High-speed Train Rescheduling Based on a New Kind of Particle Optimization Algorithm

Ning Qin, Xuelei Meng

Abstract—**Train rescheduling problem has been a hot topic in the field of railway transportation organization work. Train rescheduling plan is the key of train operation organization that determines the transportation efficiency. To improve the efficiency of generating the train rescheduling plan, we constructed a train rescheduling model, taking the total delay time as the optimization goal and interval between trains, minimum running time in sections, minimum dwelling time as the constraints. A new kind of particle swarm optimization algorithm-hybrid fuzzy particle swarm optimization algorithm is proposed to find the solution of the model. The computing case shows the computing efficiency of the novel algorithm and the effectiveness of the model. The overall consumption time of hybrid fuzzy particle swarm optimization algorithm is reduced by 9.91%, compared with typical partical optimization algorithm. The approach presented in this paper can offer decision information for the dispatchers of railways.**

Index Terms—**High-speed railway, High-speed train, Train rescheduling, Hybrid, Fuzzy, Particle swarm optimization**

I. Introduction

With the development of high-speed railway, the topology of the railway network is getting more and more complicated. Train rescheduling work is being severely challenged. Train operation and dispatching work is the key to organizing the daily transportation work of the railway, which determines the arrival, departure and passage time at the station. The train operation plan affects the preparation of the subsequent EMU operation plan and the crew plan, and it is also the basis of the arrival-departure line usage plan and the train traction control plan design. Therefore, the design of a high-quality train rescheduled timetable is seriously important.

Train rescheduling is a hot topic today and there are many publications, which is a key of train operation organization. Mixed Integer Programming (MIP) is often used to solve this problem [1]-[8]. Sato et al. (2013) presented a MIP model for train rescheduling problem, considering the reduce inconvenience for the passengers [1]. Xu et al. (2017) also designed a MIP model combined with a job shop method to minimize the train delays [2]. Ding et al. (2022) designed a memetic algorithm to sovle the MIP model of train rescheduling [3]. Gao et al. (2022) also presented a MIP model and designed a three-stage strategy to solve train rescheduling problem [4]. Zhu and Goverde (2019) constructed a MIP model with flexible stooping mode [5].

There are also some other type of linear programming models constructed to solve this problem. Veelenturf et al. (2016) constructed an integer linear programming model for solving the timetable rescheduling problem, minimizing the number of cancelled and delayed trains [6]. Binder et al. (2017) also built an integer linear program to solve this problem, considering the passenger satisfaction, the operational costs and the deviation from the undisrupted timetable as the optimizing goals [7]. Reynolds and Maher (2022) used statistical methods and historical to solve the train rescheduling problem [8].

There is also a type of dynamic approach for solving train rescheduling problem. Feng et al. (2021) proposed a dynamic programming model solve train rescheduling problem, and designed a multi-stagemethod [9].

Some researchers focus on the uncertain factors in train rescheduling problem. Wang et al. (2012) designed a fuzzy optimization model based on improved symmetric tolerance approach to achieve a new timetable [10]. Zhu and Goverde (2020) studied the train rescheduling problem under uncertain disruptions, and designed a rolling horizon two-stage stochastic programming method [11]. They also integrated train rescheduling and passenger reassignment during the disruptions [12] and studied the train rescheduling problem in case of multiple disruptions that occurred at different locations [13].

Recently, energy saving concept has also been integrated into train rescheduling problem. Yang et al. (2019) presented a deterministic policy gradient algorithm to save energy [14]. Kuppusamy et al. (2020) also took the energy saving as the optimization goal [15].

Some researchers took the passengers' requirements when solving this problem. Zhan et al. (2021) studied the integrated problem of train rescheduling and passenger reassignment [16]. Binder et al. (2021) proposed a multi-objective algorithmic approach to solve the train rescheduling problem based on passenger-centric opinion [17]. And the train rescheduling problem is often integrated with another planning problem in railway transportation. Sato et al. (2009) combined the rescheduling problem and vehicle usage planning with a network flow model [18].

In this paper, we introduce a new kind of particle swarm

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optimization algorithm, hiring a novel evolutionary strategy to solve train rescheduling problem.

II. HIGH-SPEED TRAIN RESCHEDULING MODEL

High-speed train rescheduling problem is a difficult problem in railway traffic management. It is an important work in daily management that realize the passenger transportation goal. The train rescheduling plays a core role in the organization of train operation. It is a novel plan of train operation based on the actual production situation of the train operation diagram. It is also the link between the train operation plan and the other two plans - arrival - departure plan and the crew plan. The train rescheduling plan is designed by the railway dispatchers half an hour before it is announced. The most important goal of train rescheduling problem is to decide the arrival and departure time of the trains at the stations, which genetrates the order of the trains passing the stations and the sections in a dedigned order. Generally, the difference between the rescheduled timetable and the original timetable is the most important index to judge the quality of a optimizaed timetable. And it is required that the dispatchers to consider the requirements of operation time in the sections, the stay time at the stations and the intervals between trains. So the constraints must be described when solving the problem. Thus, the objective of train rescheduling model is desigend and the constraints are listed as follows.

A. Objective of train rescheduling model

According to the analysis above, the train operation adjustment model with minimal summary delay time as the destination can be defined, as in (1).

$$\min T_d = \sum_{i=1}^{N}\sum_{j=1}^{M}[\max(d_{i,j}-d_{i,j}^0,0)+(f_{i,j}-f_{i,j}^0)] \tag{1}$$

where $d_{i,k}$ stand for the inbound time of train i at station j and $f_{i,k}$ stand for the outbound time of train i at station j. $d_{i,j}^0$ and $f_{i,j}^0$ are the original planned arrival and departure time respectively. Then the objective is to minimize the difference between the re-scheduled timetable and the original timetable.

B. Constraints of the model

Train rescheduling work is restricted by the train operation rules. The first type of constraints are the intervals between arrival and departure time of the stations, as in (2).

$$d_{i+1,j}-d_{i,j} \ge g_j, i=1,2,...,L-1, j=1,2,...,K \tag{2}$$

where g_j is the minimum interval between the arrival time of train i and train $i+1$ at station j. Likewise, there is

$$f_{i+1,j}-f_{i,k} \ge g_k, i=1,2,...,L-1, j=1,2,...,K \tag{3}$$

where g_k is the interval between the departure time of train i and train $i+1$ at station j.

Set θ_{F-D} to be the minimum time interval between a train leaving a station and another train arrival the same station. The constraints are defined, as in (4).

$$d_{i+1,j}-f_{i,j} > \theta_{F-D}, i=1,2,...,L-1, j=1,2,...,K \tag{4}$$

The running time of each train according to the rescheduled timetable must be longer than the minimum running time, which can be formulated, as in (5).

$$d_{i,j+1}-f_{i,j} \ge \gamma_{i,j}^{M,\mathrm{R}}, i=1,2,...,L, j=1,2,...,K-1 \tag{5}$$

where $\gamma_{i,j}^{M,\mathrm{R}}$ is the minimum time of train i on the section between station j and $j+1$.

Again, the dwelling time of each train must be longer than the minimum dwelling time, which produces the constraint, as in (6).

$$f_{i,j}-d_{i,j} \ge \gamma_{i,j}^{M,\mathrm{D}}, i=1,2,...,L, j=1,2,...,K \tag{6}$$

where $\gamma_{i,j}^{M,\mathrm{D}}$ is the minimum dwelling time of train i at station j.

The passenger trains cannot leave the stations before the time as it is planned to serve the public. So there is a constraint, as in (7)

$$f_{i,j}-f_{i,j}^0 \ge 0, i=1,2,...,L, j=1,2,...,K \tag{7}$$

The other constraints are the non-negativity ones, which is shown, as in (8) and (9).

$$d_{i,j} \ge 0, i=1,2,...,L, j=1,2,...,K \tag{8}$$

$$f_{i,j} \ge 0, i=1,2,...,L, j=1,2,...,K \tag{9}$$

Then the mathematical model of this problem is constructed, as in (10).

$$\begin{cases} \min T_d = \sum_{i=1}^{N}\sum_{j=1}^{M}[\max(d_{i,j}-d_{i,j}^0,0)+(f_{i,j}-f_{i,j}^0)] \\ \text{s.t.} \\ d_{i+1,j}-d_{i,j} \ge g_j, i=1,2,...,L-1, j=1,2,...,K \\ f_{i+1,j}-f_{i,k} \ge g_k, i=1,2,...,L-1, j=1,2,...,K \\ d_{i+1,j}-f_{i,j} > \theta_{F-D}, i=1,2,...,L-1, j=1,2,...,K \\ d_{i,j+1}-f_{i,j} \ge \gamma_{i,j}^{M,R}, i=1,2,...,L, j=1,2,...,K-1 \\ f_{i,j}-d_{i,j} \ge \gamma_{i,j}^{M,D}, i=1,2,...,L, j=1,2,...,K \\ f_{i,j}-f_{i,j}^0 \ge 0, i=1,2,...,L, j=1,2,...,K \\ d_{i,j} \ge 0, i=1,2,...,L, j=1,2,...,K \\ f_{i,j} \ge 0, i=1,2,...,L, j=1,2,...,K \end{cases} \tag{10}$$

where $d_{i,j}$ and $f_{i,j}$ are the arrival and departure time of the train i at station j.

III. HYBRID PARTICLE SWARM OPTIMIZATION ALGORITHM

A. Typical particle swam optimization algorithm

Inspired by the natural clustering and foraging behaviour of birds and insects, Eberhart and Kennedy (1995) created the first particle swarm algorithm (PSO) [19]. The algorithm is based on the optimization skills of group intelligence, and uses no mass or volume of particles as an individual of the population. The particles are dynamically adjusted according to their own flight experience and the flight experience of their companions, and make the group reach the optimal level through the cooperation between the particles within the group. The specific form is as follows.

$f(x)$ is the goal function. $X_i=(x_{i,1},x_{i,2},...,x_{i,m})$ is the current position of particle i. $V_i=(v_{i,1},v_{i,2},...,v_{i,m})$ is the flying speed of particle i. $P_i=(p_{i,1},p_{i,2},...,p_{i,m})$ is the best positon of particle i. $P_g=(p_{g,1},p_{g,2},...,p_{g,m})$ is the best position of all the related particles. And the motion equations are as (11), (12) and (13).

$$P_i = (p_{i,1}, p_{i,2}, ..., p_{i,m}) \tag{11}$$

$$v_{i,n}^{k+1} = \omega v_{i,n}^{k} + c_1 r_1 (p_{i,n}^{k} - x_{i,n}^{k}) + c_2 r_2 (p_{g,n}^{k} - x_{i,n}^{k}) \tag{12}$$

$$x_{i,n}^{k+1} = x_{i,n}^{k} + v_{i,n}^{k} \tag{13}$$

c_1 and c_2 are two non-negative learning factors. r_1 and r_2 are two random numbers between [0,1]. ω is an inertial factor that keeps the inertia of the particle motion, giving it a tendency to expand the search space and the ability to search for new solution space. By tuning, The balance of the algorithm between global and local search capabilities can be maintained by tuning ω. To reduce the likelihood of particles leaving the search space during evolution, set $v_{i,n}^{k} \in [-v_{\max}, v_{\max}]$. With the further research on this algorithm, new algorithms based on this algorithm are constantly emerging. Yang et al. presented a novel particle swarm optimization to accelerate the data clustering [20].

B. Hybrid PSO

The mixing mechanism first selects the particles to be crossed from all the particles with a certain cross probability, and then the pairwise random combinations perform the cross operations to produce the descendant particles. The positions and velocity vectors of the descendant particles are shown below [21].

$$child_1(x) = p \times parent_1(x) + (1-p) \times parent_2(x) \tag{14}$$

$$child_2(x) = p \times parent_2(x) + (1-p) \times parent_1(x) \tag{15}$$

$$child_1(v) = \frac{parent_1(v) + parent_2(v)}{|parent_1(v) + parent_2(v)|} parent_1(v) \tag{16}$$

$$child_2(v) = \frac{parent_1(v) + parent_2(v)}{|parent_1(v) + parent_2(v)|} parent_2(v) \tag{17}$$

The crossover operation enables descendant particles to inherit the advantages of bi-parental particles, theoretically enhancing the ability to search for inter-particle regions. Both parental particles are in different local optimal regions, so the offspring particles produced by the two cross-can often get rid of the local optima and obtain improved search results. The experiment proved that compared with the basic particle swarm algorithm and the traditional genetic algorithm [22], [23].

C. Hybrid fuzzy PSO

Fuzzy PSO differs from standard PSO in only one respect: in each neighbourhood, instead of only the best particle in the neighbourhood being allowed to influence its neighbours, several particles in each neighbourhood can be allowed to influence others to a degree that depends on their degree of charisma, where charisma is a fuzzy variable. Before building a model, there are two essential questions that should be answered. The first question is how many particles in each neighbourhood have non-zero charisma. The second is what membership function (MF) will be used to determine level of charisma for each of the k selected particles.

The answer to the first question is that the k best particles in each neighbourhood are selected to be charismatic, where k is a user-set parameter. k can be adjusted according with the required precision of the solution.The answer to the other question is that there are many possible functions for charisma MF. Popular MF choices include triangle, trapezoidal, Gaussian, Bell and Sigmoid MFs. Hybrid rule requires to select two particles from the alternative particles at a certain rate, then the intersecting operation work is done to generate the descendant particles.

The positions and velocities of the descendant particles are as follows.

$$\begin{aligned} v_{i,n}^{k+1,1} &= \omega v_{i,n}^{k,1} + c_1 r_1 (p_{i,n}^{k,1} - x_{i,n}^{k,1}) \\ &+ \sum_{h \in B(i,k)} \varphi(h) c_2 r_2 (p_{g,n}^{k,1} - x_{i,n}^{k,1}) \end{aligned} \tag{18}$$

$$\begin{aligned} v_{i,n}^{k+1,2} &= \omega v_{i,n}^{k,2} + c_1 r_1 (p_{i,n}^{k,2} - x_{i,n}^{k,2}) \\ &+ \sum_{h \in B(i,k)} \varphi(h) c_2 r_2 (p_{g,n}^{k,2} - x_{i,n}^{k,2}) \end{aligned} \tag{19}$$

where $B_{i,k}$ denotes the *k*-best particles in the neighbourhood of particle i. Each particle i is influenced by its own best solution $p_{i,n}^{k,1}$ and the best solutions obtained by the k charismatic particles in its neighbourhood, with the effect of each weighted by its charisma $\varphi(h)$. It can be seen if k is 1, this model reduces to the standard PSO model.

$$v_{i,n}^{k+1,1} = \frac{v_{i,n}^{k+1,1} + v_{i,n}^{k+1,2}}{|v_{i,n}^{k+1,1} + v_{i,n}^{k+1,2}|} |v_{i,n}^{k+1,1}| \tag{20}$$

$$v_{i,n}^{k+1,2} = \frac{v_{i,n}^{k+1,1} + v_{i,n}^{k+1,2}}{|v_{i,n}^{k+1,1} + v_{i,n}^{k+1,2}|} |v_{i,n}^{k+1,2}| \tag{21}$$

$$x_{i,n}^{k+1,1} = x_{i,n}^{k,1} + v_{i,n}^{k+1,1} \tag{22}$$

$$x_{i,n}^{k+1,2} = x_{i,n}^{k,2} + v_{i,n}^{k+1,2} \tag{23}$$

$$x_{i,n}^{k+1,1} = p \times x_{i,n}^{k+1,1} + (1-p) \times x_{i,n}^{k+1,2} \tag{24}$$

$$x_{i,n}^{k+1,2} = p \times x_{i,n}^{k+1,2} + (1-p) \times x_{i,n}^{k+1,1} \tag{25}$$

p_1 is a random variable vector with D dimensions which obeys the equal distribution. Each dimension of p is in [0,1].

D. Steps to search for solutions for the model

According to the model characteristics, the design and solution steps are as follows.

Step 1: To initialize the particle population. Set the size of the particle to be N_{swarm}. The position vector of each particle is composed of $2 \times M \times N$ variables. According to the operation plan of the south-going trains starting from Beijingxi station between 12:00 and 16:00, the initial value of each variable is set.

Step 2: The value the fitness function T_d (in this paper, T_d is taken as the fitness function directly) is calculated from Equation (1) and each particle position vector in the population. Mark the optimal position of each particle and record the number of the particle (i. e., the optimal particle) that minimize the value of the fitness function;

Step 3: According to the velocity equations, as (20) and (21), to calculate the flight speed of each particle, that is, the change amount of the decision variable;

Step 4: According to the position calculation formula, update the flight speed (i. e., the decision variable change amount) to the particle group, calculate the new position of each particle (i. e., the new value of the decision variable); according to the equations, as in (2) - (9) to judge whether the decision variable value meets the constraint conditions, if not satisfied, delete the particle, and use the optimal particle in the particle population of this generation instead;

Step 5: Determine whether the number of calculation iterations reaches the pre-set number of iterations. If yes, go to step 6; If no, go to step 2;

Step 6: According to the optimal position of the optimal particle in the population (the value of the decision variable when the optimal fitness function value is obtained), restore the arrival and the departure time of the station, and generate the train operation adjustment plan.

IV. Computing Case and Result Analysis

A. Planned timetable

It is very important to select a railway section and the related data to build the comuptation case to verigfy the validity of the model. China's railway mileage had reached 155,000 kilometers by the end of 2022. The most typical ones are the Beijing-Shanghai high-speed railway and the Beijing-Guangzhou high-speed railway. Beijing- Guangzhou high-speed railway is currently one of the busiest high-speed railway trunk lines in China. We selected a section and obtained the real operation data to form the train timetable.

And we drew the train operation diagram to show the train operation process more clearly. The data is the arrival and departure time of the trains from 12:00 to 18:00 in section between Beijingxi and Zhengzhoudong in the south-going section. And the planned train operation diagram is shown in Fig. 1. The corresponding train schedule is shown in Table I. In Fig. 1, the horizontal axis represents the time, with each interval unit of ten minutes and the vertical axis indicates the station location.

B. Minimum train running time in south-going direction

The minimum running time in each section of Beijingxi - Zhengzhoudong high-speed railway is firstly calculated out, taking for granted that the highest speed is 300km/h for safety reasons, although the operation speed can reach 350km/h. The detailed data is shown in Table II. The trains are divided into two groups according to the operation speed. G83,G95 and G91 belong to a group and the others belong to another.

C. Scene assumptions and computing results analysis

In this computation case, we took it for granted that five trains, G95, G673, G613, G91 and G757 are disturbed when running on section between Beijingxi and Zhuozhoudong. They were later 9, 13.5,10, 10.5, 20 minutes respectively than as planned when they arrived at Zhuozhoudong station. In this case, we set $\gamma_{i,k}^{M,D}$ to be 2 minutes. And the minimum running time is listed in Table II. This case involves 13 stations, 14 trains, so the dimension of each particle is $2\times13\times14=364$. The particle population size is designed to be 64, the upper limit of iterations is set to be 300, and the HFPSO particle population algorithm is used to solve the model. In the computation, we use a computer with a CPU of i5-7500 and 4G RAM. The software is Visual C# 2019.

This data experiment uses the classical PSO and the HFPSO to calculate iteratively, respectively, in order to compare the calculation accuracy of the two algorithms. We set $c_1 = 2$, $c_2 = 2$, $\omega = 0.729$ according to [24] and carried out the experiment.

For that the change amount of trains at the station arrival and departure time is basically less than 10 minutes, the maximum flight speed is set to 10. The fuzzy membership function is a a trigonal function.

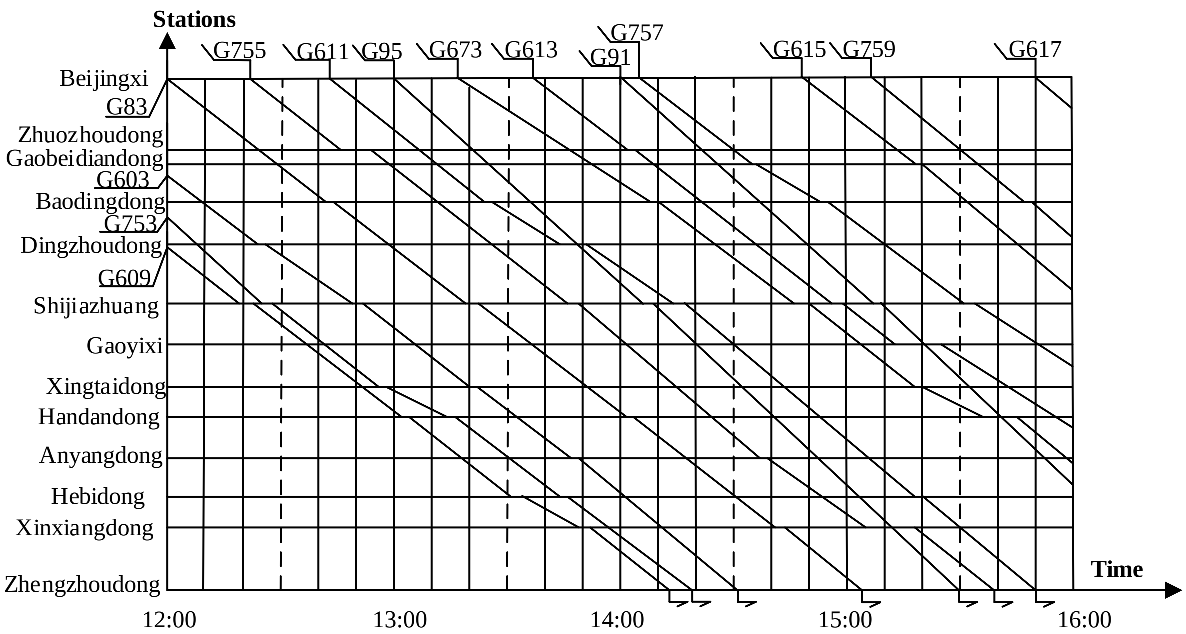

Fig. 1. Planned train operation diagram from 12:00 to 16:00 of Beijingxi-Zhengzhoudong railway section in the south-going direction

TABLE I
PLANNED TIMETABLE RROM 12:00 TO 16:00 OF BEIJING-ZHENGZHOUDONG RWAILWAY SECTION IN SOUTH-GOING DIRECTION

	G609		G753		G603		G83		G755	
	Arrive	Depart	Arrive	Depart	Arrive	Depart	Arrive	Depart	Arrive	Depart
Beijingxi								12:00:00		12:21:00
Zhuozhoudong							12:24:00	12:24:00	12:46:00	12:54:00
Gaobeidiandong							12:29:00	12:29:00	12:59:00	12:59:00
Baodingdong					12:09:00	12:09:00	12:41:00	12:43:00	13:11:00	13:11:00
Dingzhoudong			12:08:00	12:08:00	12:24:00	12:26:00	12:58:00	12:58:00	13:26:00	13:26:00
Shijiazhuang	12:19:00	12:23:00	12:24:00	12:26:00	12:49:00	12:52:00	13:19:00	13:22:00	13:46:00	13:49:00
Gaoyixi	12:37:00	12:37:00	12:42:00	12:42:00	13:06:00	13:06:00	13:36:00	13:36:00	14:01:00	14:01:00
Xingtaidong	12:52:00	12:52:00	12:56:00	12:58:00	13:20:00	13:22:00	13:51:00	13:51:00	14:15:00	14:15:00
Handandong	13:02:00	13:04:00	13:14:00	13:16:00	13:32:00	13:32:00	14:01:00	14:03:00	14:24:00	14:24:00
Anyangdong	13:18:00	13:18:00	13:30:00	13:30:00	13:47:00	13:49:00	14:17:00	14:17:00	14:37:00	14:39:00
Hebidong	13:31:00	13:33:00	13:44:00	13:46:00	14:01:00	14:01:00	14:30:00	14:30:00	14:53:00	14:53:00
Xinxiangdong	13:49:00	13:52:00	13:57:00	13:57:00	14:11:00	14:11:00	14:41:00	14:43:00	15:05:00	15:18:00
Zhengzhoudong	14:13:00		14:19:00		14:31:00		15:04:00		15:39:00	

	G611		G95		G673		G613		G91	
	Arrive	Depart	Arrive	Depart	Arrive	Depart	Arrive	Depart	Arrive	Depart
Beijingxixi		12:43:00		13:00:00		13:27:00		13:37:00		14:00:00
Zhuozhoudong	13:07:00	13:07:00	13:21:00	13:21:00	13:46:30	13:46:30	14:02:00	14:04:00	14:21:30	14:21:30
Gaobeidiandong	14:11:00	14:11:00	13:25:00	13:25:00	13:52:00	13:52:00	14:08:30	14:08:30	14:25:30	14:25:30
Baodingdong	13:24:00	13:26:00	13:36:00	13:36:00	14:08:00	14:10:00	14:21:00	14:21:00	14:37:00	14:37:00
Dingzhoudong	13:44:00	13:51:00	13:48:30	13:48:30	14:25:00	14:25:00	14:36:00	14:36:00	14:49:30	14:49:30
Shijiazhuang	14:14:00	14:17:00	14:07:00	14:09:00	14:46:00	14:50:00	14:56:00	14:59:00	15:07:00	15:09:00
Gaoyixi	14:3:000	14:3:000	14:20:30	14:20:30	15:03:30	15:03:30	15:13:00	15:25:00	15:20:30	15:20:30
Xingtaidong	14:43:00	14:43:00	14:32:00	14:32:00	15:18:00	15:20:00	15:42:30	15:42:30	15:32:00	15:32:00
Handandong	14:54:00	14:54:00	14:41:00	14:41:00	15:36:00	15:45:00	15:55:00	15:55:00	15:40:30	15:40:30
Anyangdong	15:06:00	15:06:00	14:52:30	14:52:30	15:58:00	15:58:00			15:52:00	15:52:00
Hebidong	15:18:00	15:20:00	15:03:30	15:03:30						
Xinxiangdong	15:30:00	15:30:00	15:12:00	15:12:00						
Zhengzhoudong	15:50:00		15:30:00							

	G757		G615		G759		G617	
	Arrive	Depart	Arrive	Depart	Arrive	Depart	Arrive	Arrive
Beijingxi		14:05:00		14:48:00		15:06:00		15:50:00
Zhuozhoudong	14:30:00	14:30:00	15:13:00	15:13:00	15:30:00	15:30:00		
Gaobeidiandong	14:35:00	14:37:00	15:18:00	15:20:00	15:35:00	15:35:00		
Baodingdong	14:53:00	14:55:00	15:31:30	15:31:30	15:47:00	15:49:00		
Dingzhoudong	15:10:00	15:10:00	15:45:00	15:45:00				
Shijiazhuang	15:31:00	15:34:00						
Gaoyixi	15:50:30	15:50:30						

The changes in the fitness function values in the calculation are shown in Fig. 2. As can be seen that in the HFPSO-based calculation process, the fitness function value stabilized and reached the optimal value of 487 minutes when the number of iterations reached 69 (which takes 202.35 seconds). The fitness value calculated out with PSO stabilized and reached the optimal number of 91 iterations (224.62 seconds), and the optimal value was also 487 minutes. Although the average speed of HFPSO in each iteration (2.933 seconds) was slightly lower than that of the classical PSO (the average time of each iteration takes 2.468 seconds), the overall consumption time was reduced by 9.91%. The reason was that the algorithm of "flight speed" and cross-calculation in HPSO was more complex, but with high accuracy. In addition, the fitness value we got with HFPSO was better than that with classical PSO in the first 69 generations of iterations, and it had faster convergence rate compared with PSO. So HFPSO is better than the classical particle swarm algorithm in terms of optimization efficiency. We can see that the introduction of the fuzzy processing method improve the algorithm performance and make it easy to describe the engineering computation requirements. It is a positive and meaningful attempt to improve the algorithm. According to the final value of each dimension of the optimal particle after the optimization calculation, the rescheduled train operation plan was restored, as shown in Fig. 3. Accordingly, the scheduled timetable was shown in Table III. We can see that G611, G95, G673, G613, G91 and G757 were rescheduled according to

Table I and Table III. Comparing the original train operation plan, it can be found that the operation plan of G609, G753, G603, G83, G755, G615, G759, G617 were not changed.

G95 was late when it arrived at Zhuozhoudong by 10 minutes, and it recovered the status that it ran due to the planned timetable. The station that G97 overtook G611 was changed from Dingzhoudong to Shijiazhuang. Due to the driving rules, G611 was forced to leave five minutes late from Shijiazhuang, which resumed its operation in Handandong station. G673, G613, G91 and G757 resumed their normal operation state in Shijiazhuang station. The rescheduled timetable can reduce the delay time to a large extent.

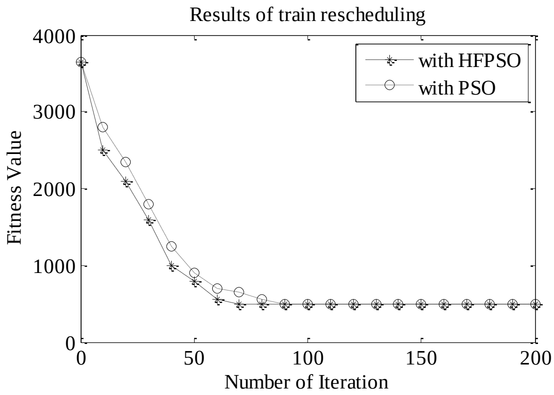

Fig. 2. The change process of fitness function value during train rescheduling calculation

TABLE II

THE MINIMAL RUNNING TIME OF ALL THE TRAINS IN EACH SECTION ($t_{i,k}^{\min,\mathrm{run}}$)

	G609,G753,G603,G755,G611,G673,G613,G757,G615,G759,G617	G83,G95,G91
Beijingxi-Zhuozhoudong	21’	20’
Zhuozhoudong-Gaobeidiandong	4’	3’
Gaobeidiandong- Baodingdong	9’	8’
Baodingdong- Dingzhoudong	10’30”	9’
Dingzhoudong- Shijiazhuang	12’30”	11’
Shijiazhuang-Gaoyixi	10’	9’30”
Gaoyixi-Xingtaidong	12’	10’30”
Xingtaidong-Handandong	9’	7’
Handandong-Anyangdong	12’	10’
Anyangdong-Hebidong	12’	9’30”
Hebidong-Xinxiangdong	10’	8’30”
Xinxiangdong-Zhengzhoudong	20’	18’

TABLE III

RESCHEDULED TIMETABLE RROM 12:00 TO 16:00 OF BEIJING-ZHENGZHOUDONG RWAILWAY SECTION IN SOUTH-GOING DIRECTION

	G609		G753		G603		G83		G755	
	Arrive	Depart	Arrive	Depart	Arrive	Depart	Arrive	Depart	Arrive	Depart
Beijingxi								12:00:00		12:21:00
Zhuozhoudong							12:24:00	12:24:00	12:46:00	12:54:00
Gaobeidiandong							12:29:00	12:29:00	12:59:00	12:59:00
Baodingdong					12:09:00	12:09:00	12:41:00	12:43:00	13:11:00	13:11:00
Dingzhoudong			12:08:00	12:08:00	12:24:00	12:26:00	12:58:00	12:58:00	13:26:00	13:26:00
Shijiazhuang	12:19:00	12:23:00	12:24:00	12:28:00	12:49:00	12:52:00	13:19:00	13:22:00	13:46:00	13:49:00
Gaoyixi	12:37:00	12:37:00	12:42:00	12:42:00	13:06:00	13:06:00	13:36:00	13:36:00	14:01:00	14:01:00
Xingtaidong	12:52:00	12:52:00	12:56:00	12:58:00	13:20:00	13:22:00	13:51:00	13:51:00	14:15:00	14:15:00
Handandong	13:02:00	13:04:00	13:14:00	13:16:00	13:32:00	13:32:00	14:01:00	14:03:00	14:24:00	14:24:00
Anyangdong	13:18:00	13:18:00	13:30:00	13:30:00	13:47:00	13:49:00	14:17:00	14:17:00	14:37:00	14:39:00
Hebidong	13:31:00	13:33:00	13:44:00	13:46:00	14:01:00	14:01:00	14:30:00	14:3:000	14:53:00	14:53:00
Xinxiangdong	13:49:00	13:52:00	13:57:00	13:57:00	14:11:00	14:11:00	14:41:00	14:43:00	15:05:00	15:18:00
Zhengzhoudong	14:13:00		14:19:00		14:31:00		15:04:00		15:39:00	

	G611		G95		G673		G613		G91	
	Arrive	Depart	Arrive	Depart	Arrive	Depart	Arrive	Depart	Arrive	Depart
Beijingxixi		12:43:00		13:00:00		13:27:00		13:37:00		14:00:00
Zhuozhoudong	13:07:00	13:07:00	*13:30:00*	*13:30:00*	*14:00:00*	*14:00:00*	*14:12:00*	*14:14:00*	*14:32:00*	*14:32:00*
Gaobeidiandong	14:11:00	14:11:00	*13:35:30*	*13:35:30*	*14:04:00*	*14:04:00*	*14:16:00*	*14:16:00*	*14:35:00*	*14:35:00*
Baodingdong	13:24:00	13:26:00	*13:44:00*	*13:44:00*	*14:16:00*	*14:18:00*	*14:27:00*	*14:27:00*	*14:43:30*	*14:43:30*
Dingzhoudong	13:44:00	13:51:00	*13:58:00*	*13:58:00*	*14:29:30*	*14:29:30*	*14:39:00*	*14:39:00*	*14:53:30*	*14:53:30*
Shijiazhuang	14:14:00	*14:22:00*	*14:17:00*	*14:19:00*	14:46:00	14:50:00	14:56:00	14:59:00	15:07:00	15:09:00
Gaoyixi	*14:32:00*	*14:32:00*	*14:29:00*	*14:29:00*	15:03:30	15:03:30	15:13:00	15:25:00	15:20:30	15:20:30
Xingtaidong	*14:45:00*	*14:45:00*	*14:39:30*	*14:39:30*	15:18:00	15:20:00	15:42:30	15:42:30	15:32:00	15:32:00
Handandong	14:54:00	14:54:00	*14:47:00*	*14:47:00*	15:36:00	15:45:00	15:55:00	15:55:00	15:40:30	15:40:30
Anyangdong	15:06:00	15:06:00	*14:57:00*	*14:57:00*	15:58:00	15:58:00			15:52:00	15:52:00

Hebidong	15:18:00	15:20:00	*15:07:00*	*15:07:00*				
Xinxiangdong	15:30:00	15:30:00	*15:14:30*	*15:14:30*				
Zhengzhoudong	15:50:00		15:30:00					
	G757		G615		G759		G617	
	Arrive	Depart	Arrive	Depart	Arrive	Depart	Arrive	Arrive
Beijingxi		14:05:00		14:48:00		15:06:00		15:50:00
Zhuozhoudong	*14:50:00*	*14:50:00*	15:13:00	15:13:00	15:30:00	15:30:00		
Gaobeidiandong	*14:55:00*	*14:57:00*	15:18:00	15:2:000	15:35:00	15:35:00		
	15:06:00	*15:08:00*	15:31:30	15:31:30	15:47:00	15:49:00		
Baodingdong	*15:18:30*	*15:18:30*	15:45:00	15:45:00				
Dingzhoudong	15:31:00	15:34:00						
Shijiazhuang	15:50:30	15:50:30						
Gaoyixi		14:05:00		14:48:00		15:06:00		15:50:00

Note: The time indicated in italics in Table III is the rescheduled time.

D. Parametric sensitivity analysis

1) Parametric sensitivity analysis of c_1 and c_2

The calculation performance of PSO is closely related to its calculation parameters. Generally, the values of c_1 and c_2 are set to be 2, but both can be adjusted to some extent in order to speed up their convergence rate or improve the calculation accuracy. In order to analyze the influence on the algorithm, the values of c_1 and c_2 were set and combined, and the calculation process was repeated 200 times respectively. It can be concluded from that the number of times falling into the local optimum increases with c_2 if c_1 was kept unchanged. The reason is that c_2 emphasized the role of the global optimal particle in the particle position update calculation, but the role of the optimal particle in the generation was relatively reduced. Similarly, the number of falling into local optima decreases with the value of c_1 if c_2 is unchanged. The reason is also that the role of the optimal particles in the particle position update is relatively reduced. The optimal solution is finally obtained in the calculations that do not trapped locally.

2) Parametric sensitivity analysis of ω

ω is an inertial factor, which is generally set to be a number between 0 and 1. In the condition that keep $c_1 = c_2 = 2$, we tried to set $\omega = 0.4, 0.5, 0.6, 0.7, 0.729, 0.8, 0.9$ to repeat the computation for 200 times and recorded the number that the solution fell into local optima. The number was 12, 12, 10, 8, 4, 6, 10 respectively. The optimal solution is finally obtained in the calculations that are not trapped locally. Then it can be concluded that the algorithm got the best performance when ω=0.729.

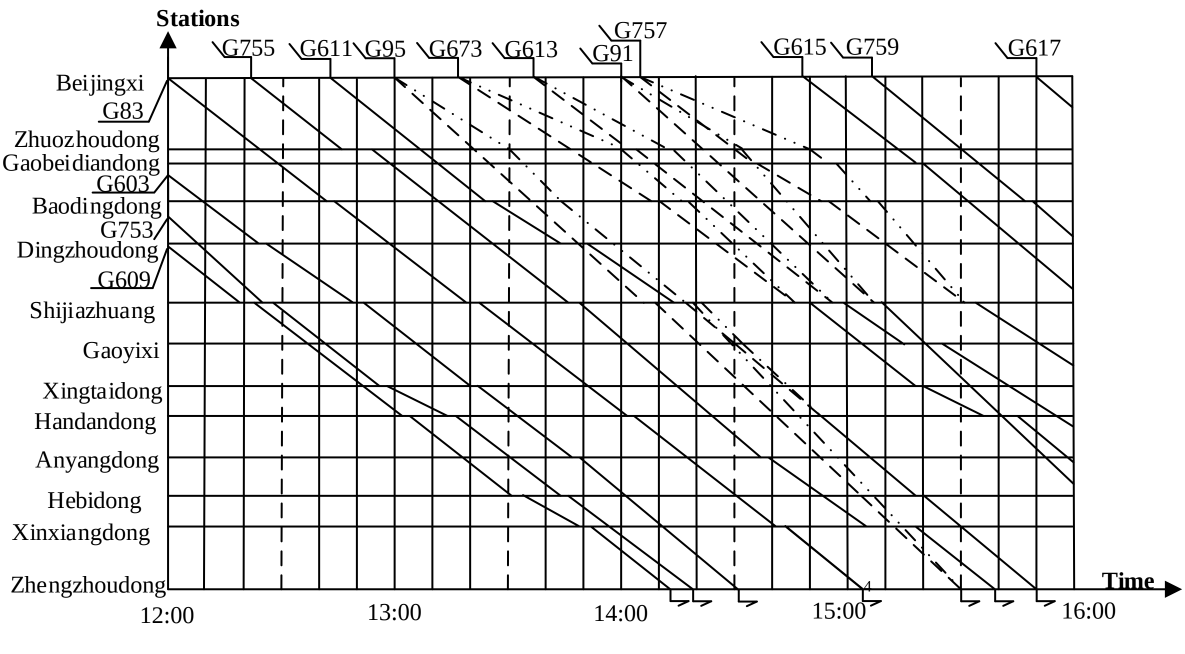

Fig. 3. Rescheduled train operation diagram from 12:00 to 16:00 of Beijingxi-Zhengzhoudong railway section in the south-going direction

V. CONCLUSION

This paper designs a high-speed train rescheduling model and introduces a new particle swarm optimization algorithm to solve it. The train rescheduling model proposed in this paper can well describe the train operation scheduling problems in train dispatching work, and the design optimization objectives and constraints can describe the actual engineering problems. The new particle swarm optimization algorithm hires the crossing calculation and the fuzzy processing method. The computing case proves that the HFPSO has better performance than PSO, reducing the computation time by 9.91% in the computing case. Future research should focus on the train rescheduling problem on the railway network, and improving the efficiency the algorithm to solve the train rescheduling problem more efficiently.

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