and design the algorithms for solving the model based on the idea of heuristic rules and genetic algorithm. Experimental results reveal that the algorithm under uncertainty is of high complexity and is time consuming, but the overall optimization ability is stable and the results are satisfactory. Besides, the changes of the number of tasks as well as the configuration of yard cranes have a certain influence on the makespan of yard cranes and the waiting time of tasks. Moreover, the experiments also indicate that the balanced assignment of handling volume of yard cranes is conducive to the improvement of the operation efficiency in container terminals.

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