A Railway Station Scheduling Algorithm Based on Multi-Objective Particle Swarm Optimization Algorithm

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***Abstract*—In the railway station scheduling system under the water-rail combined transport mode, how to reasonably allocate equipment resources according to the operation tasks, improve the efficiency of mechanical loading and unloading, and reduce the cost of loading and unloading operations, has become an urgent problem in the process of building a modern port. In this paper, a railway station scheduling algorithm based on multi-objective particle swarm optimization algorithm (RSSAMOPSO) was designed. The multi-objective particle swarm algorithm was used to solve the multi-objective optimization problem of railway station scheduling. Aiming at the problems of decreasing convergence speed and the lost of the diversity of the solutions, a compression factor and an adaptive mutation operator are introduced. The improved multi-objective particle swarm algorithm (IM_MOPSO) is combined with the compression factor and adaptive mutation operator to obtain the optimal operation sequence and various equipment task allocation schemes. Experimental results show that the above method has a large practical significance and practical value for improving the efficiency of mechanical loading and unloading in the railway yard and reducing the operating cost of the railway yard.**

***Keywords*-railway station; particle swarm optimization; task scheduling; multi-objective;**

I. Introduction

As the hub of water and land transportation, the port undertakes 90% of the world's foreign trade products handling and transportation services.In order to realize the intellectualization of port railway station and yard, it is necessary to carry out the intelligent dispatching of railway station and yard under the mode of water-railway combined transportation[1].

The task scheduling problem has been proved to be a NP(Nonpolynomial) complete combinatorial optimization problem[1][2].Combinatorial optimization problems can be divided into single objective optimization and multi-objective optimization problems from the point of view of target objects.The task scheduling problem of railway station and yard is just a multi-objective optimization problem. The multi-objective optimization algorithm is actually seeking the balance point of mutual restriction of multiple optimization objectives.For complex multi-objective optimization problems, classical algorithms such as the main objective method, linear summation method, approximation method, etc.[3][4] have certain limitations, and they cannot be solved for those multi-objective problems that have conflicts or have no commonality.Particle swarm optimization algorithm[5] (Partical Swarm Optimization,PSO) convergence is fast, simple iteration, so the multi-objective particle swarm optimization (Multi - objective particle swarm optimization,Mopso) has become a meaningful direction to solve practical engineering problems[6].The difference between the MOPSO algorithm proposed by Coello and the particle swarm optimization algorithm is that the MOPSO algorithm introduces the concept that the external population can adapt to the grid mechanism, and the swarm particles and the value range of particles are varied[7].MOPSO has the following two innovations: 1) storing external populations through the use of external archives;2) Fast convergence and the introduction of a new mutation strategy.

II. Railway station scheduling algorithm based on multi-objective particle swarm optimization algorithm

In the process of railway station and yard dispatching, it is not only necessary to consider the operation sequence of fixed machinery, Inner container truck and frontal hoisting equipment, but also to ensure that there is no conflict among the equipment. The core of railway station and yard dispatching is the fixed machinery of railway station and yard. The operation sequence of fixed machinery of railway station and yard is determined first, and then the operation sequence of Inner container truck and frontal hoisting equipment is determined, as well as the destination of goods entering the port by train.

First, initialize the particle swarm.Then, the objective function is calculated, and the operation sequence of fixed machinery in railway station and yard is given according to the idea of table scheduling.The result of the objective function is taken as the filter object of the non-dominated solution, and the non-dominated solution is screened.Then calculate the following steps in a loop: 1) the crowding degree in external files and sort it in descending order;2) Select the global optimal;3) Update external files.

A. Objective function

The goal of railway station and yard dispatching under the mode of water-railway combined transportation is to minimize the time of task completion, the waiting time of equipment and the waiting time of ship.The total time to

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complete a task refers to the time when the last device finishes the task, as shown in formula (1).The waiting time of equipment refers to the waiting time of different equipment during handover, including the waiting time of fixed machinery of railway station and yard and the waiting time of handover of Inner container truck. The waiting time of Inner container truck and frontal hoisting equipment handover is shown in Equation (2).The waiting time of the ship is shown in formula (3).

$$f_1 = \min(\max(hc_t, t \in T, t \neq t_{start})) \quad (1)$$

$$f_2 = \min(\sum_{t\in T}\sum_{c\in C} wc_t^c + \sum_{t\in T}\sum_{f\in F} wf_t^f + \sum_{t\in T}\sum_{R_s\in R} wR_t^{R_s}) \quad (2)$$

$$f_3 = \min(\sum_{t\in T_{sp}} gd_{T_{sp}} \times cv_l \times t_{tr}) \quad (3)$$

Among them, the specific calculation formula of the waiting time of each device is shown in (4) to (6).The calculation formula of the time for the fixed equipment of railway station and yard to arrive at the place where the task starts is shown in (7).The calculation formula for the time taken for the frontal hoisting equipment to travel to the handover area of the yard is shown in (8).

$$\begin{aligned} wc_t^c = \max(&\sum_{t,t_x\in T} R_{t,t_x}^s \times hx_t^{R_s} - \sum_{t,t_x\in T} c_{t,t_x} \\ &\times hx_t^c, 0) + \max(ht_t^f - \sum_{t,t_x\in T} c_{t,t_x} \times hx_t^c, 0) \end{aligned} \quad (4)$$

$$wf_t^f = \max(\sum_{t,t_x\in T} c_{t,t_x} \times ht_t^c - ht_t^f, 0) \quad (5)$$

$$R_t^{R_s} = \max(\sum_{t,t_x\in T} c_{t,t_x} \times hx_t^c - \sum_{t,t_x\in T} R_{t,t_x}^s \times hx_t^{R_s}, 0) \quad (6)$$

$$ht_t^f = \sum_{t,t_x\in T} f_{t,t_x} \times cp_{t_x}^f + \sum_{t,t_x\in T} f_{t,t_x} \times df_{t,t_x}^f \div fv_e \quad (7)$$

$$\begin{aligned} hx_t^{R_s} = &\sum_{t,t_x\in T} R_{t,t_x}^s \times cp_t^{R_s} + \sum_{t,t_x\in T} (1 - L_{t_x}) \\ &\times ds_t^{R_s} \times R_{t,t_x}^s \div rv_e \end{aligned} \quad (8)$$

B. Give the operating sequence of fixed machinery in railway yard

The loading and unloading task of railway station has a certain time sequence. DAG (directed acyclic graph) is more intuitive and easy to understand to describe the task scheduling. Therefore, DAG is used to describe the time sequence relationship of loading and unloading task of railway station.

The main objective of DAG-based method for assigning operation sequence of fixed machinery in railway station and yard is to properly assign tasks to fixed machinery in railway station and yard so as to minimize the execution time of all loading and unloading tasks. Task fitness TF_{mn} is defined to represent the similarity degree between the cargo types in task T_n and the set of all the remaining cargo types in the fixed machinery F_m of railway station and yard.

It is assumed that the number of goods types in the railway yard dispatching system is GT , the whole set of goods types is $\{1, 2, 3, ..., GT\}$, and the goods types in a task are expressed as $TG = (q_1, q_2, q_3, ..., q_{GT})$, where:

$$q_i = \begin{cases} 0, Goods\ i\ not\ in\ the\ task \\ 1, Goods\ i\ in\ the\ task \end{cases}, i \in [1, GT] \quad (9)$$

Similarly, the types of goods to be processed in real-time by fixed machinery in railway stations and yards in real time are expressed as $FG = (q_1, q_2, q_3, ..., q_{GT})$. At this time, the adaptability of task T_n corresponding to fixed machinery F_m in railway station and yard can be expressed as:

$$TF_{mn} = TG_n \times MG_m^T \quad (10)$$

Meanwhile, in order to prevent the task from starving to death,T_{ti} is set as the maximum acceptable processing time of the task, and the task processing priority of task T_n corresponding to the fixed machinery M_m of the railway station and yard is expressed as:

$$TP_{mnt} = \varepsilon \times \frac{TF_{mn}}{\left\| {TG_n}^T \right\|_1} + (1 - \varepsilon) \times \frac{dt - T_{Sys}}{T_{ti}} \quad (11)$$

Where,T_{Sys} represents the arrival time of the train at the port,ε is the weight coefficient, which can be adjusted according to on-site requirements, and dt represents the current time.

DAG task scheduling is the essence of the method of assigning the operation sequence of fixed machinery in railway station and yard.The classical algorithm of DAG task scheduling table scheduling algorithm.According to the characteristics of the problem, the table scheduling algorithm was combined with the improved multi-objective optimization algorithm, that is, the task height and the position of particles were taken as the priority of the task in the solution process.In the particle swarm, each particle has n dimensions, and each dimension corresponds to a task.The specific steps are as follows:

1) Initialization, each particle dimension corresponds to a loading and unloading task;

2) Sort in ascending order according to task height;

3) Within the same height range, sort by position in ascending order;

4) Determine whether the task list is empty, if it is empty, it will end, and if it is not empty, it will execute the next step;

5) Calculate the earliest start time $est(t_\xi, m_j)$ for assigning tasks T_i to the fixed machinery of each railway station according to formula (13);

6) Assign the task to the fixed machinery of the railway yard that minimizes the earliest start time of the task;

7) Delete the tasks that have been assigned to the machine, and repeat step 4;

8) Output the completion time of the last machine and the algorithm terminates.

C. Improved multi-objective particle swarm optimization algorithm

In order to improve the convergence speed and diversity, this paper makes the following improvements to the standard multi-objective particle swarm optimization algorithm:

1)Using archives to save the found optimal solution,so as to realize elite preservation.

2)Compression factor is introduced to improve the speed update strategy to improve the convergence speed of the algorithm.

3)The idea of adaptive mutation was introduced to increase the diversity of particles.

4)The selection of global optimal solution is improved to further ensure the diversity of particles.

D. Particle velocity update strategy

The compression factor λ is introduced to improve the speed update, and the speed update strategy is shown in Formula (12).Compression factor λ as shown in formula (13).

$$\begin{aligned} V_{id}(t) &= \lambda V_{id}(t-1) + c_1 rand_1(P_{id} \\ &-X_{id}(t-1)) + c_2 rand_2(P_{gd} - X_{id}(t-1)) \end{aligned} \tag{12}$$

$$\lambda = \frac{2}{|2-\varphi-\sqrt{\varphi^2-4\varphi}|} \tag{13}$$

$$\varphi = c_1 + c_2 \tag{14}$$

Where, t represents the current number of iterations; V_{id} represents the component of i particle in d dimensional velocity; g is the global optimal particle index number; P_{gd} is the component of all the particles in d dimension,which goes through the optimal position; X_{id} represents the position of i particle in d dimensions; P_{id} represents the best position of the i particle in the position experienced by itself in the d dimensional component; c_1 is individual learning factor, c_2 is social learning factor; $rand_1$ and $rand_2$ are random numbers between [0,1].

E. Updating and maintenance of external files

1) Design of external files: A set is designed to store the non-dominated solutions generated during previous iterations. This set is called the external archive.The idea of selecting the non-dominant solution is to select a particle from the particle swarm and judge the dominant relationship between this particle and other particles in the particle swarm. If no particle has a dominant relationship with the current particle is found, the current particle will be placed in the external archive set, that is, the current particle is the non-dominant solution.If a dominant particle is found in the particle swarm, the dominant particle is deleted from the particle swarm.Do this for the remaining particles in the current particle swarm until the set of particles in the swarm is empty.At this point, the solutions stored in external files are all the currently obtained non-dominated solutions[8].

2) Update external file set: In order to ensure the diversity of the optimal solution set, the selection and mutation operators in the genetic algorithm are selected to update and maintain the external file set.Using the roulette wheel selection method for several rounds of selection, the larger the crowded distance, the more likely it is to be selected, when search algorithm tends to be suspended, population may be trapped in local optimum, may also be close to the global optimal solution, in the particle's velocity approximate zero,the mutation operator can also help to update the position of the particle, especially in the case of population into a local optimum,the mutation operator plays a more important role,the mutation process is shown as follows.

$$\begin{aligned} &child(x) = p \times parent_1(x) + (1-p) \times parent_2(x) \\ &child(v) = \tfrac{parent_1(v)+parent_2(v)}{|parent_1(v)+parent_2(v)|}\,|parent_1(v)| \end{aligned} \tag{15}$$

$parent_1(v)parent_2(v)$ is the velocity of the parent particle; p is the probability of mutation.A possibly better external set can be obtained by replacing the dominant solution in the external file set by comparing the newly generated solution.In order to improve the global search ability of the algorithm, the adaptive mutation operation is adopted in the later period of operation, and the decreasing mutation probability is used in iteration to improve the convergence ability of the algorithm. The formula of the adaptive mutation probability is as follows.

$$p = 1 - \frac{t}{Iter} \tag{16}$$

Where, t is the current iteration number and $Iter$ is the maximum iteration number.

Therefore, the updating steps of external files are as follows: firstly, according to the congestion degree method, calculate the congestion degree of the solution in the file. Then, a probability value $b \in [0,1]$ is generated randomly, and the value of b is compared with the mutation probability. If the value of b is small, the mutation operation is carried out. Mutation operation: sort the solutions according to the crowding degree, randomly select a non dominated solution with the crowding degree ranking in the first 50% as one of the mutation operators, randomly select a non dominated solution with the crowding degree ranking in the last 50% as another mutation operator, generate two solutions through cross mutation, and randomly select one of the two solutions to be stored in solution set D, Until all pairing and crossing are completed in the external file. Finally, prune the file and delete the redundant solution.

F. Select global optimal particle

The selection of the global optimal particle is the core of the multi-objective particle swarm optimization algorithm.When selecting the global optimal solution, the crowding distance of particles is arranged in descending order, and the optimal solution is selected randomly from the top 10% particles to further ensure the diversity and distribution of solutions.

G. The overall process of the IM_MOPSO

First initialize to form an initial population.Then, the objective function value of each particle is calculated according to each objective function, and the initial archive set A is obtained.Finally, the following five steps are executed in the loop until the maximum number of iterations is reached and the algorithm is finished.The five steps are

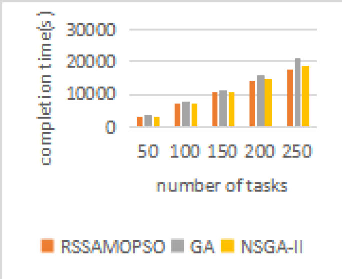

Figure 1. Completion time

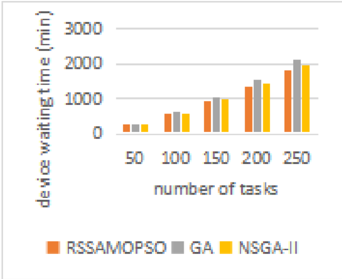

Figure 2. Waiting time of Equipment

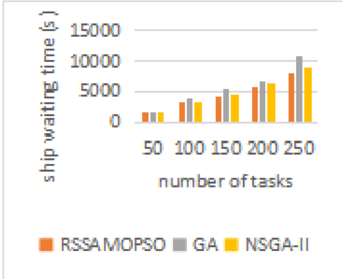

Figure 3. Waiting time of ship

as follows: 1) Calculate the crowding degree between each particle; 2) Sort the particles in descending order according to crowding degree; 3) Select one of the top 10% particles with crowding degree as the optimal solution; 4) Use formula (13) to update speed and position; 5) Calculate fitness values, update and maintain external files.

III. Experiments and Analysis

Traditional multi-objective genetic algorithm (NSGA_Π) is the classic algorithm to solve multi-objective optimization[9]. In order to verify the advantages and disadvantages of the RSSAMOPSO algorithm, the RSSAMOPSO algorithm is compared with the artificial experience, namely greedy algorithm (GA) ,and NSGA_Π.

50, 100, 150, 200 and 250 loading and unloading tasks are tested respectively, and the optimization results of each algorithm are compared. Table I shows the values of key parameters of RSSAMOPSO. The value is obtained by adjusting parameters through many experiments.

Table I
Key parameters of RSSAMOPSO

parameter	value
population size	200
external archive size	200
Inertia factor ω	0.4
learning factor c_1	2
learning factor c_2	2
Iterations	1000
weight of completion time ω_1	0.3
weight of device waiting time ω_2	0.2
weight of ship waiting time ω_3	0.5
Task processing priority weight ε	0.5

Results are shown in Figure 1 to Figure 3.When the number of tasks is greater than 150, the optimization target values of GA algorithm are obviously inferior to RSSAMOPSO algorithm and NSGA_Π algorithm.When the number of tasks is less than 200, there is little difference between the optimization objective results generated by RSSAMOPSO algorithm and NSGA_Π algorithm.When the number is greater than 200, the optimization target values generated by NSGA_Π algorithm scheduling are obviously inferior to RSSAMOPSO algorithm. It can be seen that RSSAMOPSO algorithm has better optimization ability compared with the other two algorithms when the number of railway station and field tasks is large.

IV. Conclusion

In order to improve the operation efficiency of port railway station and yard under the mode of water and railway combined transportation, this paper designs an intelligent scheduling method of railway station and yard, and uses multi-objective particle swarm optimization algorithm to solve the multi-objective optimization problem of railway station and yard dispatching.The results show that the algorithm in this paper has good optimization ability when the task quantity is large, which can effectively shorten the task completion time, ship waiting time and equipment waiting time, and improve the operation efficiency of railway stations and yards as well as the overall benefit of the port.

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