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A Modeling Method for the Driving Process of Heavy-Haul Train Based on Multi-Mass Model

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ABSTRACT Unlike the locomotive, heavy-haul trains have large carrying capacity and consist of hundreds of carriages; the longitudinal impulse in the train has significant coupled nonlinear characteristics during its operation. With the continuous increase in traction weight, problems with the existing control models gradually appear, vehicle decoupling and derailment occur, and the trains often fail to operate on schedule. Using the coupler characteristic curve, this paper comprehensively considers uncertain factors such as the train loading weight, line ramps, vehicle dynamic performance differences, and changeable operating environment to accurately model the heavy-haul train coupling force and train longitudinal dynamic multiple points. We optimize the target curve of the ideal running speed of the train and design the corresponding running tracking control strategy. The simulation results show that the ideal target speed curve optimization method designed in this paper can effectively improve key indicators such as safety, punctuality and energy saving in train operation to make trains more safely and efficiently run.

INDEX TERMS Adaptive genetic algorithm, heavy-haul train, multi-objective optimization.

I. INTRODUCTION

Heavy-haul railway has the advantages of large transport capacity, high efficiency and low cost [1]. In countries with vast area and rich resources, such as China, Canada, the United States, Brazil, Australia and South Africa, bulk cargo transport has large proportion, and freight railway has become the main power of economic development [2]. Since the functional positioning of large-scale existing railways will gradually shift from passenger to freight, the scale of heavy-haul railway will gradually expand. The number of trips for heavy-haul trains increased with each passing day [3], [4]. However, heavy-haul trains are large-inertia and highly nonlinear system that run in complex and variable line conditions. Its operation control is an extremely complicated multi-constrained, multi-objective, nonlinear time-varying process, which makes driving difficult [5]–[8]. Therefore, when the traction weight of heavy-haul trains continue to increase, the existing operating mode problems gradually become apparent, and vehicle decoupling and derailment occur. Trains often fail to operate on schedule, and the huge demand for electrical energy seriously restricts the development of heavy-haul railway transportation.

Research on ATO (automatic train operation) system began in the 1960s. Many studies and experiments on automatic train control systems were performed in Europe, Japan and western countries [9], [10]. In the 1980s, with the development of information industry technology and artificial intelligence technology, many countries have made great progress in the research and application of ATO system, such as the United Kingdom, Germany, Japan, Australia, and France [11]. In 1987, Japan developed an intelligent train automatic driving system based on fuzzy predictive control and successfully applied it to the Sendai subway in Japan. This method combined with the predictive control method and solved the shortcoming of low-accuracy fuzzy control, which became a model of the predictive control method in ATO systems [12]. Australian scholars theoretically proved that the best maneuvering strategies for train operation on an ideal line are: maximum force traction, cruise, idle and maximum force braking. The method was used in the Galler Central Railway and achieved satisfactory results [13]. The UK developed a computer-controlled train inertia system, TCAS, which could prompt the driver to perform idle maneuver

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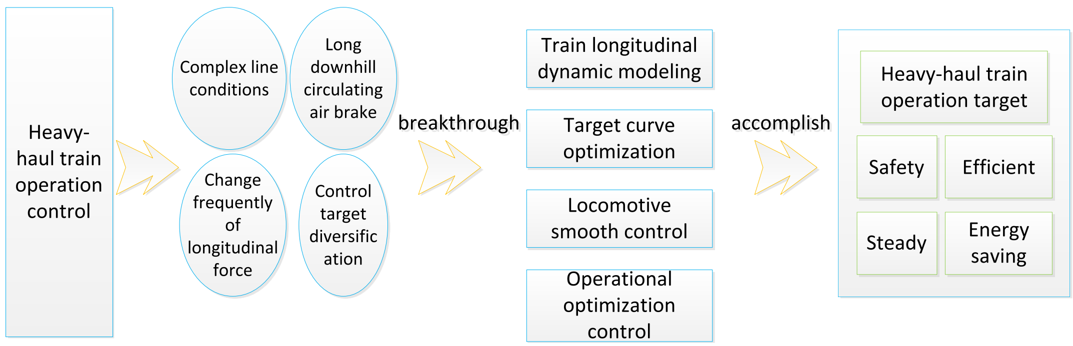

FIGURE 1. Overall framework of a heavy-haul train ATO system.

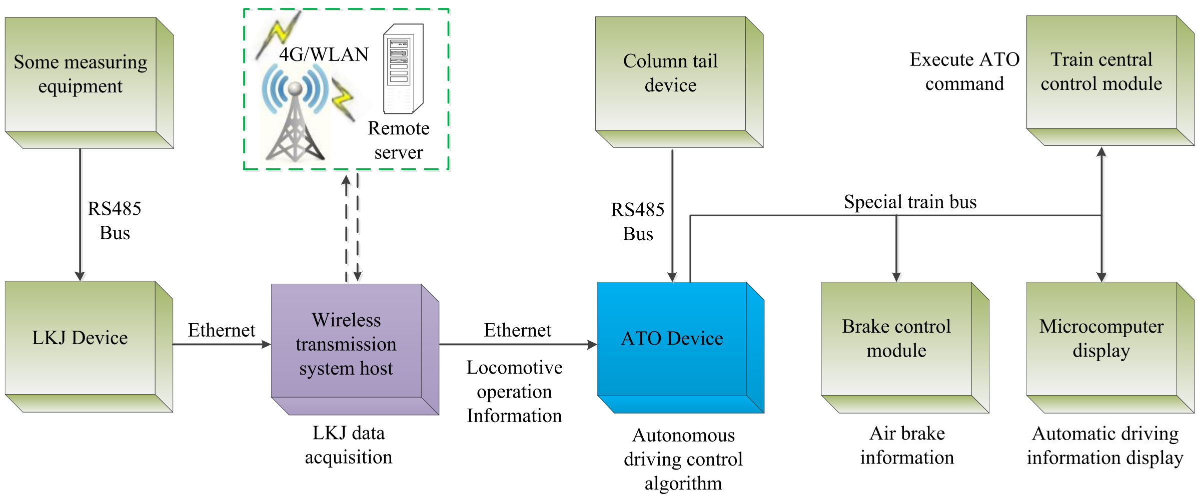

FIGURE 2. Architecture of a heavy-haul train ATO system.

in a timely manner while ensuring the punctuality of the train [14], [15]. In recent years, some researchers established an automatic driving train model based on the basic performance indicators of the train (punctuality and stability), calculated and optimized the target speed curve based on the model to achieve the efficient operation of the train. They also designed a train automatic driving simulator to verify the effectiveness of the control algorithm [16]–[18].

In summary, there are many challenges in the development of the heavy-haul train automatic driving system, e.g., the smooth control of a train on the undulating ramp, air brake cycle control of the train during a long and large growing downhill path and corresponding target curve generation with no temporary breakthrough. Therefore, this paper analyzes the characteristics and control laws of the heavy-haul train ATO system, designs the train longitudinal dynamic model, uses the multi-objective adaptive algorithm to improve the optimal running sequence, optimizes the target curve of the ideal train speed and designs the corresponding heavy-haul train running tracking control strategy to ensure that the ideal speed target curve can run stably and safely.

II. ATO SYSTEM ARCHITECTURE FOR HEAVY-HAUL TRAIN

The ATO function of a heavy-haul train is mainly complete by train operation status monitoring, data interaction, ATO device, control command response and human-computer interaction. This large system must consider the external environment, its own mechanical characteristics and the coordination of various functional modules [19], [20] to ensure the stability, efficiency and reliable operation. This paper is based on an in-depth analysis of the functional modules of the system, overall framework of the heavy-haul train ATO system as shown in Figure 1 and architecture as shown in Figure 2.

According to the above ATO system architecture of the heavy-haul train, a complex heavy-haul train ATO simulation platform can be modularly structured to ensure that the interface of simulation platform is clear and reliable. The functional module is shown in Figure 3. LKJ is the train operation monitoring and recording device, TSC is the on-board equipment of train operation status information system, TCU is the automatic transmission control unit, CCU

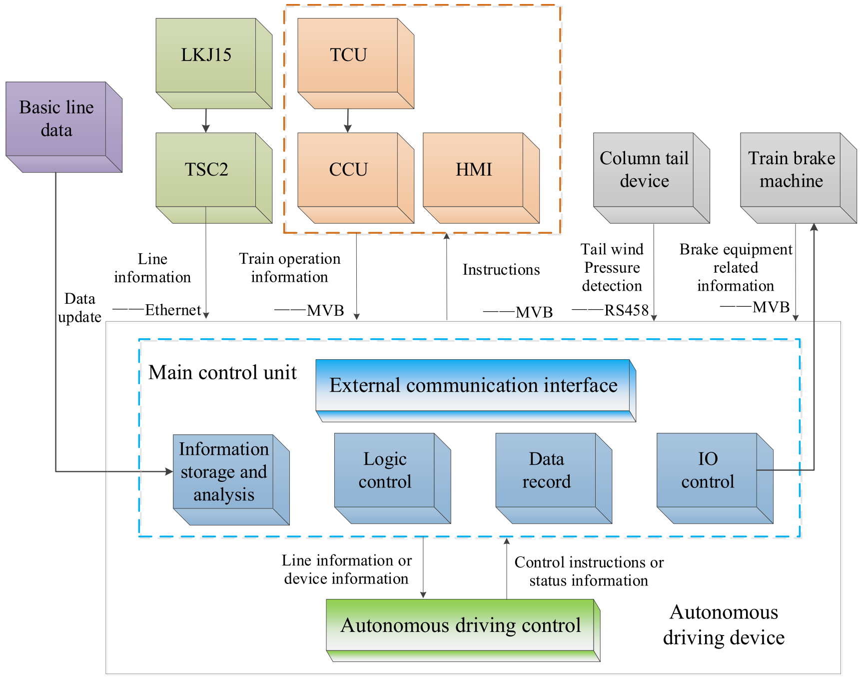

FIGURE 3. ATO control function module division.

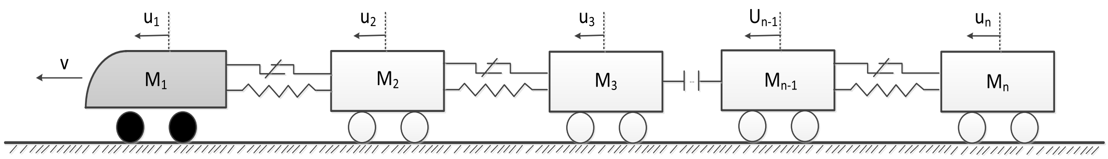

FIGURE 4. Schematic diagram of the Multi-mass model for heavy-haul train.

is the interface equipment between computer system and data circuit, HMI is a human machine interface, and MVB is a multifunction vehicle bus to communicate between devices.

III. ATO SYSTEM MODEL

The heavy-haul train ATO is based on the train running status and line condition information obtained in real time from the host TSC2 [21], [22]. This paper optimizes and adjusts the target running curve, which is generated offline, while using the fuzzy PID adaptive controller to track the current optimal target running curve, which is set in real time [23], [24]. Simultaneously, according to the feedback predicted value of the coupling force, it adjusts the control command output in time to ensure the coupler safety for heavy-haul train under various operating conditions.

A. MULTI-MASS DYNAMICS MODELING AND DESIGN OF THE COUPLING FORCE CALCULATION METHOD

Before generating the target curve of the heavy-haul train running line, we model the mass point and calculate coupling force. Based on the train operation data and actual operating environment, a Multi-mass longitudinal dynamic model of the heavy-haul train operation process is established, as shown in Figure 4.

We consider each train as a mass point and analyze the force of each mass point. Then, a longitudinal dynamic model of the i-th mass point of the heavy-haul train during operation can be established:

$$m_i a_i = F_{CRi} - F_{CFi} - F_{Ri} - W - F_{Bi} + F_{Ti} - F_{Di} \quad (1)$$

Here, $m_i a_i$ is the inertia force; F_{CRi} is the front hook force; F_{CFi} is the rear hook force; W is the additional resistance; F_{Ri} is the basic running resistance; F_{Bi} is the air braking force; F_{Ti} and F_{Di} are the locomotive traction and electric braking force, respectively. The force characteristics of the decoupling system of the heavy-haul train are mainly determined by the buffer, and the loading and unloading characteristic curves are obtained according to the impact test of the buffer. The coupler force analysis model is established based on the buffer characteristic curve. This established coupler force model fully considers the dynamic characteristics of the coupler buffer in the pull force and depressing force and includes factors such as the coupler clearance, buffer initial pressure, and chassis rigid impact. Zhai method is used to iteratively calculate the coupler force model to predict the coupler force of each mass point of a heavy-haul train under various operating conditions.

B. MULTI-OBJECTIVE OPTIMIZATION MODEL FOR THE TRAIN OPERATION

The train operation process is complicated, and conversion among multiple operating conditions is frequent. Frequent operating condition conversions increase the energy consumption of train operation and greatly affect the stability and safety of train operation. The operation and control of heavy-haul train is a multi-objective, constrained, and nonlinear complex time-varying control process. During heavy-haul train operation, there are problems such as vehicle decoupling, failure to operate on the train schedule, and energy consumption by frequent switching between traction/braking condition [28]–[30]. The operating speed curve of a heavy-haul train is mainly optimized based on these problems to achieve safety, punctuality and energy saving.

The evaluation index for safe operation of the heavy-haul train is mainly based on the running speed and coupling force of the train. Moreover, the running speed of the train should be less than the line speed limit [31]. During the operation of a heavy-haul train, the coupling force is divided into two types: pulling force and pressing force. When the current car has a greater speed than the rear car, the buffer is in a stretched state, and there is a pull force between two cars. When the current car has a lower speed than rear car, the buffer is in a compressed state, and there is a pressing force between two cars. The coupler force during train operation should be less than the value recommended by the China Academy of Railway Sciences: the maximum coupler force is ≤1000 KN (normal train operating conditions), and the maximum coupler force is ≤2250KN (train emergency braking conditions). The safe operation evaluation model of the train is:

$$F_{NUM} = \sum\nolimits_{i=1}^{N} \frac{Fi_{coupler}}{F_{UMAX}} > \gamma \tag{2}$$

$$\overline{F}_{NUM} = \frac{\sum_{j=1}^{N} F_{NUMj}}{N} \tag{3}$$

$$\overline{F}_{MAX} = \frac{\sum_{j=1}^{N} F_{MAXj}}{N} \tag{4}$$

$$\overline{F}_{MIN} = \frac{\sum_{j=1}^{N} F_{MINj}}{N} \tag{5}$$

$$f_s = k_1 * \left(\frac{F_{MAX}}{\overline{F}_{MAX}}\right) + k_2 * \left(\frac{F_{MIN}}{\overline{F}_{MIN}}\right) + k_3 * \left(\frac{F_{NUM}}{\overline{F}_{NUM}}\right) \tag{6}$$

Fi_{coupler} is the coupling force of the train at the i-th moment; F_{UMAX} is the rated maximum coupling force when the train is running; γ is the proportionality factor, whose value is 0.75-1. F_{NUM} is the number of times that thecoupling force is greater than the rated maximum coupling force γ factor during the j-th operation of the train; F_{MAX} is the maximum drag force value during the j-th operation of the train; F_{MIN} is the absolute maximum cramping force value during the j-th operation of the train; $\overline{F}_{MAX}$ is the average maximum pull force of the train in the population; $\overline{F}_{MIN}$ is the average maximum hook force of trains running in the population; $\overline{F}_{NUM}$ is the average number of times that the coupler force is large during train operation; N is the population size; k_1, k_2, k_3 are the weight factors, which satisfy $k_1 + k_2 + k_3 = 1$.

The energy saving operation evaluation index of the train requires the train to operate with the least or less energy consumption under the condition of safe operation and punctuality. Referring to ''Train Traction Calculation Rules'' [32], we establish an evaluation model for train energy saving operation:

$$Q = Q_y + Q_0 \tag{7}$$

The traction running power consumption is calculated according to formula (8):

$$Q_y = \frac{U_w \sum (I_p * t_y)}{60} \tag{8}$$

The power consumption of idle running, braking and stopping is calculated according to formula (9):

$$Q_0 = \frac{U_w \sum (I_{p0} * t_0)}{60} \tag{9}$$

U_w is the grid pressure of the locomotive; t_y is the traction running time of the locomotive, and the unit of 60 is minutes; t_0 is the time of the locomotive in the idle running, air braking and stopping states; I_p is the electric active current for locomotive traction; I_{p0} is the electric active current when the locomotive is in the idle running, braking and stopping states.

The on-time running evaluation index of the train refers to the difference between running time of the train and time specified in the train operating chart, and a smaller value is better within a certain range. The punctual running evaluation model of the train is:

$$T = \sum\nolimits_{i=1}^{n} T_i - T_U \tag{10}$$

T_U is the prescribed time of the train running chart; T_i is the running time of each section of the train; there are n intervals in total.

During the operation of the train, the safety optimization goal of the train requires that the running speed of the train is less than the line limit speed. In general, it is difficult to realize the traction and braking of the locomotive when the limit speed is 100 km/h, so it is appropriate to set the limit speed equal to or less than 100 km/h. Simultaneously, the operating conditions of the train should be less changed to ensure that the coupler force of the train is relatively stable. The on-time optimization goal of the train is to maintain a consistent running time of the train with the time specified in the train operating chart. In this case, more frequent changes in operating conditions may occur during the train operation. The train's energy saving optimization goal is to require less changes in operating conditions during the train operation and

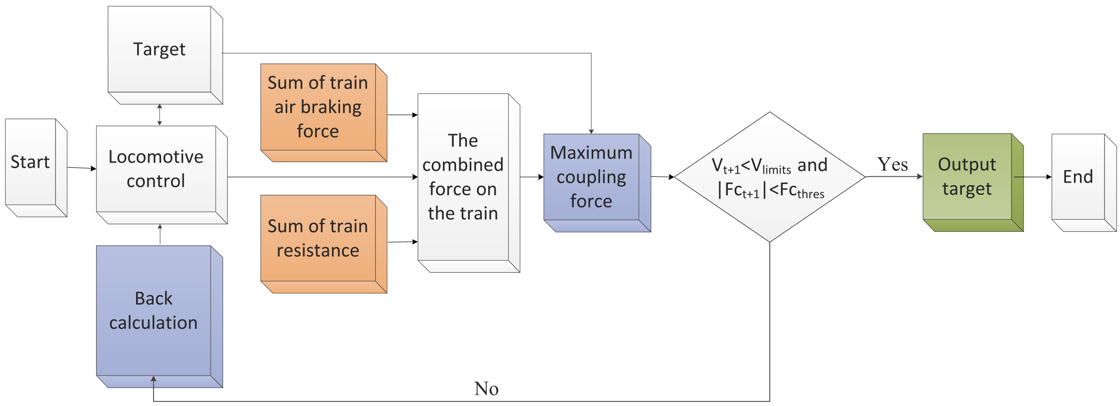

FIGURE 5. Flow chart of target train curve generation for heavy-haul train.

less use of traction and braking condition to make the train run more in the idle mode. Among these three optimization goals, there are conflicts between punctuality and safety and between punctuality and energy saving. It is difficult to ensure that these objectives are simultaneously optimized.

Based on the above analysis, considering the importance of safety, punctuality and energy saving in the train running process, the train multi-objective optimization model is designed:

$$f = w_1 * f_s + w_2 * \frac{Q_j}{\bar{Q}} + w_3 * \frac{T_j}{\bar{T}} \tag{11}$$

In this equation, $\bar{Q} = \frac{\sum_{j=1}^{N} Q_j}{N}$; $\bar{T} = \frac{\sum_{j=1}^{N} T_j}{N}$; N is the population size; w_1, w_2, and w_3 are weight factor, which satisfy $w_1+w_2+w_3 = 1$. The security weight coefficient w_1 is 0.5, positive point weight coefficient w_2 is 0.3, energy saving weight coefficient w_3 is 0.2, and these weight coefficients are set based on our experience.

C. DYNAMICALLY GENERATING THE OPTIMAL TARGET OPERATING CURVE

Driving heavy-haul train is multi-constrained and multi-target operation control process. It is necessary to consider both speed limit, coupling force and front line condition (for air brake predictive control). The target operation curve also needs to be performed during operation optimize and adjust in real time [33], [34]. Therefore, according to dynamic constraint during the operation, backtracking algorithm is used to generate a target operating curve of 5 kilometers ahead of heavy-haul train, as shown in Figure 5:

The current development and continuous improvement of intelligent optimization algorithms have provided favorable tools to obtain the optimal target operating curve. One of the difficulties in multi-objective optimization is that the dimensions of each index are not uniform. Using the penalty function method, each performance index can be converted into commensurable, e.g., all of them are transformed into the shape expression of energy consumption [35], [36]. For the large number of generated target operating curves, the following multi-objective optimization indicators are established for evaluation and screening:

① Safety: speed limitation, not exceeding the ATP emergency braking trigger speed: $v_t < v_{em}$.
② Precision stop: $\left\| s_t - s_{stop} \right\| < L$.
③ Punctuality: $\left\| T_{real} - T_{plax} \right\| = \Delta t$.
④ Stationarity: the acceleration and change rate cannot be greater than the specified standards $\|a\| < a_{max}$, $\left\| \frac{da}{dt} \right\| < J_{max}$.
⑤ Energy consumption:

$$J = \frac{1}{\xi_M} \int F_T dt + J_A t + \xi_D \int F_D v dt$$

v is the train speed; ξ_M the is multiplication factor to convert traction electrical energy into mechanical energy; ξ_B is the multiplication factor to convert braking mechanical energy into electrical energy; $J_A$is the train auxiliary power; t is the train running time; F_T and F_D are the traction force and electric braking force of the train, respectively; t is the running time of the train.

D. SPEED TRACKING CONTROLLER DESIGN

The generalized predictive control algorithm has good control performance, but due to the introduction of Diophantine equation, it increases the amount of calculation. The vertical dynamic model established in this paper must calculate the resistances of all carriages at each moment [37]–[39]. To speed up the calculation, this paper use an improved generalized predictive control algorithm, which has basic characteristics and advantages of generalized predictive control, abandons Diophantine equation and improves the calculation speed [40]. Based on the established longitudinal dynamics model, this paper uses an improved predictive control algorithm to design the running speed tracking controller that controls the ideal running speed target curve obtained by heavy-haul train tracking for safety, punctuality and energy saving. The train longitudinal dynamics model can be described as a controlled autoregressive integrated

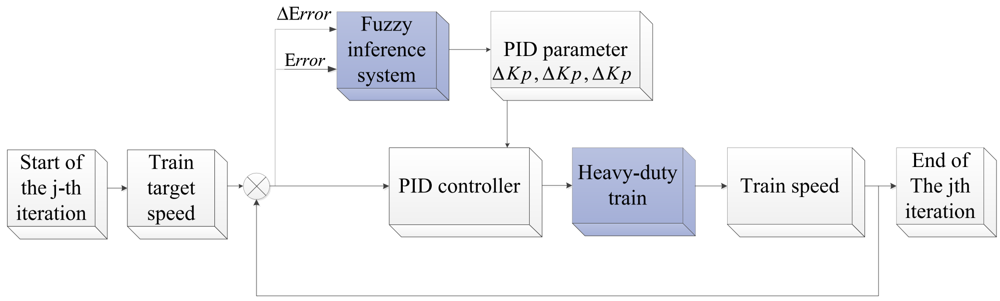

FIGURE 6. Speed following control of heavy-haul train.

moving average process model (CARIMA):

$$a(z^{-1})y(t) = z^{-d}b(z^{-1})u(t) + c(z^{-1})\xi(t) \tag{12}$$

In the formula above:

$$\begin{cases} a(z^{-1}) = 1 + a_{1,1}z^{-1} + a_{1,2}z^{-2} + \cdots + a_{1,n_a}z^{-n_a} \\ b(z^{-1}) = b_{1,0} + b_{1,1}z^{-1} + b_{1,2}z^{-2} + \cdots + b_{1,nb}z^{-n_b}, \\ \qquad b_{1,0} \neq 0 \\ c(z^{-1}) = 1 \end{cases}$$

$y(\cdot)$, $u(\cdot)$ and $\xi(\cdot)$ are the model output, model input and white noise; $d = 1$ is the delay coefficient; n_a and n_b are the orders of model output and input, respectively.

To obtain the control law, we construct the following performance index function:

$$J = E\left\{(Y - Y_r)^T(Y - Y_r) + \Delta U^T R \Delta U\right\} \tag{13}$$

In the formula above,

$$\begin{aligned} Y &= [y(t+d)|t, y(t+d+1|t), \cdots, y(t+N|t)]^T \\ \Delta U &= [\Delta u(t), \Delta u(t+1), \cdots, \Delta u(t+N-d)]^T \end{aligned}$$

Y_r is the predicted output, which is obtained by the ideal target curve; N is the predicted length; R is the control weight matrix; $\Delta = 1 - z^{-1}$.

Due to the complex and changeable line condition of freight train and large hysteresis characteristics of air braking of heavy-haul train, the changes in operating conditions of heavy-haul train are complicated, and the control accuracy and response efficiency of the speed following control algorithm have high requirements [41], [8]. The fuzzy PID control algorithm has the high precision of the PID control method and the high robustness and fast response characteristics of the fuzzy control algorithm. Therefore, this paper uses the fuzzy PID control algorithm for speed following control and adjust the locomotive control force output level based on the online self-learning of train running status, as shown in Figure 6.

In this model, the interaction force between the carriages of a heavy-haul train is described by the longitudinal dynamic model, and the change in control force output by the PID controller on the running state of subsequent carriages is obtained by solving the longitudinal dynamic model. Based on the collected expert driving experience and analysis of air braking characteristics, an air braking control rule model was established, and the triggering and mitigation control of air braking was performed based on the model.

IV. SIMULATION EXPERIMENTS

A. COUPLER FORCE EFFECT SIMULATION

After we established the dynamic longitudinal dynamics model and decoupling device model of the train operation process, according to the conditions and control requirements of the international benchmark tests of heavy-haul train longitudinal dynamics simulators of nine international authoritative organizations in the literature [42], [43] of the University of Central Queensland, Spiryagi *et al.*, the corresponding simulation tests are performed in this paper. The results of the maximum coupling force of 9 mechanisms in Spiryagi's paper [43] are shown in Figure 7. The results of the simulated maximum coupling force in this paper are shown in Figure 8. The paper selects the simulation results of coupler force change trend of the 10th coupler for comparison.

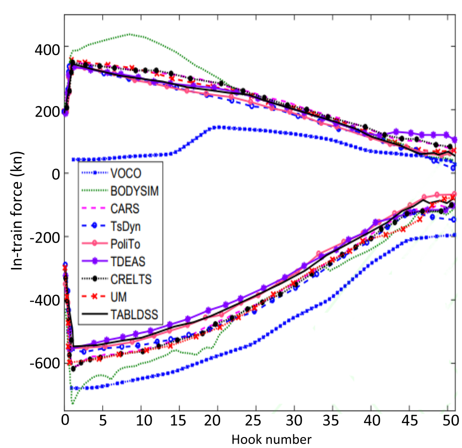

FIGURE 7. Maximum coupling force simulated by 9 mechanisms in reference [43].

Figure 7 shows that the experimental results of several dynamic simulators with better effects in the 9 mechanisms

TABLE 1. Data comparison between multiple target optimal policy in this paper and actual operation.

	Time (s)	energy consumption (kW)	safety factor(maximum hook) (kN)	maximum crimp (kN)
This Paper	3383.4	3505.7	-822.3	1161.2
Driver Driving	3510.6	4200.3	-1347.2	1787.5

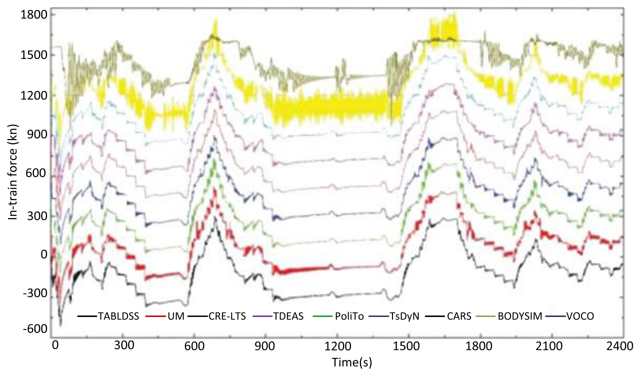

FIGURE 8. Tendency of the coupler force change of coupler No.10 coupler in reference [43].

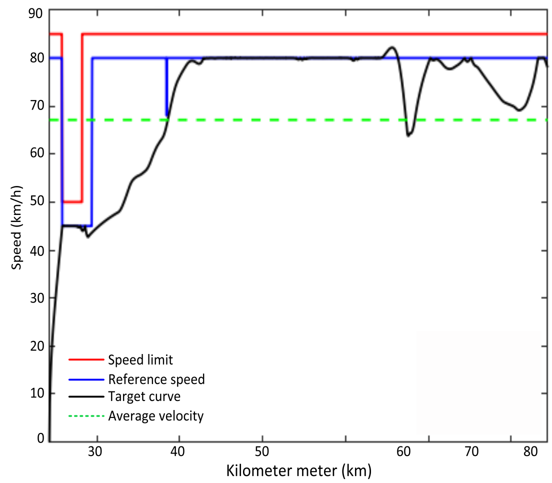

FIGURE 9. Target running curve obtained from the dynamic generation and online adjustment.

are mostly concentrated at 350 kN, and the pull force is approximately 540 kN. In the simulation result of our method, the maximum hook force is 350 kN, and the pull force is 530 kN, which are very similar to the experimental results with better values in the paper [43]. The TANLDSS simulation curve at the bottom of Figure 8 is the actual simulation curve of the TANLDSS mechanism. The coupler force change curves above the TANLDSS curve add effects of 200, 400, …, 1600 kN to the real coupler force change curves simulated by different software for convenience to compare the simulation results of different software.

Figure 8 shows that the top seven software programs have good simulation results, and the trends are generally consistent with specific values. Figure 8 has better effects than simulation result, it can be found that regardless of the trend of coupler force or specific value of coupler force, simulation results of this article are very similar experimental results of the seven software. The international benchmark test of the dynamic train simulator for heavy-haul train is compared with the simulation results of many domestic and foreign institutions. The simulation results in this paper are better than or similar to those of many domestic and foreign institutions. The accuracy of the established dynamic longitudinal dynamics model and hook release device model in this paper is verified.

B. SIMULATION OF THE TARGET CURVE AND SPEED TRACKING EFFECT

According to the established vehicle ditch force model, the optimally designed running target curve dynamic generation and online adjustment effect in this paper are shown in Figure 9.

The tracking effect is shown in Figure 10, and the tracking error is shown in Figure 11.

Based on Figures 10 and 11, we conclude that the heavy-haul train speed tracking controller designed by the improved generalized predictive control method has a good tracking effect during the entire train operation. The ideal running speed target curve is obtained from the aforementioned multi-objective optimization, which satisfies the train safety, punctuality and energy saving requirements; its high-precision tracking shows the effectiveness and accuracy of the designed controller. Table 1 compares the target curve optimization method, actual driving time, energy consumption and safety factor (maximum hook) between this paper and actual operation, it that the target curve obtained by this method has better safety factor, punctuality rate and energy saving than the actual driver, which indicates the superiority and effectiveness of our method. And the traction/braking curve in Figure 12 basically maintains a constant traction force in the start-up phase and can adapt to the changeable line conditions by adjusting the traction/braking force in the midway operation stage. The entire operation process gently changes, the condition conversion is smooth, and there is no overshoot phenomenon, which satisfies the traction/braking force characteristics of heavy-haul train.

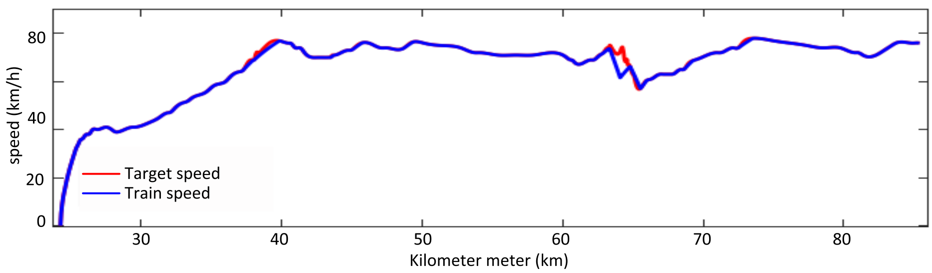

FIGURE 10. Tracking effect of the train on the target curve.

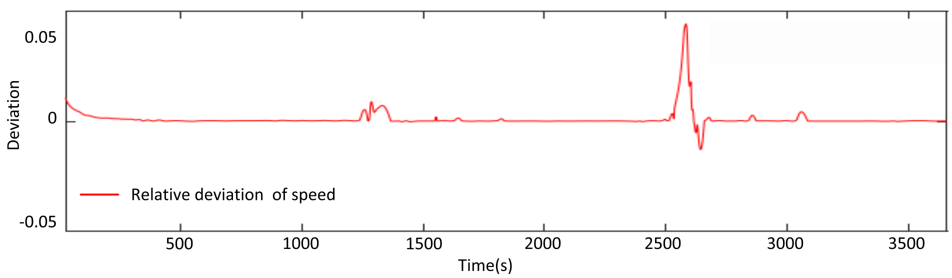

FIGURE 11. Speed tracking control effect of the heavy-haul train.

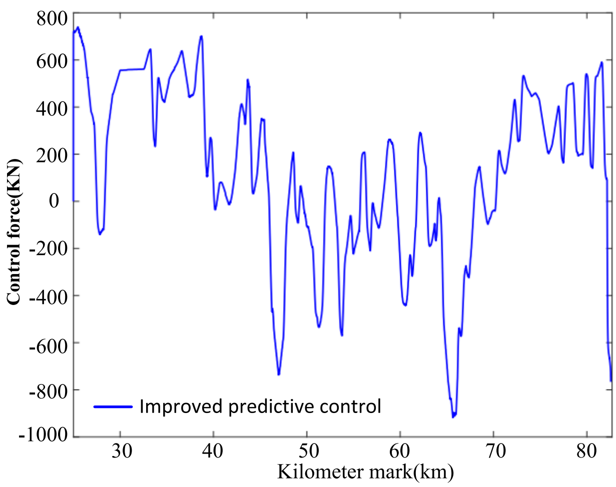

FIGURE 12. Improved predictive control traction/braking curve.

V. CONCLUSION

Based on the actual operating line condition and restraint of a decoupling system, a dynamic longitudinal dynamics model of trains and a coupler-force restraint model are designed. Considering the restraint of the decoupling force, several operational optimization indicators such as safety, energy saving and punctuality are the goals. The ideal running speed target curve of a heavy-haul train is obtained by the adaptive genetic algorithm. Compared to the performance of the actual running speed curve, the result show that the multi-objective optimized running speed curve guarantees the safety of train operation and better evaluates both energy saving and punctuality indicators than the driving result of an actual driver.

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