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Multiobjective Scheduling for Cooperative Operation of Multiple Gantry Cranes in Railway Area of Container Terminal

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ABSTRACT Railway station plays an important role in improving the operation efficiency of rail-sea intermodal container terminal. The cooperative scheduling of multiple gantry cranes (GCs) can reduce the production and operation cost of railway station. Most studies look into discarding the conflict schemes of GCs, which may obtain excellent scheduling results. These existing conflict-free strategies can not contribute to enhancing the cooperative scheduling performance of multiple GCs. This study integrates container trucks into multiple GCs scheduling environment to eliminate those conflicts, and proposes a mixed-integer programming model considering cooperation between multiple GCs and trucks. The model aims to simultaneously minimize the makespan of the container handling system in station, the total empty travel time of GCs and the total energy consumption of both cranes and trucks. To solve the proposed model, a conflict-free operation strategy for multiple GCs based on hybrid indirect loading and unloading (CFHI) is proposed. CFHI strategy is implemented according to the cooperation between GCs and trucks. An effective multi-objective artificial bee colony algorithm (EMOABC) based on CFHI and fuzzy correlation entropy (FCE) is developed. Within the developed algorithm, an encoding/decoding method based on CFHI is designed to represent and decode the population solutions. The FCE is adopted to evaluate and select the better solutions for next iteration evolution. The effectiveness of the proposed CFHI strategy is verified by comparing it with two popular equipment allocation strategies. Extensive experimental results show that proposed EMOABC is effective to the proposed model. Our findings here have significant implications for the cooperative operation of multiple GCs considering energy consumption in container terminal.

INDEX TERMS Rail-sea intermodal, cooperative scheduling, conflict-free strategy, multi-objective optimization, artificial bee colony algorithm.

I. INTRODUCTION

Rail-road intermodal transportation, sea-rail intermodal transportation and air-rail intermodal transportation are receiving increased attention in recent years. The rapid development of sea-rail transportation actively adapts to the trend of logistics market and the change of demand structure. It not only fully expands the radiation range of rail and sea transport, but also effectively fills the shortcomings of their respective transport functions. For the rail-sea intermodal container transportation, the operation efficiency of the railway central station has a significant impact on the overall operation of the

terminal. In the railway area, the gantry crane (GC) plays an important role, undertaking the work of container grabbing, transshipment and stacking. Moreover, a batch of container tasks are usually operated by multiple GCs. The coordinated scheduling of multiple GCs considering collision-free and safety distance can determine the operation sequence of GCs. It can improve the production and operation efficiency of rail central station by reducing the operation time of GCs. With the increased attention in automated terminals and environmental pollution, the objectives of carbon emission reduction and processing time have made an urgent concern in future terminals.

Enhancing the operation efficiency is one of the primary goals for the sea-rail intermodal terminal. Some of the

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studies, conducted to date, not only focused on improving collaborative problem of multiple GCs in station, but also considered allocation strategy and algorithm for conflict-free operation. Chen *et al.* [1] adopted the strategy with fixing operation area of GCs. They transformed the GC scheduling problem into a travelling salesman problem with time window, aiming at minimizing the task tardiness. Fan *et al.* [2] studied the slot allocation and collaborative optimization problem of multiple yard cranes. They used the regional balance strategy to plan the yard crane operation area. Then, they proposed a simulated annealing genetic algorithm to solve this problem. Wang *et al.* [3] introduced a dynamic allocation strategy of GC, aiming at study the reaction of GC scheduling scheme to the bay allocation. And they proposed a three-layer hybrid heuristic algorithm to solve the joint optimization model. Zhao *et al.* [4] used the dynamic allocation strategy to solve the cooperated operation problem of multiple yard cranes. Boysen *et al.* [5] studied the operation areas of GCs. They proposed an accurate dynamic programming algorithm to divide the area into different size, aiming at ensuring rationality of processing time on each GC and reducing the makespan of total train system. Abourraja *et al.* [6] proposed a multiple GCs collaborative scheduling model, which can adjust the working area of GCs dynamically. The purpose of this paper is to reduce the waiting time of train at station and the unproductive movement of GCs. Boysen *et al.* [7] proposed a dynamic programming algorithm based on the strategy. This strategy can fix the operation area for GC. Liang *et al.* [8] studied the operation efficiency of multiple GCs by adopting the relay operation strategy. Kress *et al.* [9] applied the relay strategy to the scheduling problem for two GCs at a single storage block. Li *et al.* [10] put forward a mixed operation mode of rail-sea intermodal transport. Under this mode, the time window of trains and ships are not completely coincident. They established a cooperative scheduling model of GCs and trucks. A hybrid genetic algorithm was designed to solve this model. Jaehn *et al.* [11] considered the conflict-free scheduling problem of twin cranes at a seaport. They referred to the cranes as seaside crane and land side crane.

A review of the crane scheduling problem has indicated that scholars only focused on the GC independently. These studies ignored the cooperation between GC and other equipment in container terminals. On the other hand, they seldom considered the negative influence caused by high-power equipment such as GCs. The dispatching strategy for GCs in railway container central station can be summarized as two categories conflict-free operation strategy. The first category strategy is defined as follows: each GC completes container handling tasks within the fixed bay area, and all areas does not overlap each other (Conflict-free operation strategy for multiple gantry cranes based on direct loading and unloading in the fixed area, CFDF). CFDF strategy was used for collision avoidance in above given literatures [2], [5], [7]–[9], [11]. The second category strategy was defined as bellow: each GC completes container handling tasks within the dynamic

bay area, and these areas often overlap (Conflict-prevented operation strategy for multiple gantry cranes based on direct loading and unloading in the dynamic area, CPDD). If the collision can not be avoided, many GCs' scheduling tasks will be discarded by CPDD [3], [6], [10].

With above two strategies, all operations in station are only carried out by GCs, which may cause a long-distance movement of GC. In addition, both CFDF and CPDD increase the idle time of each GC. In view of the above research contents, this paper proposes a conflict-free equipment assignment strategy based on hybrid indirect loading and unloading (CFHI). If there arise an operation conflict between two GCs when the operation area of GC changes dynamically, a truck will be introduced for indirect loading and unloading. Using the trucks instead of GCs for horizontal transportation, not only the operation conflict between GCs can be resolved, but also the energy consumption will be reduced.

GC scheduling problem considering makespan has been studied widely in recent years. Wang *et al.* [12] proposed a hybrid particle swarm optimization algorithm to minimize the completion time of GCs in railway central station. They described the operation of cranes as point-to-point movement. Wei *et al.* [13] studied the cooperative scheduling problem of GCs. They proposed a fusion algorithm of genetic and ant colony to solve the model with the objective of minimizing the completion time. Guo *et al.* [14] studied the influence of train parking position on the operation efficiency of GCs. They established a GC scheduling model aiming at minimizing the maximum completion time. Wang *et al.* [15] used ant colony to solve scheduling model of GCs with the minimum no-load operation time. Zhou *et al.* [16] used an improved sparrow search algorithm to solve the GCs collaborative scheduling problem by taking the completion time into consideration. It is not difficult to find that existing researches typically consider on optimization objective, and there are few studies on the objectives of considering environmental pollution, carbon emission reduction and processing time at the same time.

Above all, a multi-objective GCs collaborative scheduling (MOGCCS) model considering makespan, total energy consumption and total empty travel time of all GCs is established.

In recent years, the popularity of various meta heuristic algorithm based on related population for solving complex multi-objective collaborative and scheduling problems has increased.

ABC is a well-known meta heuristic optimization algorithm for solving continuous optimization problems [17]. This is owing to its simplicity as well as properties such as a small number of parameters, quick convergence, parallel search ability, easy to code, and extendibility to other problems. Compared with the common meta heuristic algorithm, ABC algorithm uses fewer control parameters and has strong robustness. ABC algorithm can balance the global search and local search in each iteration.

Despite its strength in solving continuous optimization problems, many discrete ABCs also exist in the literature

for various discrete scheduling problems. For instance, Dong *et al.* [18] proposed a discrete adaptive artificial bee colony algorithm to solve the container scheduling problem between container yards and wharf apron. Li *et al.* [19] proposed an improved artificial bee colony algorithm (IABC) for the hybrid flow shop scheduling problem to minimize the makespan and processing cost. Zhang *et al.* [20] used an IABC to solve a bi-objective job shop scheduling problem by taking total production time into consideration. Li *et al.* [21] proposed a hybrid artificial bee colony algorithm to solve the parallel batch distributed flow shop scheduling problem.

However, there are no studies in the literature that use ABC to solve the multi-objective scheduling for cooperative operation of multiple GCs in railway area of container terminal.

Motivated by the excellent performance of ABC in solving continuous scheduling problems, we propose an effective multi-objective artificial bee colony algorithm (EMOABC) based on fuzzy correlation entropy (FCE) [22]–[24], and an encoding/decoding method based on CFHI and FCE is designed to represent and decode the population solutions. Additionally, it is meaningful to find an efficient multi-objective ABC which can produce multiple Pareto solutions effectively.

The rest of the paper is organized as follows. Section II describes and models the multiple GCs scheduling problem with horizontal transportation by trucks. Section III introduces CFHI in detail. Section IV proposes an EMOABC based on FCE. Section V makes a comparative analysis of results. Finally, Section VI concludes this paper.

II. PROBLEM DESCRIPTION AND MODELING

The multi-objective scheduling for cooperative operation of multiple GCs in railway area of container terminal can be described as follows. Taking the process of loading containers by train as an example, this paper expounds the conflict problems existing in the cooperative operation of multiple GCs in railway area. When the containers are transported to the train area, they usually need to be stacked in the yard of the train station, then loaded after the train arrives at the station. This loading process is usually only completed by the GC. The GC transports the container from the initial position in the yard to the target position on the train. Since each GC moves laterally on the same track, the two GCs can not cross each other during operation. When GC be assigned to the container handling tasks, it is very easy for multiple GCs to cross in the same time and space. As shown in Fig. 1, if GC2 is working at its current position and GC1 is assigned to the container movement task represented by the red arrow, the final handling process will lead to the conflict between GC1 and GC2.

Therefore, in order to avoid the conflict of GCs during their processing state, maintain a certain safety distance and improve the overall operation efficiency, this paper puts forward the cooperative operation strategy of GC and container truck in the process of container transportation. Similarly, taking the container moving operation task represented by the

red arrow in Fig. 1 as an example. If the container trucks are used for indirect unloading, the target container needs to be unloaded to the container truck by GC1 first, which is called container taking operation. Then, the container is transported by truck to the parking spot corresponding to the target position, which is called transportation operation. Finally, the GC2 loads the container to the target position on the train, which is called container releasing operation. This strategy uses trucks to replace the horizontal transportation operation of GC1, and avoids collision between the two GCs without waiting another GC. Additionally, as the energy consumption of GC is far greater than of truck, the CFHI strategy can effectively reduce the total energy consumption of equipment in the operation process.

On the other hand, if conflicts of multiple GCs do not occur during the processing, the CPDD strategy is still adopted.

In this paper, each yard position and carriage position are represented by coordinate points. The number the GCs, train carriages and yard bay positions in turn from left to right. The direction perpendicular to the yard and close to the railway loading and unloading line is defined as the positive direction, and number the row of the yard. According to the above regulations, the positions of all train carriages and containers in the railway container central station are represented by specific coordinate points.

A. MODEL ASSUMPTIONS

The assumptions are as follows:

- 1) All the origin and the destination position of each container are given.
- 2) Special situations such as failure of GC and truck are not considered.
- 3) The speed of GC and truck can not be changed once they begin to process an operation.
- 4) All the containers are 40ft.
- 5) All the container tasks do not need to be turned over.
- 6) All the GCs, containers and trucks are simultaneously available at time zero.

B. MODEL BUILDING

1) PARAMETERS

n : The total number of containers.

g : The total number of GCs.

q : The total number of trucks.

L_s : Safety distance.

M : A huge positive number.

p_k : The load power of GC k .

p_k^e : The no-load power of GC k .

p_k^t : The load power of GC k trolley.

p_k^{te} : The no-load power of GC k trolley.

v_m : The traveling speed of truck m under load.

v_m^e : The traveling speed of truck m under no-load.

V_k : The traveling speed of GC k .

V_k^t : The traveling speed of GC k trolley under load.

V_k^{te} : The traveling speed of GC k trolley under no-load.

p_m^t : The traveling power of truck m .

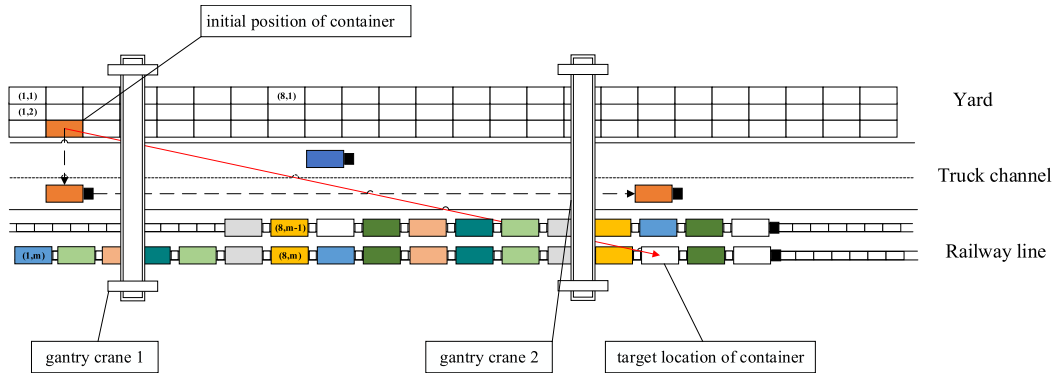


FIGURE 1. Layout diagram of railway central station.

2) VARIABLES

P_k^t : The position of GC k at time t .

P_m^t : The position of truck m at time t .

S_i^k : The time of the GC k starts to perform container i .

C_i^k : The time of GC k completes container i .

S_i^m : The time of truck m starts to perform container i .

C_i^m : The time of truck m completes container i .

P_i : The initial position of container i .

PT_i : The target position of container i .

t_k : The traveling time of GC k under load.

t_m^t : The total operation time of truck m .

t_k^e : The empty travel time of GC k .

t_k^f : The traveling time of GC k trolley under load.

t_k^e : The empty travel time of GC k trolley.

t_k^f : The earliest available time of GC k .

t_m^f : The earliest available time of truck m .

C_{max} : The maximum completion time.

T : The total empty travel time of equipment.

W : The total energy consumption.

W_R : The total energy consumption of GCs.

W_T : The total energy consumption of trucks.

3) DECISION VARIABLES

x_{im}^k : Binary value that is set to 1 when i is processed jointly by GC k and truck m , otherwise is set to 0.

y_i^k : Binary value that is set to 1 when i is processed by truck k , otherwise is set to 0.

z_i^m : Binary value that is set to 1 when container i is unloaded indirectly by truck m , otherwise is set to 0.

u_{ij}^k : Binary value that is set to 1 when container j is processed immediately after container i on GC k , otherwise is set to 0.

$\mu_i^{kk'}$: Binary value that is set to 1 when container i is processed by GC k and k' , otherwise is set to 0.

4) OBJECTIVE FUNCTION AND CONSTRAINTS

The objective functions:

$$\min C_{max} = \max\{C_i^k\} \quad (1)$$

$$\min T = \sum_{k=1}^g t_k^e \quad (2)$$

$$\min W = W_R + W_T \quad (3)$$

where C_{max} is the maximum completion time, T is the total empty travel time of equipment, and W is the total energy consumption.

The constraints are as follows:

$$C_{max} \geq C_i^k \quad (4)$$

where $\forall i = 1, 2, \dots, n; k = 1, 2, \dots, g$

$$x_{im}^k = z_i^m \cdot y_i^k \quad (5)$$

where $\forall i = 1, 2, \dots, n; k = 1, 2, \dots, g; m = 1, 2, \dots, q$

$$\sum_{k=1}^g y_i^k = 1 \quad (6)$$

where $\forall i = 1, 2, \dots, n; k = 1, 2, \dots, g$

$$\sum_{i=1}^n y_i^k \leq 2 \quad (7)$$

where $\forall k = 1, 2, \dots, g$

$$\sum_{i=1}^n z_i^m \leq q \quad (8)$$

where $\forall m = 1, 2, \dots, q$

$$\sum_{m=1}^q z_i^m \leq n \quad (9)$$

where $\forall i = 1, 2, \dots, n$

$$S_j^k - C_i^k + M \cdot (1 - u_{ij}^k) \geq 0, \quad i, j = 1, 2, \dots, n \quad (10)$$

where $\forall i, j = 1, 2, \dots, n; k = 1, 2, \dots, g$

$$|P_k^t - P_{k'}^t| + M \cdot (1 - \mu_i^{kk'}) \geq L_s \quad (11)$$

where $\forall k, k' = 1, 2, \dots, g; k \neq k'$

$$\sum_{i=1}^n \sum_{j=1}^n u_{ij}^k - \sum_{i=1}^n \sum_{j=1}^n u_{ji}^k = 0 \quad (12)$$

where $\forall k = 1, 2, \dots, g$

$$C_i^k \leq t_m^f \quad (13)$$

where $\forall i = 1, 2, \dots, n; m = 1, 2, \dots, q$

$$S_i^{k'} \leq t_m^f + \frac{|PT_i - P_k^t|}{v_m} + M \cdot (1 - x_{im}^k) \quad (14)$$

where $\forall i = 1, 2, \dots, n; k = 1, 2, \dots, g; m = 1, 2, \dots, q$

$$\sum_{k=1}^g \sum_{k'=1}^g \mu_i^{kk'} \leq 1 \quad (15)$$

where $\forall k \neq k'$

$$x_{im}^k \in \{0, 1\} \quad (16)$$

where $\forall i = 1, 2, \dots, n; k = 1, 2, \dots, g; m = 1, 2, \dots, q$

$$y_i^k \in \{0, 1\} \quad (17)$$

where $\forall i = 1, 2, \dots, n; k = 1, 2, \dots, g$

$$z_i^m \in \{0, 1\} \quad (18)$$

where $\forall i = 1, 2, \dots, n; m = 1, 2, \dots, q$

$$u_{ij}^k \in \{0, 1\} \quad (19)$$

where $\forall i, j = 1, 2, \dots, n; k = 1, 2, \dots, g$

$$\mu_i^{kk'} \in \{0, 1\} \quad (20)$$

where $\forall i = 1, 2, \dots, n; k, k' = 1, 2, \dots, g$

Equation (4) is the maximum completion time constraint in all tasks. (5) represents the constraint relationship between GC and truck. (6) represents the restriction on the number of operations of a single GC, and each GC can only operate one container task at a time. (7) represents the restriction on the number of operation equipment for a single container task. Each container task can be operated by two GCs in turn at most. (8) indicates the restriction of loading and unloading mode of each container task, and each container task can be loaded and unloaded indirectly by one truck at most. (9) represents the task quantity constraint of each truck. (10) represents the time constraint of two continuous tasks in the same GC, only after the completion of the first container task can the GC be able to operate one container after operation. (11) represents the safety distance constraint between two GCs. (12) represents the continuity constraint between tasks. (13) and (14) represent the constraints of GC operation time and truck operation time. (15) indicates the restriction of the number of GCs for indirect container operation, only one GC can operate in each operation stage of an indirect operation task. (16) to (20) represent the value constraints of decision variables.

III. CONFLICT-FREE EQUIPMENT ASSIGNMENT STRATEGY BASED ON HYBRID INDIRECT LOADING AND UNLOADING

Fig. 2 is the flow chart of the CFHI proposed in this paper. According to this strategy, the container task is allocated to one GC or two GCs and a truck, and the operation sequence of each container task is determined. In order to clearly describe

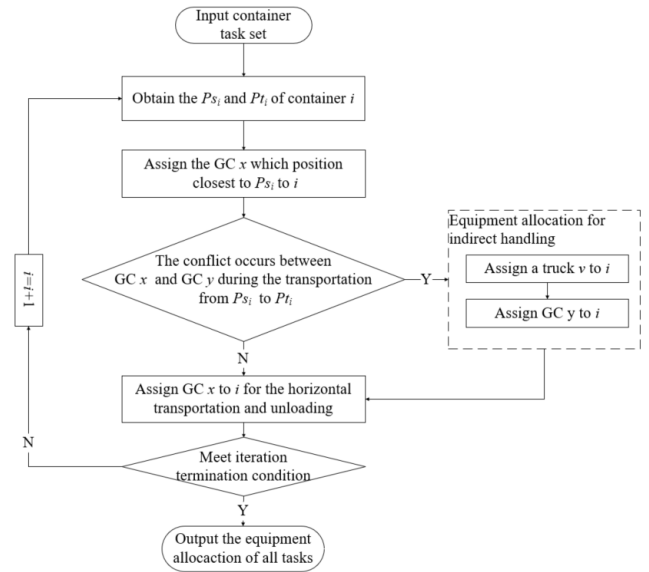


FIGURE 2. The flow chart of the CFHI strategy.

TABLE 1. Equipment assignment strategy symbols description.

Symbol	Description
i	task number
P_{si}	initial position of i
P_{ti}	target position of i
P_1	position of GC1 after completing the previous task
P_2	position of GC2 after completing the previous task
T_1	the earliest available time of GC1
T_2	the earliest available time of GC2
T_{t1}	the earliest available time of truck 1
T_{t2}	the earliest available time of truck 2

the equipment allocation strategy proposed in this paper, the design symbols are given in advance, as shown in Table 1.

Based on the generated task sequence, each GC and truck are assigned to each task according to the following allocation steps. The equipment sequence can be obtained finally.

Step1: Input task sequence.

Step2: Read P_{si} and P_{ti} of the current task i .

Step3: If $P_{si} \leq P_1$, assign i to GC1, and then judge the conflict, if there is no conflict, go to step7; if there is a conflict, delete i from the operation sequence of GC1 and go to step6; else, go to step4.

Step4: If $P_{si} \geq P_2$, assign i to GC2, and then judge the conflict; if there is no conflict, go to step7; if there is a conflict, delete i from the operation sequence of GC2 and go to step6; else, go to Step5.

Step5: If $T_1 \leq T_2$, assign i to GC1, and then judge the conflict; if there is no conflict, go to step7; if there is a conflict, delete i from the operation sequence of the GC1 and assign it to GC2 to judge the conflict; if there is no conflict, go to step7; if there is still a conflict, delete i from the operation sequence of the GC2 and go to step6; else, follow the same steps.

Step6: Divide i into three stages for operation, judge the positional relationship between P_{si} and P_1 and P_2 respectively, select the GC which is the earliest available and conforms to the positional relationship to perform the first stage of i , add the third stage of i to the operation sequence of another GC, and select the smaller truck in T_{i1} and T_{i2} from the truck pool to perform the third stage of i .

Step7: Update the time and position of GC.

Step8: Update the time and position of truck.

Step9: If i is the last task, go to step10; else $i = i + 1$ and return to step2.

Step10: Output the equipment allocation of all tasks.

IV. PROPOSED ALGORITHM

A. STANDARD ARTIFICIAL BEE COLONY ALGORITHM

The standard artificial bee colony algorithm (ABC) divides the artificial bee colony into three categories: employed bee, onlooker bee and scout bee by simulating the honey collecting mechanism of bees. The goal of the whole colony is to find the nectar source with the largest amount of nectar. In the ABC algorithm, the employed bees uses the previous nectar source information to find a new nectar source and share the source information with the onlooker bee. The onlooker bees are waiting in the hive and look for new nectar sources based on the information shared by the employed bees. The task of scout bees is to find a new and more valuable nectar source, they randomly look for a nectar source near the hive.

Assuming that the solution space is D -dimensional, the number of employed bees and onlooker bees is SN , the number of employed bees or onlooker bees is equal to the number of nectar sources, the position of each nectar source represents a feasible solution of the problem, the nectar amount of the source corresponds to the fitness of the corresponding solution, and an employed bee corresponds to a nectar source.

The employed bee corresponding to the i th nectar source looks for a new source according to the following formula.

$$x'_{id} = x_{id} + \vartheta_{id}(x_{id} - x_{kd}) \quad (21)$$

where $i = 1, 2, \dots, SN, d = 1, 2, \dots, D, k \neq i$, and ϑ_{id} is a random number in $[-1, 1]$, and. The standard ABC algorithm compares the newly generated possible solution with the original solution.

$$\text{new} : X'_i = \{x'_{i1}, x'_{i2}, \dots, x'_{iD}\} \quad (22)$$

$$\text{old} : X_i = \{x_{i1}, x_{i2}, \dots, x_{iD}\} \quad (23)$$

The greedy selection strategy is adopted to retain the better solution. Each onlooker bee selects a nectar source according to the probability. The probability formula is as follows:

$$p_i = \frac{fit_i}{\sum_{j=1}^{SN} fit_j} \quad (24)$$

where fit_i is the fitness of the possible solution X_i . For the selected source, the onlooker bee searches for a new possible solution according to the above probability formula. When all employed bees and onlooker bees have searched the whole

space, if the fitness value of a nectar source is not improved within a given step, the source is discarded, and the employed bee corresponding to the source becomes a scout bee. The scout bee searches for a new possible solution through the following formula:

$$x'_{id} = x_{id} + \vartheta_{id}(x_{id} - x_{kd}) \quad (25)$$

where r is a random number on $[0, 1]$, x_d^{min} and x_d^{max} are the bounds of the solution.

B. ENCODING

This paper adopts integer coding based on container number. H -dimensional vector is generated randomly, and each bee represents a sequence composed of H container numbers.

$$X_i = [x_{i,1}, x_{i,2}, \dots, x_{i,H}] \quad (26)$$

where H is the quantity of container tasks, $x_{i,j}$ is the container number on the i th bee individual.

C. DECODING DESIGN BASED ON CFHI

In X_i , GCs are assigned to each container task, and one or none of q trucks is assigned to each container task.

Firstly, based on the rule of the fastest completion time, the GC $r(h)$ which can minimize C_{max} is selected for the task to picking up the container $x_{i,h}$. The vector $R = [r(1), r(2), \dots, r(H)]$ with the length of H is obtained, where $r(h)$ is the number of the GC.

Then, the GC operation of each container task is judged whether a conflict occur. If the GC $r(h)$ is assigned to the container $x_{i,h}$, and a conflict is occurring, then the value of $y(h)$ is 1, otherwise it is 0. The vector $y = [y(1), y(2), \dots, y(H)]$ of length H can be obtained.

When the value of $y(h)$ is 1, it is necessary to introduce a truck for transportation, that is, CFHI is adopted. The truck with the smallest t_m^f is selected from those available trucks for indirect operation, then the number of the selected truck is assigned to $t(h)$. When $y(h)$ is 0, $C_{max} = C_h^{r(h)}$, $e = t_{r(h)}^e$, $w = w_{r(h)}$ and $t(h) = 0$. The vector $T = [t(1), t(2), \dots, t(H)]$ is obtained, and the value of $t(h)$ is the truck number or 0.

Finally, the GC $r(h)'$ which can minimize C_{max} is selected to complete the unloading operation of $x_{i,h}$, where $r(h)'$ is the container number. At this time, $C_{max} = C_h^{r(h)'}$, $e = t_{r(h)}^e + t_{r(h)'}^e$, $w = w_{r(h)} + w_{t(h)} + w_{r(h)'}$. The vector $R' = [r(1)', r(2)', \dots, r(H)']$ is composed of $r(h)'$.

To sum up, each container needs to determine whether to adopt the CFHI, that is, the value of $y(h)$ is 0 or 1. If the value is 0, the whole process including loading, transporting and unloading of $x_{i,h}$ is completed by GC $r(h)$. If the value of $y(h)$ is 1, it is necessary to determine the GC $r(h)$ in the loading operation, the truck $t(h)$ in the horizontal transportation and the GC $r(h)'$ in the unloading operation. Therefore, a feasible solution can be expressed as $S = [X; R; Y; T; R']$.

D. FUZZY CORRELATION ENTROPY

As for multi-objective optimization problems, the fitness evaluation mechanism (FEM) is a key factor affecting the

performance of multi-objective optimization algorithms. The common FEM can be divided into two categories: the weighted sum is the most used scalar aggregation function. However, it is difficult to assign relatively impartial weights to the objectives in those weighted-sum approach. Moreover, it has been identified that specification of weights may impact the distribution of the solution set, which is an important metric for evaluating a multi-objective algorithm’s performance. The second category is Pareto dominance FEMs, which employ the dominance concept to evaluate and sort solutions. It should be noted that many Pareto-based algorithms are time-consuming for large-scale problems; and when the number of objectives increases, their performance decreases rapidly.

Given the above, the FCE [23] is used as the criterion to judge the advantages and disadvantages of multi-objective optimization solution, and can overcome the defects of the fitness allocation strategy of traditional multi-objective optimization algorithm. FCE contributes to the fast convergence of a multi-objective algorithm. Therefore, this paper uses the multi-objective artificial bee colony algorithm based on FCE to solve the above three-objective optimization model.

Suppose $A, B \in FS_s(X)$, $FS_s(X)$ are the set of all fuzzy subsets on the finite discrete domain X , then the fuzzy partial entropy $E_B(A)$ of fuzzy set A about fuzzy set B and the fuzzy partial entropy $E_A(B)$ of fuzzy set B about fuzzy set A are as follows:

$$E_B(A) = - \sum_{i=1}^n \{u_B(x_i) \ln u_A(x_i) + [1 - u_B(x_i)] \ln [1 - u_A(x_i)]\} \quad (27)$$

$$E_A(B) = - \sum_{i=1}^n \{u_A(x_i) \ln u_B(x_i) + [1 - u_A(x_i)] \ln [1 - u_B(x_i)]\} \quad (28)$$

where $E_B(A)$ is the partial entropy of fuzzy set A about fuzzy set B , which represents the measurement of the uncertainty of fuzzy set A under the condition of given fuzzy set B and $E_A(B)$ is the opposite of $E_B(A)$. μ_A and μ_B are the membership function of fuzzy set A and B respectively.

The fuzzy correlation entropy of the two fuzzy sets is as follows:

$$E(A : B) = E_B(A) + E_A(B) \quad (29)$$

The fuzzy correlation entropy coefficient of the two fuzzy sets is as follows:

$$C_e(A : B) = \frac{1}{K} \cdot \frac{[E(A) + E(B)]}{E(A : B)} \quad (30)$$

where $K = \frac{1}{n \cdot \ln 2}$, which is the normalization factor.

The membership function is as follows:

$$u_M(x_i) = \begin{cases} 1 & f_M(x_i) \leq y_{Ma} \\ \frac{f_M(x_i) - y_{Mb}}{y_{Ma} - y_{Mb}} & y_{Ma} < f_M(x_i) < y_{Mb} \\ 0 & f_M(x_i) \geq y_{Mb} \end{cases} \quad (31)$$

where y_{Ma} and y_{Mb} are the bounds of sub objective M . The method of obtaining the bounds is to carry out multiple single objective optimization for each sub objective, the average value of the optimization value is taken as the lower bound of the sub objective, and the average value of the maximum value of each objective is taken as the upper bound of each objective.

E. MULTI-OBJECTIVE ARTIFICIAL BEE COLONY ALGORITHM BASED ON FUZZY CORRELATION ENTROPY

Each solution in a multi-objective problem has multiple objective function values that can construct a comparison point (CP). Suppose that there is a high-quality reference point (RP), which is the reference objective value sequence. The RP and CP can be converted into a reference fuzzy set and a comparison fuzzy set, respectively, by a membership function. Then, the similarity between the reference and comparison fuzzy sets can be evaluated by FCE.

The RP can be obtained by multiple single objective optimization for each sub objective, and according to (31), the RP set is mapped to the RP fuzzy set, and the CP set is mapped to the CP fuzzy set. Then (30) is used to calculate the fuzzy correlation entropy coefficient of RP fuzzy set and the CP fuzzy set as the fitness value of the multi-objective problem. High similarity signifies that the CP is closer to the RP, which means that the corresponding solution is better. Therefore, FCE can play a role in guiding evolution. The implementation steps of the algorithm are as follows:

Step1: Initialize the population and randomly generate the position of each nectar source.

Step 2: Construct RP fuzzy set. For each sub objective, the artificial bee colony algorithm is used for single-objective optimization, so as to obtain the bounds of each sub objective value and the ideal solution, and the RP fuzzy set is constructed by using the membership function.

Step3: Construct CP fuzzy set.

Step4: Calculate the fuzzy correlation entropy coefficient of RP fuzzy set and multi-objective optimization solution fuzzy set as individual fitness value.

Step5: Update external archives. Non-dominance sorting and crowded distance calculation are carried out on the feasible solutions generated in each generation, and the elite retention strategy is used to improve the population diversity.

Step6: Update the nectar source position according to (21), (24), (25). The LOV rule [24] is used to transform continuous individuals into discrete individuals, and a CP fuzzy set is constructed according to the selected membership function.

Step7: If the iteration meets the termination condition, the algorithm is terminated, otherwise return to step4.

Step8: Output external archives.

V. EXPERIMENT AND RESULT ANALYSIS

In order to verify the efficiency of the EMOABC for the MOGCCS in railway central station, eight scales with different number of containers ($H = 15, 30, 45, 60, 75, 90, 105,$

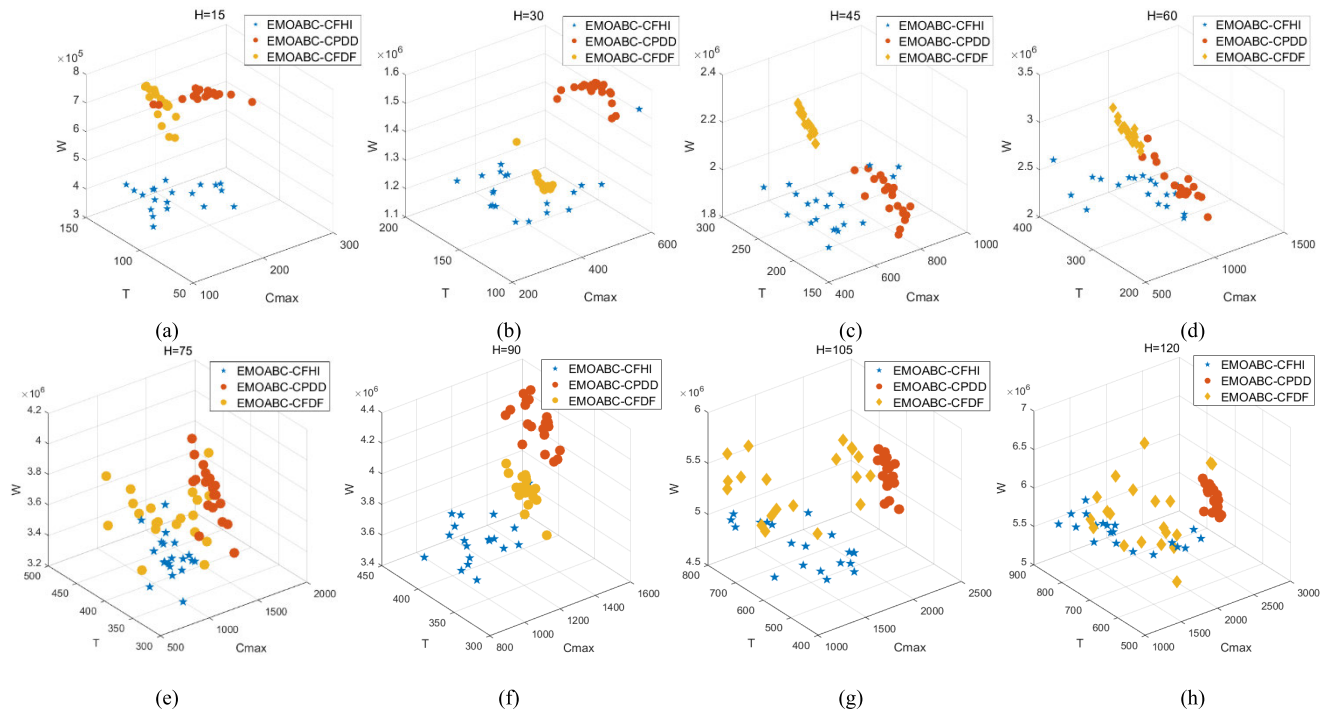


FIGURE 3. Pareto fronts of the three strategies on eight instances.

120) were selected. The ranges of speed and power of the trucks and GCs are shown in table 2.

In order to verify the effect of CFHI, the results were compared among CFHI, CFDF and CFDD at the same time.

Three strategies were embedded into the EMOABC respectively, then we obtain EMOABC_CFHI decoding by CFHI, EMOABC_CFDF decoding by CFDF, and EMOABC_CPDD decoding by CPDD.

All algorithms were independently repeated 50 times for each instance because of the stochastic nature of the algorithms. The mean of 50 runs was deemed the final result. The key parameters of the EMOABC were set as follows. The population size $N = 100$, the number of employed bees and onlooker bees were both set to be 50% of the population, the limit was set to the number of onlooker bees times H , the maximum number of iteration $G_{max} = 100$, the capacity of external archive $E_{max} = 20$. All the strategies and algorithms were coded by MATLAB R2014a, and conducted on a computer with an Intel (R) core (TM) i5- 10400 CPU of 2.90GHz and 8GB RAM.

To visualize the Pareto fronts of the three algorithms, we chose eight instances under eight scales ($H = 15, 30, 45, 60, 75, 90, 105, 120$) from the tested instances. Fig. 3 shows the Pareto fronts of the three algorithms, in which we observe that the solutions obtained by the EMOABC_CFHI are closer to the coordinate origin (i.e. closer to the real Pareto front) and dominate the solutions obtained by the other two strategies. This means that CFHI have better performance of searching collision-free solutions. This is because some conflict schemes of GCs, which may obtain excellent scheduling results, are transformed to collision avoidance by the CFHI.

TABLE 2. Basic parameters of equipment.

GC	Value	Truck	Value
V_k^r	U (3.5,4.5) m/s	v_m	U (5.5,8.0) m/s
$V_k^{r,e}$	U (3.5,4.5) m/s	v_m^e	U (5.5,8.0) m/s
V_k	U (0.6,0.8) m/s	p_m^t	U (14,21) KW
p_k	U (2000,2500) KW		
p_k^i	U (110,150) KW		
p_k^e	U (2000,2500) KW		
$p_k^{t,e}$	U (110,150) KW		

The above experimental results showed that the MOGCCS meets the actual operation requirements of intermodal transport container terminal, and the EMOABC can solve the actual problem effectively and obtain a better task scheme quickly.

Table 3 shows the mean values of three objectives obtained by independently running 50 times with three different equipment allocation strategies under different task scales, where C_{max} is the maximum completion time, T is the total empty travel time of equipment, W is the total energy consumption of the equipment. The better experimental results are marked in bold. As shown in Table 3, when the same optimization algorithm is adopted, CFHI can obtain less energy consumption under different task scales and ensure higher operation efficiency in most instances. CPDD can not get good results in terms of makespan, total empty travel time of equipment and total energy consumption of equipment. With the increasing of task scale, CFHI can still ensure the ability to optimize the total energy consumption of equipment. Additionally, with

TABLE 3. Solution results of different strategies.

Cases	EMOABC_CDFD			EMOABC_CPDD			EMOABC_CFHI		
	C_{max}	T	W	C_{max}	T	W	C_{max}	T	W
15	146.401	109.477	6.72E+05	262.224	100.882	6.73E+05	126.142	104.157	3.50E+05
30	336.204	114.245	1.33E+06	565.16	122.279	1.47E+06	305.900	131.651	1.19E+06
45	483.920	218.798	2.36E+06	791.285	197.944	1.96E+06	500.628	182.811	1.85E+06
60	769.178	291.344	3.16E+06	897.871	283.053	2.78E+06	733.393	345.280	2.47E+06
75	891.602	462.118	3.46E+06	1141.754	393.591	3.60E+06	874.864	377.640	3.49E+06
90	1289.528	493.256	3.96E+06	1495.016	423.288	4.30E+06	1183.413	395.248	3.57E+06
105	1478.651	568.195	5.04E+06	2165.415	561.776	5.11E+06	1347.690	565.982	4.97E+06
120	1845.140	605.933	5.76E+06	2383.420	649.429	5.78E+06	1563.760	617.246	5.58E+06

TABLE 4. A scheduling case when $h = 30$.

Task	Container number	Operation	Equipment	Task	Container number	Operation	Equipment
1	14	(11,5)-(14,12)	R2	16	10	(2,1)-(17,12)	R1-T2-R2
2	18	(8,1)-(14,11)	R1	17	1	(14,3)-(8,12)	R1
3	30	(23,3)-(22,10)	R2	18	29	(16,5)-(23,10)	R2
4	24	(20,5)-(13,9)	R2	19	3	(19,5)-(10,11)	R1
5	12	(17,4)-(9,8)	R2	20	23	(9,4)-(2,9)	R1
6	6	(23,4)-(9,11)	R2	21	27	(5,4)-(3,8)	R1
7	13	(7,5)-(11,9)	R1	22	9	(11,5)-(3,12)	R1
8	21	(21,1)-(13,8)	R2	23	11	(16,5)-(7,10)	R2
9	15	(8,3)-(8,8)	R1	24	19	(7,6)-(12,9)	R2-T2-R1
10	4	(7,5)-(24,9)	R1-T1-R2	25	16	(14,5)-(12,10)	R2-T2-R1
11	22	(19,2)-(11,9)	R2	26	8	(18,3)-(4,9)	R2-T1-R1
12	7	(17,2)-(9,10)	R2	27	25	(3,3)-(24,10)	R1-T1-R2
13	17	(10,1)-(4,12)	R2	28	20	(1,2)-(25,8)	R1-T2-R2
14	28	(7,4)-(13,12)	R2	29	26	(19,1)-(4,11)	R2
15	5	(21,4)-(25,10)	R2	30	2	(13,2)-(10,10)	R2-T1-R1

Note: equipment R1 indicates that this task is carried out by GC 1. R1-T1-R2 indicates that the task is unloaded by GC 1, then transported horizontally by truck 1, and finally loaded by GC 2.

the continuous expansion of task scales, the probability of conflict between GCs is increasing. Compared with CFHI strategy, CPDD strategy needs to avoid conflicts between GCs constantly, so the three objectives including C_{max} are inferior to the results obtained by CFHI strategy. Due to the CDFD strategy does not need to consider conflicts between GCs, the results obtained by using this strategy are close to that of CFHI strategy. Nevertheless, CFHI strategy is still better than the other two strategies in general.

Table 4 shows the optimal transportation scheme obtained by EMOABC_CFHI when $H = 30$. The containers of NO.4, NO.10, NO.19, NO.16, NO.8, NO.25, NO.20, and NO.2 are operated by two different GCs and one truck respectively, each of the rest containers are processed by one crane respectively.

VI. CONCLUSION

This paper studied a problem of the cooperation scheduling of multiple GCs with conflict-free in the container terminal railway station, and formulated a multi-objective optimization model for MOGCCS. The CFHI strategy was proposed to dispatch GC and truck to each container task with conflict-free. In this strategy, trucks were used to replace the GCs to complete the horizontal transportation of containers in a conflict situation. To solve this model effectively, EMOABC based on CFHI strategy and FCE was designed. FCE was

used to evaluate and select the better solutions for next iteration evolution. Finally, some benchmark instances were generated by realistic data for experiments. We compared CFHI strategy with the other two popular equipment assignment strategies by embedding them into the EMOABC respectively. The experimental results showed that the CFHI strategy could ensure the conflict-free operation of GC, shorten the time of the train at station and reduce the total energy consumption of equipment. Our findings here have significant implications for cooperative operation of multiple GCs considering energy consumption in a container terminal. For the future works, except the EMOABC, some of the most representative computational meta heuristic optimization algorithm can be considered to solve the MOGCCS, such as monarch butterfly optimization algorithm, earthworm optimization algorithm, and harris hawks optimization algorithm. Additionally, we intend to consider the impact of applying the CFHI strategy when there is no conflict between GCs, improve the EMOABC to improve its local search ability, and compare the optimization results with other intelligent optimization algorithms.

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