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Optimization Study of Line Planning for High Speed Railway Based on an Improved Multi-Objective Differential Evolution Algorithm

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ABSTRACT The combination optimization of the train operation plan is an ongoing challenge: while computing power has improved, it is difficult to obtain a complete train operation plan system. With the aim of generating system-optimal operation strategies, a new collaborative optimization method is proposed for line planning problem. Through a set of constraints, the problem is formulated as a two-objective model with the objectives of economic benefits and market effects. An optimization approach with adaptive improvement of control parameters based on the multi-objective differential evolution (MODE) algorithm is proposed to solve the model, and a heuristic algorithm is designed to get a better initial solution. Finally, computational results on benchmark multi-objective problems show that the improvements of the strategies are positive and the optimization result of the improved algorithm has better stability. Meanwhile, based on a numerical example of a practical case study involving a 397-kilometer railway corridor to demonstrate the effectiveness of the proposed model and solution. As the basis of successive decisions, this method can adjust the number of trains according to the passenger flow demand, which greatly saves operating costs.

INDEX TERMS Line planning, high-speed railway, collaborative optimization, multi-objective optimization problem, MODE.

I. INTRODUCTION

Railway transport is the main means of transportation, and it plays an important role in passenger services for long-distance transportation for both China and the world due to its advantages of high capacity, safety and resistance to poor weather in comparison with other transportation modes. Today, China is extensively developing the infrastructure of a high-speed railway (HSR). In 2017, the total number of passengers sent across the country reached 3.084 billion people in China, an increase of 270 million over the previous year, and it grew by 9.6%. The target is to cover all provincial capital cities across the country, with eight horizontal and eight vertical lines in next several years, and the network scale is much larger than any existing country in the world. With the increasing demands for travel, high-speed train is becoming more and more popular. A high quality passenger railroad system has a great impact on the resource utilization efficiency of the railway traffic system and the convenience of passenger travel, which means that the optimization of the railroad system before the train operation is indispensable.

The operation of the high-speed train consists of the number and type of trains, train marshaling, the stop planning and the timetable. It forms two kinds of combination optimization methods: line planning and train scheduling. Generally, line planning is a procedure of allocating trains with specific travel demands of many origins and destinations to appropriate lines or line sections. Railway management typically operates at three levels: strategic, tactic, and operational [1]. The railway planning process has many aspects, as shown in Fig. 1. Over the last few decades, extensive research efforts have been focused on scheduling problems and transportation services, especially with regard to the development of mathematical formulations and solution algorithms. On the

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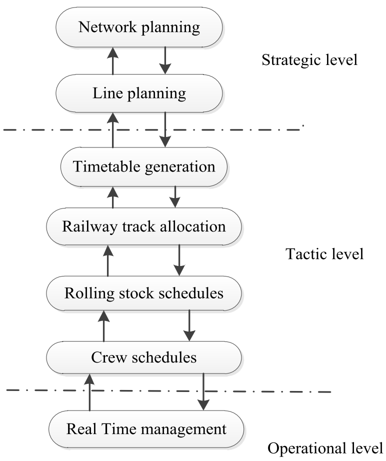

FIGURE 1. **The railway planning process.**

one hand, just as Lin D said, in current research, we focus on the work done at tactic level [2]. Some scholars pay attention to the combination optimization of train scheduling and train stop planning. For instance, a new collaborative optimization method for both train stop planning and train scheduling problems was studied by Yang *et al.* [3]. Qi J et al proposed a collaborative optimization method for both train stop planning and train scheduling considering the passengers distribution [4]. Suh *et al.* [5], Zheng *et al.* [6], and Jiang *et al.* [7] proposed a mathematical model based on skip-stop operation separately. Yue Y et al proposed a mathematical model for optimizing a train timetable for an HSR system, and also designed a column-generation based heuristic algorithm to account for both passenger service demands and train scheduling [8]. By considering passenger travel convenience, D Chen et al proposed a multi-objective model, and designed a hybrid genetic algorithm to solve the model [9]. Zyngier D et al proposed a novel formulation for train scheduling using Unit-Operation-Port-State Superstructure to maintain consistency in system modeling [10].

On the other hand, line planning [11] is a key comment in providing high-quality transport service. In the stage of line planning one needs to specify the number of trains, type of trains, the stop plan for each train, etc. [3], among them, the stop plan for each train is usually performed as part of the line planning process, and it is the primary strategic level element in the railway planning process. In practice, train stop planning is usually made on the predictions of the potential passenger flow for different origin-destination (OD) pairs, and the stop planning needs to be constantly adjusted in order to satisfy the dynamic requirements. Schöbel A et al introduced some of the basic line planning models and algorithm for line planning [12]. Wang L et al proposed a two-layer optimization model for high-speed railway line planning [13]. Xiao J et al proposed a model to optimize train formation plan which generates the one-block train formation plan firstly and then combines some one-block trains to form two-block trains based on the ant colony algorithm [14]. Xiao J et al proposed a hybrid algorithm of genetic algorithm and tabu search to solve the Train Formation Plan (TFP) network problem [15]. Qi J et al proposed a method for train operation zone, stop planning and passenger distribution optimization problems on the basis of a train stop planning model based on GAMS [16]. Yang X et al proposed a method that include four indicators to find the critical stations in the urban rail networks. And to obtain the final importance degree for each station through a multi-agent based simulation and min-max normalization [17]. The analysis of the importance degree for each station helps to guide the generation of the stop plan for each train. Specifically, a systematic line planning includes the running route, the number of railway rolling stock, train classes and the stopping plan. Therefore, reasonable system optimization is beneficial to timetable generation.

In a large number of studies, train operation section, train type, the number of trains, and train marshaling are all known conditions, and the optimization results are difficult to adapt to the dynamics of passenger travel. Therefore, as a novel idea in literature, this study is different from previous research in that it first systematically optimizes the line planning problem, including the number and type of the train, the train marshaling and its stop patterns. In other words, above method forms a static map about the operation of the train. In order to achieve the above combinatorial optimization, the optimization process includes two stages. First, in order to make the individual's code length consistent in each generation of optimization process, the number of trains was adjusted by neighborhood search. Meanwhile, when the number of train is determined to be a certain value, each generation of evolution will focus on finding the optimal solution for other variables (train type, train marshaling and the stop pattern), and this process will still determine whether the number of trains is optimal. To put it in another way, a neighborhood search is performed to determine if the number of trains needs to be adjusted after a period of evolution. During the period, the number of trains is a fixed value and is mainly optimized for other decision variables.

In order to solve such a complicated optimization problem as described above, in this paper, we also proposed an improved MODE algorithm. The improvement specifically includes two parts, one of which is to enhance the adaptability of the control parameters in the algorithm; the other is that MODE algorithm can handle 0-1variables, not just real values. The population is divided into multiple populations, and the parameters are adaptive during the optimization process in the proposed algorithm. Therefore, the algorithm is called multiple population adaptive multi-objective differential evolution (MA-MODE).

Based on the improved algorithm, numerical examples are implemented to demonstrate the effectiveness and efficiency of our proposed methods and algorithm. Exactly, the efficiency of the MA-MODE is measured by the inverted general distance (IGD) and the Spacing (SP) in the optimization

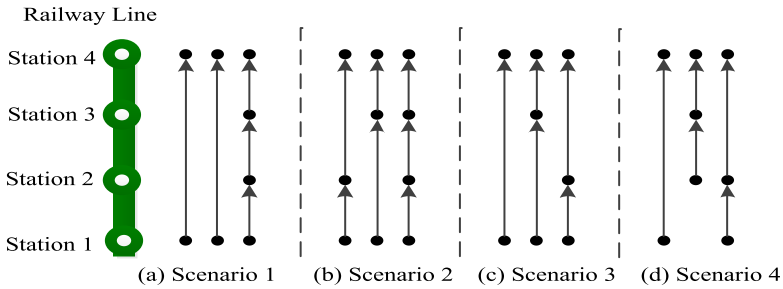

FIGURE 2. Illustration of feasible scenario.

process and the final optimization results are compared with the non-dominated sorting genetic algorithm II (NSGA-II), which proves its effectiveness. Then, the proposed model was processed with MA-MODE and the results of the optimization were compared with the MODE and the original scheme of the Guangzhou High Speed Railway. The evaluation indicators for the train operation plan shows that the operation plan generated by proposed methods and algorithm has better evaluation indicators.

In summary, we provide the following contributions to the research of line planning:

(1) We introduce a method for optimizing the combination of line planning problem using the model presented in this paper.
(2) We propose a heuristic algorithm to generate an initial stop planning.
(3) We design an improved algorithm MA-MODE to solve the problem.

II. PROBLEM STATEMENTS AND ASSUMPTIONS

A. PROBLEM STATEMENTS

In general, a route plan can be described as a train line from an origin to a destination with a definite stop planning. The number of trains and their station stop pattern must satisfy the travel demands for each of the OD pairs. To illustrate the concept of a ''train service plan'', in Fig. 2, the solid dot ''●'' represent stop operation at current station, we illustrate four scenarios of different train service plans for three trains and four stations. Scenario 1 and 2 have a train which is all-stop operation, so that, no matter the other two trains are skip-stop trains or through trains, passengers can travel from any station to any other station; in scenario 3, passengers traveling from station 2 to station 3 cannot be served; and in scenario 4, passengers from station 1 to station 3 can only transfer from station 2. Because transfer may consume a lot of time and energy of the passengers, neither scenario 3 nor scenario 4 is desirable. In practice, these trains also have different marshaling numbers (including 8-car marshaled and16-car marshaled in China). Meanwhile, at least two types of trains with different speeds are operated on the high-speed railway corridor; the two types of trains respectively represent ''G'' and ''D'', in which the train of type G is faster than the train of type D.

In the real-life operation planning, due to the volatility of passenger flow, the plan is related to the number of trains, train stop planning and train marshaling. Clearly, the train stop planning is often formulated from predicted passenger demands. When the change in passenger flow is small, passenger demands can be satisfied by adjusting the train marshaling, and when the passenger flow changers greatly, it is necessary to meet passenger demands by changing the number of trains.

B. MODEL ASSUMPTIONS

Some assumptions will be given in the following discussion for the convenience of formulating the mathematical model:

Assumption 1: The number of passengers with travel demand in each section will not change due to the change of the train operation plan.

Assumption 2: In practice, passenger's flow of each OD pair is usually based on the predicted value of passenger. So, we only assume that passenger's flow of every OD pair is known condition.

Assumption 3: In order to improve the quality of passenger travel services, passengers do not need to transfer to their destination.

Assumption 4: Because passengers consume amount of time while traveling, to simplify the problem, all passengers have the same time value.

Assumption 5: As high-speed trains generally operate at full capacity, tickets for standing room are not accepted. Therefore, if there is no ticket for the corresponding section, passengers will be detained in this station.

Assumption 6: Finally, the same type of train has same running time in the same section.

III. MATHEMATICAL MODEL OF TRAIN OPERATION PLAN

A rigorous formulation to collaboratively optimize the number of trains, train marshaling, train type and train stop planning will be provided in this chapter. The following discussion mainly focuses on specifying each part of the model, including parameters, decision variables, objective function, and systematic constraints.

The railway industry has market attributes, corporate attributes, and social welfare attributes in China. Therefore, the formulation of the high-speed railway operation plan should consider both economic benefits and market effects. The economic benefits refer to the operating income of the trains operating in the railway sector, which is mainly reflected in the operating costs and operating income. The market effect refers to the degree of passenger travel satisfaction, which is generally reflected in the cost of passenger. The passengers' expenses generally include fares and time. In summary, a multi-objective optimization model is established in this paper, including two objective functions: maximizing the economic efficiency and minimizing passenger travel costs.

A. NOTATIONS AND PARAMETERS

In order to make the model clearer, it lists all the relevant subscripts and parameters used in the formulation in Table 1.

B. DECISION VARIABLES

It focuses on generating optimal strategies for the number of trains, train marshaling, train type and train stop planning simultaneously in this paper. Thus, four types of decision variables will be considered hereinafter, as shown in Table 2.

C. OBJECTIVE FUNCTION

As previously mentioned, the formulation of the high-speed railway operation plan should consider both economic benefits and market efficiency. The one of objective of the optimization models is to maximize the profit.

The economic benefits of operating passenger trains in the railway industry can be expressed through operating income and costs. With this concern, the revenue of the ticket is treated as operating income, the operating expenses of trains and the service fees of station parking as the operating expenses for high-speed trains. The objective function is established as follows:

$$\max Z_1 = \sum_{h=1}^{H}(\sum_{T=1}^{T_h}(\sum_{i=1}^{n-1}\sum_{j=j+1}^{n} f_{l_T^{h,\tau}}(s_i, s_j) \cdot R_h(s_i, s_j)) - C_1^{h,\tau} d_{l_T^{h,\tau}} - C_2^h \sum_{i=1}^{n} x_{l_T^{h,\tau}}(s_i))) \tag{1}$$

It is clear that formulation (1) is essentially the relationship between passenger ticket revenue, operating costs and station parking fees for each train in different types. Among them, passenger ticket of different section can be formulated as follows:

$$R_h(s_i, s_j) = \varphi(h) d_{e_{ij}} \tag{2}$$

According to the regulations of the China Railway Corporation, the tax rate for taxpayers who provide rail transport services is 11% of value added tax (VAT). Therefore, high-speed train operation can be formulated as follows:

$$Z = (1 - \mu) Z_1 \tag{3}$$

When the number of train stops increases, passengers can choose more trains with travel requirements at each station, but the service fees for train stops increase at the same time.

TABLE 1. Subscript and parameters used in formulation.

Notations	Definition
S	Set of considered stations.
H	Set of considered train type.
s_i, s_j	Index of stations, $s_i, s_j \in S$.
n	The total number of stations.
G	Set of high-speed trains.
D	Set of relevant low speed trains compared with those in G .
e_{ij}	Station section from station i to station j .
$d_{e_{ij}}$	Distance of station i to station j
h	Index of train type.
T_h	The number of trains of type h
T	Index of trains.
τ	Train marshaling
$\varphi(h)$	One-kilometer fare rate for trains of type h .
R_h	Ticket prices for different stations
$C_1^{h,\tau}$	One-kilometer operating cost for trains of type h and the train marshaling is τ .
C_2^h	Station service fee for trains of type h .
v^h	The speed of trains of type h .
$l_T^{h,\tau}$	For trains of type h , the train marshaling is τ and the index is T .
$d_{l_T^{h,\tau}}$	Single direction distance for $l_T^{h,\tau}$.
$f_{l_T^{h,\tau}}$	Number of passengers on $l_T^{h,\tau}$.
t_k	Stop time at the station.
t_d	Loss of time during train start and stop.
α	The factor of time value.
ρ	Fixed number of persons.
θ_d	Seat occupancy rate.
N_{od}	Total passenger flow of the day.

Therefore, the purpose of the optimization plan for high-speed trains is to reduce the number of train stops and to ensure the continuity of trains while meeting the needs of passengers.

On the other hand, improving the market efficiency is an important measure to enhance the image of the railway. The market efficiency is usually measured by the travel cost of the traveler. The travel cost includes both the ticket and time loss. The time loss mainly includes the time consumption caused by the train is running or stops at the station and

TABLE 2. Decision variables in the optimization model.

Variable type	Variable	Definitions
Main decision variables	x	Set of train stop planning, =1, if train stops at station; =0, otherwise.
	h	Train type, =1, if train type is G; =0, if train type is D.
	τ	Train marshaling, =1, if the train is 16-car marshaled; =0, if the train is 8-car marshaled.
Assisting decision variables	N	The number of trains operating in this section.

passenger detention when the tickets cannot meet the passenger demand. In order to get closer to the actual process of stopping at the station, consider the loss of time during the start and stop of the train. Therefore, in this paper, we consider that the two forms of ticket prices and time constitute the travel cost of passengers. The objective function is established as follows:

$$C_{tk} = \sum_{h=1}^{H}(\sum_{T=1}^{T_h}(\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} f_{l_T^{h,\tau}}(s_i, s_j)R_h(s_i, s_j))) \tag{4}$$

$$C_{tm} = \sum_{h=1}^{H}(\sum_{T=1}^{T_h}(\sum_{i=1}^{n-1}(\sum_{j=i+1}^{n} f_{l_T^{h,\tau}}(s_i, s_j)(\frac{d_{e_{ij}}}{v^h} + (\sum_{i}^{j} x_{l_T^{h,\tau}}(s_i)-2)\cdot t_k + (\sum_{i}^{j} x_{l_T^{h,\tau}}(s_i)-1)\cdot t_d))))) \tag{5}$$

It is clear that formulation (4) is the cost of the ticket in the travel cost, and formulation (5) is the time consumption of passenger travel cost.

In the new development plan, unallocated passengers may be present due to limited capacity, resulting in detention. In order to maximize the benefits, the number of stranded passengers should tend to zero as much as possible. Therefore, there will be a large penalty factor for the stranded passengers as a time loss. With the above analysis, the other objective of the optimization model in this paper is to minimize travelers' travel costs. The objective function is established as follows:

$$\min C = C_{tk} + \omega(C_{tm} + Mf_{\overline{k}}) \tag{6}$$

where notation ω is the passenger time value factor, M is the penalty factor, and $f_{\overline{k}}$ is the number of stranded passengers.

D. SYSTEMATIC CONSTRAINTS

"0-1" constraint: for the type of high-speed train, it is divided into G and D. These two types are denoted by the 0-1variable $h = \{0, 1\}$. $h = 0$ indicates that the type of train is D, and $h = 1$ indicates that the type of train is G. Furthermore, for the number of train marshaling, it has two types of 8-car marshaled and 16-car marshaled. These two types are denoted by the 0-1 variable $\tau = \{0, 1\}$. $\tau = 0$ indicates that the train is 8-car marshaled, and $\tau = 1$ indicates that the train is 16-car marshaled. Last but not least, for train T at station s, its states can only be stopped or not stopped. This state is also denoted by the 0-1variable $x = \{0, 1\}$. $x = 0$ indicates that train T does not stop at station s, and $x = 1$ indicates that train T stops at station s.

Passenger capacity constraints: to guarantee the safe operation on the railway line, trains marshaling usually consists of two types in China, one is 8, the capacity is 600, and the other is 16, the capacity is 1100, the same as shown in Table 4. Then, the capacity constraints can be formulated as follows:

$$\rho(\tau) = \begin{cases} 600, & \tau = 0 \\ 1100, & \tau = 1 \end{cases} \tag{7}$$

Train capacity constraints: to ensure the convenience and comfort of travelers, high-speed trains generally do not sell ticket for standing room. Therefore, passengers at each station cannot exceed the capacity of the train. The train capacity constraint is expressed as follows:

$$\sum_{i=1}^{i'}\sum_{j=i'+1}^{n} f_{l_T^{h,\tau}}(s_i, s_j) \leq \rho(\tau) \quad i' = 1, 2, \ldots, n-1 \tag{8}$$

Seat occupancy rate constraints: to guarantee a certain degree of economic benefits, occupancy rate needs to meet certain standards. Occupancy rate constraints can be expressed as below:

$$\theta_d \leq \frac{\sum_{i,j\in e_{ij}} f_{l_T^{h,\tau}}(s_i, s_j) d_{l_T^{h,\tau}}^{e_{ij}}}{\rho(\tau) d_{l_T^{h,\tau}}} \tag{9}$$

IV. SOLUTION ALGORITHM

The optimization of high-speed train line planning is an NP hard problem. As the number of trains station and the number of trains increase, the solution space increases explosively, and the difficulty of obtain the global optimal solution increase in geometric progressing. Differential evolution algorithm (DE) is a heuristic random search algorithm based on population difference. Its unique competitive survival strategy can dynamically track the current search situation. It reduces the complexity of the genetic algorithm (GA), and has the characteristics of simple structure, easy implementation, fast convergence and strong robustness. Considering the fact, this study uses the improved MODE to solve the optimization model of high-speed trains.

In the optimization model, the decision variables include stop planning, train type, and train marshaling, which are all 0-1 variables. Meanwhile, the number of trains operating is a positive integer variable. As shown in Table 3, the notation N is used to indicate the number of trains operating, and notation n is used to indicate the total number of stations. Then, the individual code length L_1 of the train stop planning is $L_1 = N \cdot n$, and the individual code length of the train

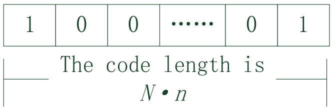

FIGURE 3. Coding scheme for train stop planning.

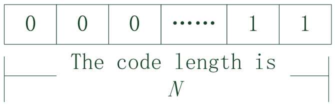

FIGURE 4. Coding scheme for train type.

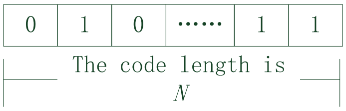

FIGURE 5. Coding scheme for train marshalling.

type L_2 and the train marshaling L_3 respectively is $L_{2,3} = N$. In summary, there are three individual coding schemes as below:

(1) The train stop planning. When the code is 1, it means that the train stops at the station. And when the code is 0, it means that the train does not stop at the station. The coding scheme is shown in Fig. 3.

(2) Train type. When the code is 1, it means that the train type is G. And when the code is 0, it means that the train type is D. The coding scheme is shown in Fig. 4.

(3) Train marshaling. When the code is 1, it means that the train is 16-car marshaled. And when the code is 0, it means that the train is 8-car marshaled. The coding scheme is shown in Fig. 5.

In addition, due to the dynamic nature of the passenger demand, the number of trains is uncertain. However, the number of trains N determines the dimensions of the three individual coding schemes. If the number of trains is randomly generated, the dimension of the population will not be uniform and the algorithm will be difficult to operate normally. Therefore, the number of trains was adjusted by neighborhood search in the process of population evolution, and the number of trains will gradually adjust from a large value to a fixed value. Thus, we define the larger value above as the maximum number of trains that can be received per day in the study section. When the number of trains is determined, the evolution of other optimization variables in the population makes sense. Based on the above ideas, taking into account the high demand of dynamic passengers flow at the peak of the period, when generating the initial solution, the maximum number of trains A that can be received per day in the study section is used as the number of initial trains N. Verified by calculation examples, the number of trains will be gradually adjusted to the optimal area at the beginning of the evolutionary iteration of the algorithm.

A. MODE ALGORITHM

DE is a heuristic random search algorithm based on population difference, its principle is very similar to GA. The framework of DE consists of three parts: mutation operation, cross operation and selection operation. There are many evolutionary patterns, which are mainly reflected in the difference between the difference vector and the base vector in the mutation operation. Due to the fact that the number of trains may change during the course of evolution iterations, the stored Pareto efficiency is no longer applicable. Therefore, we select DE/ rand/1 and DE/best/1 as mutation operations. Formulation (10) is used in the mutation operation when the evolution starts and the number of trains is changed. Formulation (11) is used in the mutation operation when the number of trains does not change.

$$\text{DE/rand/1}: v_i^{k+1} = X_{i_3}^k + F(X_{i_1}^k - X_{i_2}^k) \tag{10}$$

$$\text{DE/best/1}: v_i^{k+1} = X_{best}^k + F(X_{i_1}^k - X_{i_2}^k) \tag{11}$$

where F is the scaling factor, k is current evolution generation. $(X_{i_1}^k - X_{i_2}^k)$ is a random difference vector, and $X_{i_3}^k$, X_{best}^k are base vectors.

The cross operation is generating a new individual by crossing the parent and the mutated individuals according to the crossover probability CR. The cross operation is formulated as below:

$$u_{ij}^{k+1} = \begin{cases} v_{ij}^{k+1} & rand < CR | j = randn(i) \\ X_{ij}^k & otherwise \end{cases} \tag{12}$$

The selection operation is based on a dominant relationship. There is another way to say, only individuals with high economic benefits and good market effects will be selected.

B. ALGORITHM IMPROVEMENT

In the MODE algorithm, scaling factor F and crossover probability CR have great influence on the performance of the algorithm. The efficiency of the mutation operation is largely determined by the choice of the scaling factor F, and the diversity of the population depends to a large extent on the crossover probability CR. In the basic differential evolution algorithm, the scaling factor and crossover probability are fixed. However, in different evolutionary periods, the algorithm has different requirements for convergence speed and population diversity. At the beginning of evolution, population diversity can generally be met. At this time, it is only necessary to speed up the convergence of the algorithm; in the later stage, in order to avoid falling into a local optimal situation, the diversity of the population should be improved. Therefore, if the control parameters are fixed or linearly changed with the evolution algebra, individuals with different degrees of evolution in each generation will be difficult to fully evolve, thus, reducing the convergence speed of the algorithm. In summary, we propose the adaptive control parameters based on the differences in evolutionary degrees of individual generations. Specific steps are described as follows:

step 1: The individuals in the population are sorted according to the value of fitness, and the population is divided into three parts. According to the ranking results, the top 30% of the individuals are the better individuals, the last 30% of the individuals are the poor individuals, and the middle 40% of the individuals are the general individuals.

step 2: Calculate the average fitness $f_{mean}^{i,j}$ and the best fitness $f_{best}^{i,j}$ of each objective function j in the i generation.

step 3: Calculate the difference between $f_{mean}^{i,j}$ and $f_{best}^{i,j}$. The difference Δ can be expressed as follows:

$$\Delta = \sum_{j=1}^{obj} |f_{best}^{i,j} - f_{mean}^{i,j}| \tag{13}$$

step 4: For different evolutionary generations, the selection of individual control parameters for different degrees of evolution is different. In other words, we should consider the individual's strengths and weaknesses in the current population and also consider the evolution of the current population. Meanwhile, for multi-objective optimization, the quality of an individual is determined by the quality of each objective function. Therefore, we have devised a rule for individual division. The details are as follows:

(1) When the individual f_k^i is a poor individual. In this case, the global search capability should be strengthened so that poor individuals can quickly search for better areas. At the same time, we must balance the evolution of the current population. Therefore, the scaling factor F should satisfy the following equation. It is clear that F_k increases with Δ^*, and the larger Δ^*, the closer F is to $F_{\max}$. It means that poor individuals can get a large F, allowing individuals to quickly approach a better area.

$$\Delta^* = \sum_{j=1}^{obj} (f_k^{i,j} - f_{mean}^{i,j}) \tag{14}$$

$$F_k = F_{\max} - (F_{\max} - F_{\min})(\alpha \frac{1}{1+e^{\Delta^*}} + \beta \frac{i}{MAXGEN}) \tag{15}$$

where $F_{\max}, F_{\min}$ indicate the upper and lower limits of the scaling factor F. α, β are the weights of the degree of individual's strengths or weaknesses and the degree of the current population evolution. Since poor individuals may appear at different stages of evolution, β should be smaller and the maximum number of iterations is expressed as $MAXGEN$.

(2) When the individual f_k^i is a general individual. At this point, both global search and local search capabilities should be taken into account. Therefore, the scaling factor F should satisfy the following equation:

$$F_k = F_{\min} + (F_{\max} - F_{\min}) \frac{MAXGEN - i}{MAXGEN} \tag{16}$$

(3) When the individual f_k^i is a better individual. In this situation, local search capabilities should be strengthened and the evolution of the current population should also be considered. Therefore, the scaling factor F should satisfy the following equation:

$$F_k = F_{\max} - (F_{\max} - F_{\min})(\alpha \left| \frac{\sum_{j=1}^{obj} (f_k^{i,j} - f_{best}^{i,j})}{\Delta} \right| + \beta \frac{i}{MAXGEN}) \tag{17}$$

(4) In this paper, the self-adaptive improvement of crossover probability can be expressed as follows:

$$\alpha_i = \frac{\sum_{j=1}^{obj} \sqrt{\sum_{k=1}^{NP} (f_k^{i,j} - f_{mean}^{i,j})^2 \Big/ NP}}{obj} \tag{18}$$

$$CR = CR_{\max} - \frac{\alpha_i}{\max(\alpha_I)} (CR_{\max} - CR_{\min}) \tag{19}$$

where α_i is the adaptation coefficient of crossover probability in generation i, and α_I is the set of the adaptive coefficients of the crossover probability from the first generation to current generation. Notation NP is population size.

(5) Since in the MODE algorithm, the scaling factor is usually between (0, 1), this algorithm is mainly used for real value optimization. However, in this paper, the main decision variables are all 0-1 variables. When using MODE algorithm to solve the optimization model, the mutation operation needs to be improved so that the MODE algorithm can apply to the optimization of 0-1 variables. It can be expressed as follows:

1) The scaling factor processed as follows, so that it mapped at 0 and 1.

$$F = \begin{cases} 1 & rand < F_k \\ 0 & otherwise \end{cases} \tag{20}$$

1) Afterwards, the base vector, scaling factor, and differential vector in the mutation operation will all be 0-1 variables, the mutation operation can be expressed as follows:

$$v_i^{k+1} = X_{i_3}^k \wedge [F \& (X_{i_1}^k \wedge X_{i_2}^k)] \tag{21}$$

Refer to (21), the symbol '∧' is an XOR operation and the symbol '&' is an AND operation.

C. THE GENERATION OF INITIAL SOLUTION

A heuristic algorithm for generating an initial solution is presented in this section.

Due to the characteristics of high-speed trains with less stops and faster speeds, a heuristic method to generate initial solutions was constructed to improve the quality of the initial solution, making the initial train stop planning includes the following characteristics: more trains are stopped at stations with larger passenger traffic, and stations with less passenger traffic also have a number of trains.

1) STATION WEIGHTS

The weight of each station symbolized as ω is based on the ratio of the number of passengers received at each station to the number of passengers received at all stations.

2) ATTENUATION RATIO OF STOPS

Taking into account the characteristics of high-speed trains operating at high speed and fewer stoppages at stations, and the differences between the actual operation of train D and G in China, attenuation ratios of different numbers of stops for different types of high-speed trains symbolized as λ are used to limit the stops of high-speed trains.

3) THE NUMBER OF STOPS AT EACH STATION

In order to ensure that stations with small weights can have trains to stop, and at the same time avoiding too many stops for stations with heavy weights, it is necessary to record the number of existing stops η at each station during the process of initialization. According to the existing number of stops at the station, reduce the probability of the station with a significant weight, and increase the probability of a station with a low weight.

In summary, the probability P_{ij} that a train i stops at each station j during the initial population can be expressed as:

$$P_{ij} = \omega_j \alpha \lambda_\tau^\xi \frac{i}{\eta_j + 1} e^{-\frac{\eta_j}{A}} \tag{22}$$

Refer to (22), λ_τ^ξ is used to indicate attenuation ratio of a train which the type is τ and has already stopped ξ times. α is used to extend the weight ω to (0, 1], it can be expressed as follows:

$$\alpha = \frac{1}{\max(\omega)} \tag{23}$$

D. NEIGHBORHOOD SEARCH STRATEGY

The neighborhood search strategy for two types of high-speed trains is as follows:

1) Reduce train marshaling

For trains are 16-car marshaled, if the attendance is lower than a certain threshold, the train marshaling is reduced to 8.

2) Increase train marshaling

For trains are 8-car marshaled, if the attendance is higher than a certain threshold, the train marshaling is increased to 16.

3) Reduce or increase the number of trains

For trains of the same type and formation number of 8 whose seating ratio is lower than a certain threshold, if the sum of these train occupancy ratios is still lower than the threshold, the train is deleted. Otherwise, when these trains are deleted, a new train is reopened and its stop stations are generated by the stop stations of the deleted trains. In other words, if the frequency of a station in the deleted trains is higher than a certain threshold, the station will serve as the stop for the newly added train.

4) Splicing trains

For trains of the same type with the formation number of 8, if they have the same parking plan, they will be spliced into a new train which the number of train marshaling is 16.

5) Add trains

For trains with a train formation number of 16, if the attendance is higher than a certain threshold, add a new train of the same type with a certain probability of 8 vehicles.

After the neighborhood search, the number of trains may change accordingly. In this case, the value of fitness for each objective function in the multi-objective model needs to be sorted, and the number of trains with better fitness for each target is selected as the number of trains to be optimized afterwards. In addition, individuals with the same number of trains in the neighborhood search process form a new population. If the reconstituted population is not satisfied with the initially set number of populations, several individuals are randomly generated for composing a new population, and a set of non-inferior solutions is updated; if the number of trains does not change, individuals with the same number of trains in the neighborhood search process are merged with the original non-inferior solutions, and non-inferior solutions need to be re-screened.

V. EXAMPLE ANALYSIS IN TEST PROBLEMS

To test the performance of MA-MODE algorithm, experiments based on benchmark test problems are carried out. The MA-MODE algorithm is implemented using MATLAB language and all the experiments are performed on a PC with the Intel Core 7500U CPU (2.70GHZ for each single core) and the Windows 10 operation system.

A. TEST PROBLEMS

4 bi-objective benchmark problems presented in the literature are chosen as the test problems. These problems are often used in many published papers dealing with evolutionary algorithms for MOPs.

The bi-objective problems are the ZDT series: ZDT1, ZDT2, ZDT3 and ZDT6 [18].

B. PERFORMANCE METRICS

For the selected test problems, the true Pareto fronts of them are known. In this paper, we adopt two performance metrics that are often used in many research papers: the inverted general distance (IGD) [19], [20] and the Spacing (SP) [21], [22].

C. PARAMETER SETTING

Since the range of variables for test problems are between 0-1, the scaling factor F cannot be too large. If the scaling factor is too large, the variable is easily out of range and the search process is equivalent to a random search. Therefore, $F_{\max} = 0.36$ and $F_{\min} = 0.01$, and $CR_{\max} = 0.5$, $CR_{\min} = 0.3$; and $\alpha = 0.3$, $\beta = 0.35$; and $NP = 300$, $MAXGEN = 250$.

D. EXPERIMENTAL RESULTS

In this section, first, we analyzed the performance of the MA-MODE in different evolutions. The IGD and SP results of 20 independent runs for each problem in different evolutions are shown in Table 3 and Table 4. From Table 3, as the

TABLE 3. Algorithm performance analysis of different evolution (IGD).

Problems	100		150		200		250	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
ZDT1	$1.12E-2$	$6.58E-4$	$3.8E-3$	$1.48E-4$	$2.0E-3$	$8.49E-5$	$1.37E-3$	$4.86E-5$
ZDT2	$1.66E-2$	$1.02E-2$	$4.2E-3$	$1.1E-3$	$1.9E-3$	$1.46E-4$	$1.34E-3$	$3.92E-5$
ZDT3	$1.12E-2$	$1.3E-3$	$5.8E-3$	$2.96E-4$	$4.4E-3$	$2.62E-4$	$3.8E-3$	$2.76E-4$
ZDT6	$2.16E-2$	$2.74E-2$	$5.1E-3$	$2.16E-3$	$3.6E-3$	$2.18E-4$	$2.17E-3$	$3.67E-4$

TABLE 4. Algorithm performance analysis of different evolution (SP).

Problems	100		150		200		250	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
ZDT1	$4.6E-3$	$7.4E-3$	$2.1E-3$	$2.49E-4$	$2.1E-3$	$3.16E-4$	$2.15E-3$	$2.83E-4$
ZDT2	$3.6E-3$	$9.37E-4$	$2.7E-3$	$9.31E-4$	$2.6E-3$	$4.04E-4$	$2.81E-3$	$4.7E-4$
ZDT3	$1.08E-2$	$5.4E-3$	$1.11E-2$	$1.7E-3$	$1.09E-2$	$1.1E-3$	$1.08E-2$	$1.30E-3$
ZDT6	$1.76E-2$	$3.4E-3$	$1.54E-2$	$3.4E-3$	$1.32E-2$	$1.83E-3$	$1.14E-2$	$1.44E-3$

TABLE 5. Comparison results of IGD mean and standard deviation with NSGA-II.

Problems	NSGA-II		MA-MODE	
	Mean	Std	Mean	Std
ZDT1	$1.82E-3$	$3.6E-4$	$1.37E-3$	$4.86E-5$
ZDT2	$3.07E-3$	$3.0E-4$	$1.34E-3$	$3.92E-5$
ZDT3	$8.12E-3$	$3.0E-3$	$3.8E-3$	$2.76E-4$
ZDT6	$6.35E-3$	$2.2E-3$	$2.17E-3$	$3.67E-4$

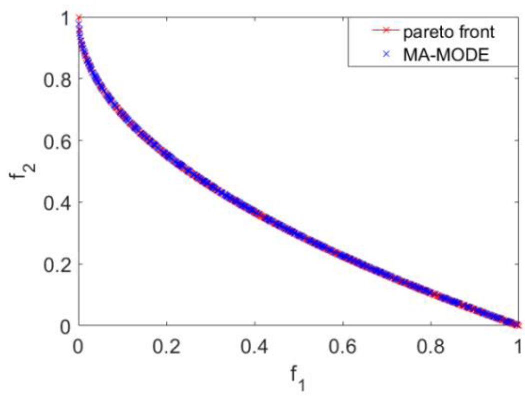

FIGURE 6. The comparison results of ZDT1 test problem.

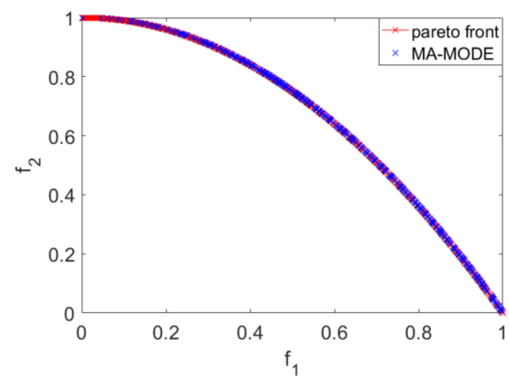

FIGURE 7. The comparison results of ZDT2 test problem.

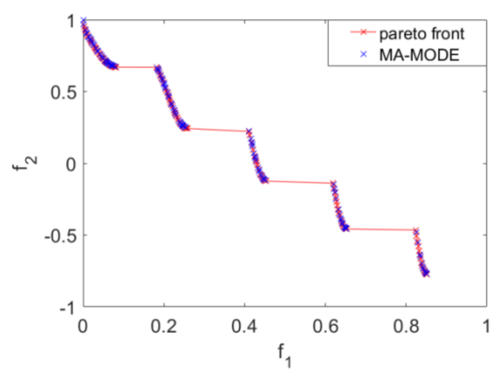

FIGURE 8. The comparison results of ZDT3 test problem.

number of evolutions increases, the IGD metrics decrease significantly, especially between the 100th and 150th generation, but the difference between the 200th and 250th generation is small. Meanwhile, the stability of the results of each generation also has a good effect. It is clear that, after 250 generations, each test problem obtains a set of uniform Pareto-optimal solutions.

In order to show the effectiveness of the archive, we compared our algorithm MA-MODE with the nondominated sorting genetic algorithm II (NSGA-II) algorithm [24], with the same number of evolutions and populations. The comparison results of 20 independent runs for each problem are shown in Table 5. It can be seen that the MA-MODE algorithm has obtained good results on all four test problems.

Finally, the comparison between the real Pareto front and the optimal solution set found by MA-MODE algorithm is shown in Fig. 6∼ Fig. 9, and it can be seen that the optimal solution found by the MA-MODE algorithm can approximate the real Pareto front. Last but not least, the four test functions take 41.9531s, 41.5625s, 13.484s and 32.495s, respectively.

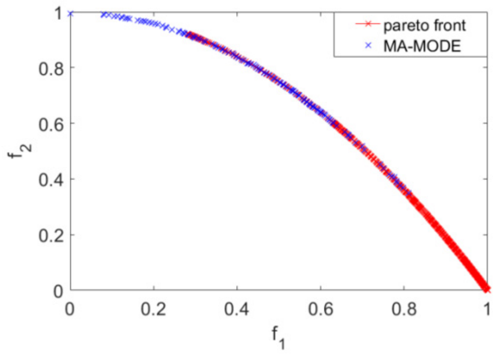

FIGURE 9. The comparison results of ZDT6 test problem.

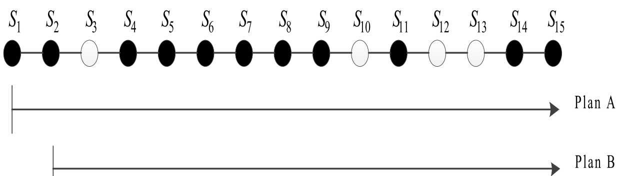

FIGURE 10. Train operation sections and operation lines.

TABLE 6. Related parameter settings.

Parameter	Parameter description	Value
t_k	Stop time at the station.	3min
t_d	Loss of time during train start and stop.	5min
ω	The factor of time value.	0.4yuan / min
C_1	The train operating cost	150yuan/km

The above experimental results show that the proposed algorithm has good convergence and diversity, and can effectively obtain the optimal solution of multi-objective function. The optimized solution has better convergence, diversity and uniformity.

VI. EXAMPLE ANALYSIS IN GUANGZHOU HIGH -SPEED RAILWAY

In this section, an example in Guangzhou high -speed railway is given to analyze the economy benefits and market effects of the proposed model and algorithm. A high-speed railway section with 15 train stations was constructed, of which high-speed train does not stop at $S_3, S_{10}, S_{12}, S_{13}$. As shown in Fig. 10, the solid dot "●" represent the train could stop at current station, and the hollow dot "◯" represent the train could not stop at current station. In addition, there are two originating schemes for trains, one of which originates from S_1 and the other originates from S_2. Assume that train D and train G operate at the speeds of $200km/h$ and $300km/h$. In addition, it is assume that each stop made by a train D costs c_2 yuan, each stop made by a train G costs c_1 yuan, and $c_1 = 2.5c_2$ [9]. Other parameters are shown in Table 6.

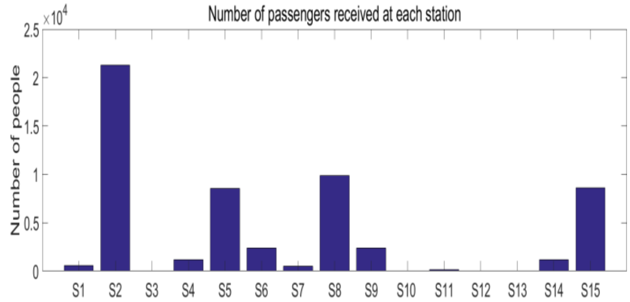

FIGURE 11. Number of passengers received at each station.

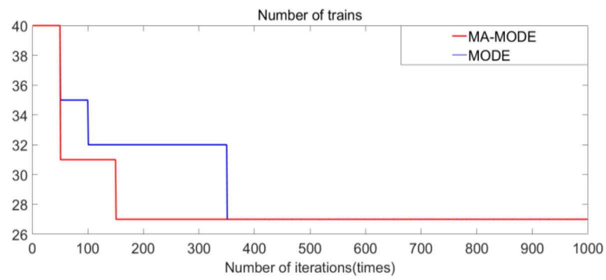

FIGURE 12. Iterative solution process about number of trains.

Passenger's flow of each OD pair is shown in Table 7, and the number of passengers received at each station per day is shown in Fig. 11. It can be seen from the Fig. 11, station 2, 5, 8, 15 receives a large number of passengers. An improved multi-objective differential evolution algorithm that combines heuristic algorithm and neighborhood search strategy was adopted, and MATLAB R2016b software program was used to solve the example case. The parameters of the MA-MODE algorithm were set to the following: population size $popsize = 50$, the maximum number of iterations $Maxgen = 1000$, scaling factor regulation parameters $F_{\max} = 0.9$ and $F_{\min} = 0.3$, crossover possibility regulation parameters $CR_{\max} = 0.4$ and $CR_{\min} = 0.2$. In addition, the maximum number of trains A that can be received per day in the study section is $A = 40$, attenuation ratio of a train $\lambda_0 = 0.7$ and $\lambda_1 = 0.5$. Considering the actual operation process, train D runs on the high-speed railway and also runs on the ordinary railway, if the number of train D changes, it may affect the train operation on ordinary railway. Therefore, the number of train D remains a constant value. For instance, after 150 iteration times, the number of trains converges to a constant value using the MA-MODE in Fig. 12, but at the same conditions, it needs 350 iteration times using the standard MODE algorithm. In order to be more convincing, we conducted 20 independent experiments on the two algorithms, and recorded the number of iterations in which the number of trains converges to a constant value. Then the average of the 20 recorded values is obtained, the average number of iterations of the MA-MODE algorithm is 160, and the average number of iterations of the MODE algorithm is 285. Through the above analysis, the MA-MODE converges at a faster rate. After 1000 iteration times, the result of Pareto

TABLE 7. **Passenger's flow of every OD pair.**

OD	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}
S_1	—	133	—	4	116	40	3	123	5	—		—	—	32	91
S_2	—	—	—	758	5673	1440	247	5891	785	—	111	—	—	749	5471
S_3	—	—	—	—	—	—	—	—	—	—		—	—	—	—
S_4	—	—	—	—	137	76	2	94	7	—	0	—	—	0	71
S_5	—	—	—	—	—	259	135	1012	175	—	23	—	—	134	858
S_6	—	—	—	—	—	—	0	327	49	—	0	—	—	28	185
S_7	—	—	—	—	—	—	—	69	0	—	0	—	—	0	75
S_8	—	—	—	—	—	—	—	—	870	—	28	—	—	141	1301
S_9	—	—	—	—	—	—	—	—	—	—	0	—	—	28	485
S_{10}	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
S_{11}	—	—	—	—	—	—	—	—	—	—	—	—	—	0	19
S_{12}	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
S_{13}	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
S_{14}	—	—	—	—	—	—	—	—	—	—	—	—	—	—	70
S_{15}	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—

TABLE 8. **The evaluation indicators for the train operation plan.**

Plan	Z	C	Stranded crowd number	The number of trains
Original scheme	7.1799×10^5	2.8643×10^6	0	32
Optimize scheme(standard MODE)(1)	7.5761×10^5	2.6903×10^6	0	27
Optimize scheme(MA-MODE)(2)	7.5734×10^5	2.6706×10^6	0	27
Optimize scheme(MA-MODE)(3)	8.1799×10^5	2.6862×10^6	0	27

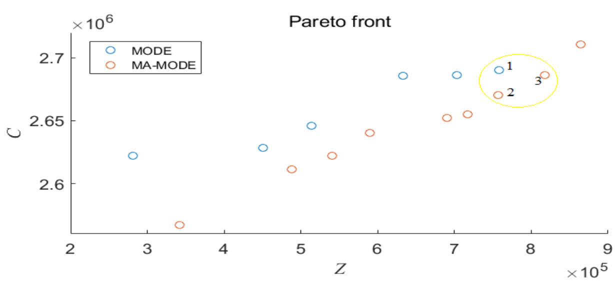

FIGURE 13. **Pareto solution set of two optimization methods.**

solution set of two optimization methods is shown in Fig. 13. It can be seen that the Pareto solution set of MA-MODE is superior to the standard MODE. The Pareto solution set is the optimal solution after the balance. Decision makers can choose one of them based on their emphasis on different indicators.

Specifically, we choose a pair of Pareto solutions for comparison. The comparison results are shown in Table 8. It can be seen that the selected non-inferior solutions (point 1, point 2, and point3 in Fig. 13) can dominate the solution of the original scheme. Namely, the result of point 3 can dominate the result of point 1 clearly; and the result of point of 2 and the result of point 1 are not dominated by each other, although the economic benefit of point 2 is 270 lower than point 1, but the passenger travel cost of point 2 is reduced by 19700 compared with point 1. From the perspective of market efficiency C, the result of point 2 is better than point 1. In summary, the optimization result of MA-MODE is better than MODE. Moreover, the plan ensures a certain degree of accessibility between OD pairs, thus this plan meets the travel requirement of passengers. The result of this Pareto solution (point 2) generated by MA-MODE is shown in Fig. 14 (Time consuming 841s). It contains four types of information for the trains, including the number and type of trains, train marshaling (0: train is 8-car marshaled; 1: train is 16-car marshaled) and stop scheme of each train. It can be seen there are more trains at station 5 and station 8. Meanwhile, the number of stops for each train is fewer stops and less than or equal to 6. In general, railway rolling stock is one of the most expensive assets of railway operators [23]. The number of trains in the optimized scheme is smaller

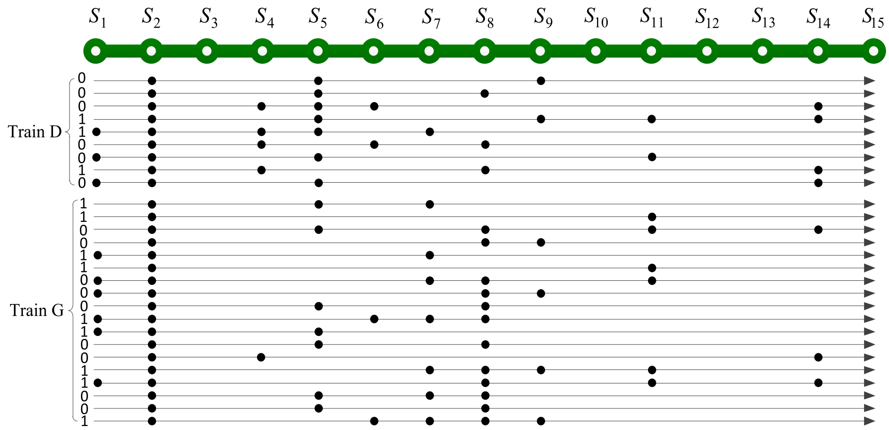

FIGURE 14. Optimization result.

than original scheme, which could save lots of operating costs.

VII. CONCLUSION

Aiming to provide a system-optimization framework for line planning, this paper first integrated the number and the type of train, train marshaling and stop planning together into a fundamental collaborative optimization model on a high-speed railway corridor. To establish the connection between the train stop planning, train type, train marshaling and the number of train, binary variables were introduced to determine whether a train stops at a station or not, whether a train type is D or G, and whether a train is 8-car marshaled or 16-car marshaled. Meanwhile, a positive integer variable was introduced to indicate the number of train. Due to the dynamic nature of the passenger demand, the number of trains is uncertain. However, the number of trains determines the dimensions of the individual coding schemes. Therefore, the number of trains was adjusted by neighborhood search in the process of population evolution. If the number of trains has changed, the individuals that match the number of trains changed will be saved during the neighborhood search. Meanwhile, the population may need to be filled. In addition, it is also necessary to screen the non-inferior solution from the current population to replace the non-inferior solution for the next iteration. On the other hand, if the number of trains has not changed, the individuals with the same number of trains are extracted and merged with the non-inferior solutions, and the non-inferior solutions are screened again. Through an optimization model that aims to maximize the income of Railway Company and minimize passenger travel cost, the collaborative optimization model was realized. Meanwhile, we proposed MA-MODE to solve this problem. Prior to this, the efficiency and convergence of the MA-MODE were proved by some test problems. Then, a real case study was performed on the Guangzhou high-speed railway with the practical operation data. The computational results showed that this strategy can change the number of trains according to the passenger flow demand, and give a reasonable operation plan, which greatly saves operating costs.

Further research will focus on a better and quantified mathematical model to combine the train scheduling.

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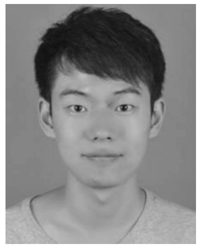

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