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Dynamic Simulation of Electrically Controlled Heavy-Haul Train under Fuzzy PID Control

Zhiwei Bo, Shuang Liu, Mingxing Zhang
(School of Transportation Engineering, Liaoning, Dalian Jiaotong University, Dalian 116028, China)
Corresponding Author: Zhiwei Bo.

Abstract: *To address the issues of insufficient speed control accuracy and delayed emergency braking response of heavy-haul trains under complex operating conditions, this paper proposes a hierarchical cooperative control strategy based on fuzzy PID and electronically controlled pneumatic (ECP) braking. A high-precision multibody dynamic model of the train is constructed on the TSDynamic (Train System Dynamics Simulation) platform, and a nonlinear pneumatic circuit model of the ECP braking system is developed in conjunction with AMESim to achieve refined simulation of the dynamic characteristics of braking pressure. A fuzzy PID controller is designed for conventional target speed tracking, with its output coupled to the ECP emergency braking command through a dynamic switching logic, thereby preventing abrupt changes in braking force, improving energy efficiency, and ensuring driving safety. The two systems are integrated within the TSD environment, enabling real-time data interaction among control, braking, and dynamics modules.*

Key words *：loadFuzzy PID Control ；TSDynamic Co-Simulation ；Heavy-Haul Trains*

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I. Introduction

[1-2] Railway transportation has been widely applied worldwide due to its advantages of high safety, high speed, large carrying capacity, low cost, and minimal environmental impact. As an efficient carrier for bulk cargo transportation across continents, heavy-haul railways have become a key component of the modern logistics system. With the continuous development of the national economy and the rapid growth of transportation demand, accelerating the development of electric traction and maintaining the reasonable operation of diesel traction to enhance the transportation capacity of busy mainlines has become an important approach to alleviating capacity constraints, improving traction power structure, conserving energy, and enhancing overall national economic efficiency.

To further improve the operational efficiency and control accuracy of heavy-haul trains, this study constructs multiple control rule bases based on the fuzzy PID control method and conducts systematic comparative analysis. By examining the response speed and energy consumption characteristics of traction control under different rule bases, the study explores the balance between dynamic adaptability and steady-state performance of fuzzy control under complex operating conditions.

The conventional proportional–integral–derivative (PID) control, though widely used in train automatic driving systems due to its simple structure, has limitations in addressing the nonlinear dynamic characteristics of heavy-haul train operation (such as coupler slack and wheel–rail adhesion variation) and multi-objective constraints (trade-offs among safety, energy efficiency, and stability). These limitations can lead to control overshoot or response delay, thereby increasing energy consumption [3]. To overcome these issues, various improved strategies have been proposed. Reference [4] presents a fuzzy adaptive model predictive control (MPC) approach that integrates fuzzy logic with the rolling optimization capability of MPC to enhance system adaptability under complex conditions. Reference [5] designs a sliding-mode PID composite controller that leverages the strong robustness of sliding-mode control to achieve high-precision speed regulation and stopping performance.

However, these methods still rely heavily on expert experience for fuzzy rule design and PID parameter tuning, resulting in limited real-time adaptability and generalization. Moreover, most existing studies focus primarily on traction control, with relatively few investigations into the coordinated optimization of braking systems and overall train control [6]. Therefore, the design of multiple rule bases based on fuzzy PID control holds significant theoretical and engineering value for improving the comprehensive control performance of heavy-haul trains and achieving a better balance between dynamic response and energy efficiency.

II. Design of Fuzzy Adaptive PID Control

During train operation, the coupler force of the draft gear is influenced by the number of vehicles in the consist and various external disturbances. To achieve effective control of the traction and braking forces acting on the draft gear, it is necessary to continuously adjust the proportional, integral, and derivative parameters of the PID controller in real time. Therefore, a fuzzy adaptive PID controller is adopted to dynamically regulate the inter-vehicle traction forces within the train.

$$o(t) = k_p e(t) + K_i \int_o^t e(t)dt + K_d \frac{de(t)}{dt} \tag{1}$$

As shown in Equation (1), $e(t)$ represents the coupler or traction force of the draft gear at time t, and $o(t)$ denotes the feedback-adjusted coupler or traction force. By appropriately tuning and adjusting the proportional, integral, and derivative coefficients K_P, K_i, and K_d in real time, the PID controller can fully exert its superior control performance, enabling the overall system to achieve optimal control effectiveness.

The fuzzy controller employed here is a two-dimensional controller with two inputs and three outputs. The input variables are e and e_c, where e represents the speed deviation, and e_c denotes the rate of change of the speed error. The system outputs three parameters— K_P, K_i, and K_d—which are dynamically adjusted to accommodate the fuzzy relationship between the target speed, the actual speed error, and the rate of change of that error at different moments.

$$e = e_t - e_v \tag{2}$$

$$e_c = \frac{e_{cr} - e_p}{\Delta t} \tag{3}$$

As shown in Equations (2) and (3), e_t denotes the target speed, e_v represents the actual speed, t e_{sr} is the speed error at the current moment, e_p is the speed error at the previous moment, and Δ denotes the time step.

The output variables K_P, K_i, and K_d of the PID controller are represented by fuzzy linguistic variables, and their fuzzy sets are divided into seven levels: Negative Big (NB), Negative Medium (NM), Negative Small (NS), Zero (ZO), Positive Small (PS), Positive Medium (PM), and Positive Big (PB). The numerical ranges are determined according to the magnitude of the speed error, which is classified into NB, NM, NS, ZO, PS, PM, and PB, respectively. Let the system's output force be denoted as FFF, representing either traction or braking force. When $o(t) > 0$, the system operates in the traction mode; when $o(t) < 0$, the system performs braking; and when $o(t) = 0$, the train is in the coasting mode.

The rule bases for adjusting K_P, K_i, and K_d are shown in the following tables. When e and e_c have the same sign and their absolute values are large, it indicates a rapid change in error. In this case, larger values of K_P, K_i, and K_d are required for regulation. Generally, increasing K_P accelerates the system response, increasing K_i eliminates steady-state error, and increasing K_d enhances predictive capability, suppresses overshoot, and provides anticipatory adjustment.

If e and e_c share the same sign, and $|e|$ is large while $|e_c|$ is relatively small, it suggests that the system is dominated by acceleration error. In this scenario, a larger Δk_p and smaller Δk_i and Δk_d should be applied to reduce the overall error. When both eee and ececec are close to zero, Δk_p, Δk_i, and Δk_d are all set to zero—this represents the "center point" of the control space.

Three separate rule bases are established to adjust Δk_p, Δk_i, and Δk_d, corresponding to Table 1, Table 2, and Table 3, respectively. The rule bases are initially constructed by mapping the linguistic variables {NB, NM, NS, ZO, PS, PM, PB} of the inputs to the corresponding linguistic variables of the outputs {NB, NM, NS, ZO, PS, PM, PB}. These rule bases can then be fine-tuned according to actual operating conditions. For example, if the system response is insufficient and the current corresponding output is PM, it can be increased to PB. Similarly, other parameters can be modified to optimize control performance.

It is worth noting that adjustments to the rule bases only modify the membership distribution of the fuzzy inference outputs; the defuzzification process, which adopts the centroid (center-of-gravity) method, remains unchanged.

Table 1: Rule Base 1

		E						
		NB	NM	NS	ZO	PS	PM	PB
EC	NB	(PB,PB,PB)	(PB,ZO,PM)	(PM,NS,PS)	(PS,NS,ZO)	(PM,NS,PB)	(PM,NS,ZO)	(ZO,NM,NM)
	NM	(PB,NM,PB)	(PM,NB,PM)	(PS,NS,PS)	(PS,NS,ZO)	(PS,ZO,ZO)	(PM,ZO,ZO)	(PS,NS,NB)
	NS	(PB,NM,NS)	(PS,NS,PB)	(ZO,NS,PS)	(PS,PS,PS)	(ZO,ZO,PS)	(PS,ZO,NB)	(PB,Z0,NS)
	ZO	(PB,NM,NB)	(PS,NM,NS)	(ZO,ZO,PS)	(ZO,ZO,ZO)	(PS,ZO,PS)	(PM,ZO,NS)	(PB,PS,NS)
	PS	(PB,NS,NB)	(PS,NM,PB)	(ZO,ZO,PS)	(ZO,ZO,PS)	(PS,ZO,NB)	(PM,PS,ZO)	(PB,PS,PS)
	PM	(PS,ZO,NB)	(PM,ZO,PB)	(NS,PS,ZO)	(NM,PS,ZO)	(PS,PS,PM)	(PB,PM,PM)	(PB,PM,PM)
	PB	(ZO,ZO,NB)	(PM,NB,PB)	(NM,PS,NS)	(NB,PS,ZO)	(PM,PS,PS)	(PB,PB,PB)	(PB,PB,PB)

Table 2: Rule Base 2

		E						
		NB	NM	NS	ZO	PS	PM	PB
EC	NB	(ZO,ZO,ZO)	(NB,NM,ZO)	(PS,NS,PS)	(ZO,ZO,ZO)	(PS,ZO,ZO)	(PM,NS,ZO)	(ZO,NM,NM)
	NM	(ZO,ZO,ZO)	(NB,NM,NS)	(PS,NS,PS)	(ZO,ZO,NS)	(PS,ZO,NS)	(PM,ZO,NB)	(ZO,NM,NM)
	NS	(ZO,ZO,ZO)	(NB,NM,NS)	(PS,NS,PS)	(ZO,ZO,NS)	(PS,ZO,NS)	(PM,ZO,NB)	(ZO,NM,NM)
	ZO	(ZO,ZO,ZO)	(NB,NM,NS)	(PS,NS,NS)	(ZO,ZO,PS)	(PS,ZO,PS)	(PM,ZO,NB)	(ZO,NM,NM)
	PS	(ZO,ZO,ZO)	(NS,NS,ZO)	(ZO,ZO,NS)	(ZO,NSNS)	(ZO,NS,ZO)	(PM,PS,ZO)	(PS,NS,NB)
	PM	(ZO,ZO,ZO)	(ZO,ZO,NS)	(NM,NS,NB)	(ZO,ZO,NS)	(ZO,ZO,PS)	(PM,PS.PS)	(PB,PM,PM)
	PB	(ZO,ZO,ZO)	(ZO,ZO,NM)	(NM,PS,NS)	(NS,ZO,NS)	(PS,ZO,ZO)	(PB,PM,PM)	(PB,PM,PM)

Table 3: Rule Base 3

	E						
	NB	NM	NS	ZO	PS	PM	PB
NB	(PB,PM,PM)	(PM,PM,PM)	(PS,NS,PS)	(ZO,NS,NS)	(PS,NS,ZO)	(PM,NS,ZO)	(PB,NB,NB)
NM	(PB,PM,PM)	(PM,PS.PS)	(PS,NS,PS)	(ZO,ZO,NS)	(PS,NS,NS)	(PM,ZO,NB)	(PB,NM,NM)
NS	(PS,NS,NB)	(PM,PS,ZO)	(PS,NS,PS)	(ZO,ZO,NS)	(PS,ZO,NS)	(PM,ZO,NB)	(PB,NM,NM)
ZO	(PB,NM,NM)	(PM,ZO,NB)	(PS,NS,NS)	(ZO,ZO,ZO)	(PS,ZO,PS)	(PM,ZO,NB)	(PB,NM,NM)
PS	(PB,NM,NM)	(PM,ZO,NB)	(ZO,ZO,NS)	(ZO,NS,NS)	(PS,ZO,ZO)	(PM,PS,ZO)	(PB,NS,NB)
PM	(PB,NM,NM)	(PM,ZO,NB)	(NM,NS,NB)	(NS,PS,NS)	(PS,PS,PS)	(PM,PS.PS)	(PB,PM,PM)
PB	(PB,NM,NM)	(PM,NS,PB)	(NM,PS,NS)	(NM,PS,NS)	(PS,PS,PS)	(PM,PM,PM)	(PB,PM,PM)

In Tables 1, 2, and 3, Δk_p, Δk_i, and Δk_d represent the correction values for the original design parameters Δk_p, Δk_i, and Δk_d of the system's PID controller. The real-time parameter values of the system are thus given by:

$$Kp = Kp0 + \Delta Kp \tag{4}$$

$$Ki = Ki0 + \Delta Ki \tag{5}$$

$$Kd = Kd0 + \Delta Kd \tag{6}$$

where K_{P0}, K_{i0}, and K_{d0} are the initial controller parameters, and Δk_p, Δk_i, and Δk_d are the corresponding adjustments determined through fuzzy inference.

The values of Δk_p, Δk_i, and Δk_d may be positive or negative, depending on the real-time control conditions and system state, enabling the controller to adaptively adjust its behavior to achieve optimal performance.

The fuzzy control variable UUU is inferred using the Mamdani fuzzy-logic inference algorithm [7]; the inference is given by formula (7) as follows.

$$U = (E \times EC)\# R \tag{7}$$

In the formula: U denotes the fuzzy control variable, R denotes the operational relation, and $\#$ denotes the composition operation of fuzzy relations. The centroid (center-of-area) method is used to convert the fuzzy control variable UUU into a crisp value, which is then scaled to obtain the precise control quantity that can act on the actuator. The centroid method is given by Formula (8) as follows:

$$u_{cen} = \frac{\sum_{j=1}^{n} u_j A(u_j)}{\sum_{j=1}^{n} A(u_j)} \tag{8}$$

Where U_{cen} denotes the precise control quantity, and $A(u_j)$ represents the membership function.

III. Simulation Results and Analysis

The heavy-haul train dynamics simulation platform employed in this study is the TSDynamic (Train System Dynamics Simulation System) software, independently developed by Liu Shuang et al. at Dalian Jiaotong University [8]. This software constructs a full-degree-of-freedom dynamic model of the train based on a rigid-body model and encompasses multiple subsystems, including the locomotive and vehicles, coupler-buffer devices, draft gear, track, coupler angular motion, traction, braking, suspension, and track excitation. It is capable of simulating the coupled interactions of the train in longitudinal, lateral, and vertical directions.

Using the algorithm described in this paper, a program was developed in Fortran and executed within the TSD software environment to perform the simulations. The resulting simulation effects, line longitudinal profile, and velocity control are illustrated in Figures 1 and 2 [9].

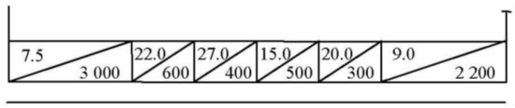

Figure 1:Track Longitudinal Profile

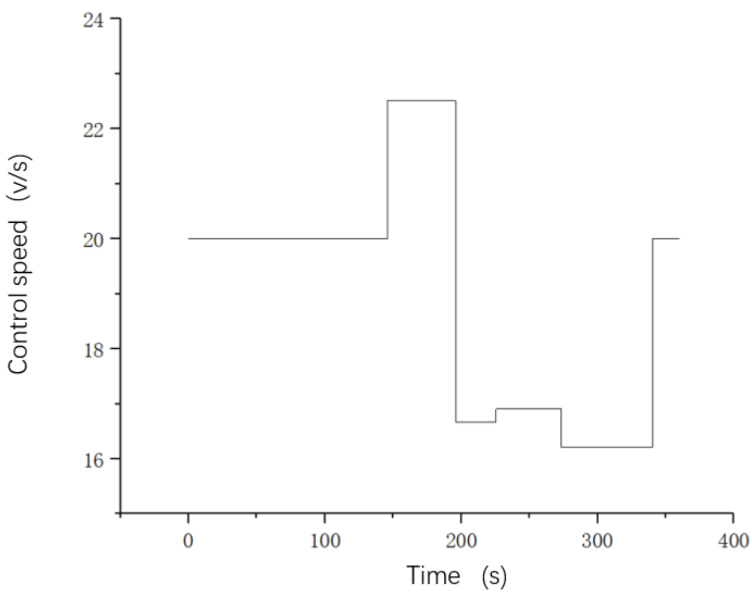

Figure 2:Control Speed Curve

The simulation results of Rule Base 1, Rule Base 2, and Rule Base 3 are shown in Figure 3.

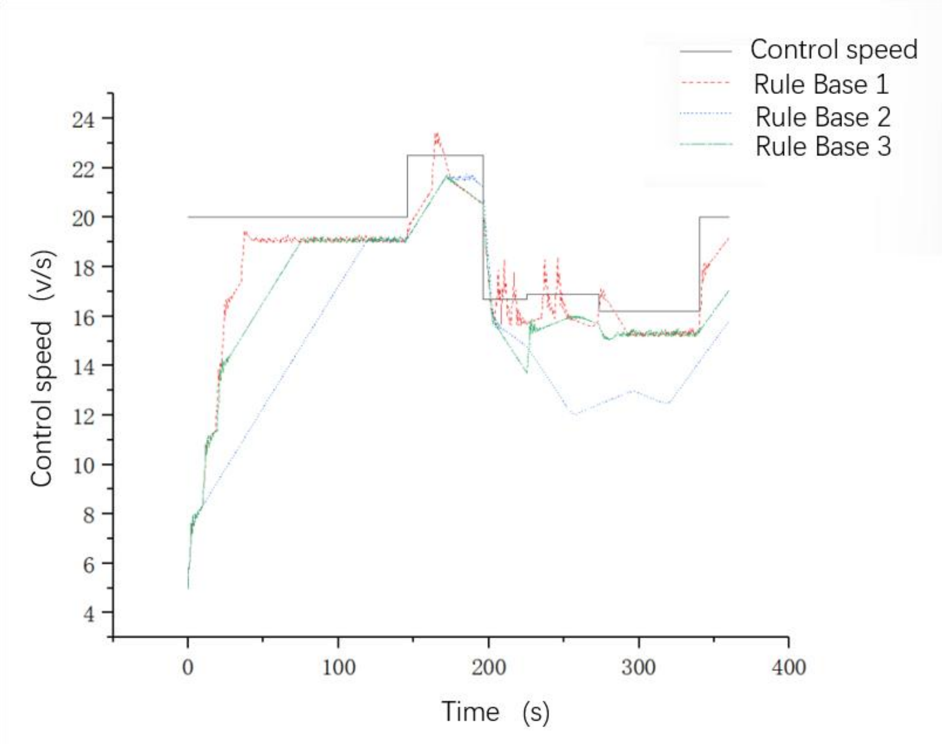

Figure 3:Simulation Results

As shown in the simulation results in Figure 3, Rule Base 1 exhibits higher agility in dynamic response and superior performance in steady-state metrics, demonstrating overall control performance superior to the other rule bases.

IV. Conclusion

In summary, this study established three initial rule bases for the fuzzy controller design based on the fuzzy sets of error and error rate, and performed targeted optimization of the rules in accordance with the system's operating characteristics. This optimization strategy effectively balances the dynamic response speed and steady-state accuracy of the system by adjusting the ranges and variation trends of Δk_p, Δk_i, and Δk_d. During the defuzzification stage, the centroid method was consistently employed to convert the fuzzy inference results into precise control quantities, thereby ensuring the consistency and interpretability between the rule base optimization and the output computation method.

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