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OPTIMIZATION SEARCH METHOD FOR MAXIMUM ADHESION POINT OF HEAVY HAUL LOCOMOTIVE BASED ON INTERVAL TYPE-2 FUZZY CONTROLLER

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Abstract. *The safe and efficient operation of high-speed trains requires precise adhesion control under uncertain track conditions. Traditional methods based on type-1 fuzzy logic or single PID regulation often have the problem of limited robustness and cannot reliably utilize the maximum point of adhesion. To solve this problem, this paper proposes an interval type-2 fuzzy-based adhesion maximum point search method, which combines PID control with an interval type-2 fuzzy logic system and uses a WOA for parameter optimization of PID. Unlike existing adhesion control strategies, this method can directly search and stay at the maximum adhesion point, thus improving the traction efficiency. In order to verify the feasibility of the designed method, simulations were performed on the Modeling Tech platform developed based on NI. The results show that the designed method can improve the adhesion utilization by 5% and shorten the system dynamic response time by 20%-40% compared with the traditional method, which can realize the optimal creep speed and adhesion control of locomotive under the track change condition.*
Keywords: Interval type-2 fuzzy controller, Optimal creep speed search, Whale optimization algorithm, Hardware-in-the-loop simulation

1. **Introduction.** In railroad transportation, whether it is passenger transportation or freight transportation, safety has always been people's concern, and the adhesion control between wheels and rails is closely related to the safety of trains [1,2]. Therefore, in rail transportation, how to use the adhesion force efficiently and improve the adhesion utilization is the focus of attention of scholars at home and abroad. Wheel-rail adhesion is limited by the road adhesion capacity, such as rain, snow, oil, leaves and other third media will lead to a significant reduction in the adhesion coefficient [3], and when the traction braking torque on the wheels exceeds the maximum adhesion that the wheel-rail can provide, the phenomenon of wheel idling occurs, and if the idling and sliding of the wheels on low adhesion surfaces cannot be controlled in a timely manner, it may result in serious safety problems.

The traditional adhesion control method is mainly based on the classical combination correction method [4,5], which analyzes the train operation data to determine whether the train is in the idling-sliding state, and then controls the torque in real time according

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to the preset strategy, so as to make the train wheels and rails resume the adhesion state, but this method is a control that works after the idling-sliding occurs, so it cannot obtain the optimal utilization of adhesion force, and is affected by the road surface conditions. PID control is widely used in adhesion control because of its simple structure and easy implementation, but its parameter tuning is difficult. For this reason, researchers have introduced intelligent optimization algorithms to achieve PID parameter optimization, thus improving the control performance [6,7]. At the same time, optimization of adhesion control methods such as virtual coupled train coordination control method, which can achieve nonlinear virtual coupled train tracking control, but does not take account of the effect of communication delay [8]. Observer-based adhesion control method utilizes a full-dimensional state observer to observe the adhesion coefficients and perform adhesion control [9]. The sliding mode control method is robust and has strong suppression of external perturbations, but suffers from serious jitter problem [10]. Adaptive control method can autonomously adapt to the changes of system dynamic characteristics over time and environment, but it requires high model structure and recognizable parameters [11,12]. Predictive control method can deal with the constraint problem and consider the next behavior of the system in advance, which has a better control effect, but its real-time computation is large and very dependent on the accuracy of the model [13,14]. Traditional type-1 fuzzy control does not rely on precise mathematical models and is simple to implement and less computationally intensive, but the degree of affiliation of traditional fuzzy sets is an exact value and its ability to process fuzzy information is weak [15,16]. Type-2 fuzzy controller replaces the traditional fuzzy set with the value of affiliation degree, which can better handle fuzzy information [17]. Currently type-2 fuzzy controller is less used in the field of train adhesion control due to its high computational complexity, while interval type-2 fuzzy neural network reduces the computational complexity while retaining a strong ability to process fuzzy information [18]. Some scholars have used fuzzy PID control in the speed control of electric vehicles to improve the transient response speed of the control system [19]. In summary, interval type-2 fuzzy controller retains the advantages of the traditional type-1 fuzzy controller while still has a strong ability to process fuzzy information and is easy to realize. Therefore, this paper proposes a maximum adhesion point search algorithm based on interval type-2 fuzzy controller. The method uses the wheel speed and motor torque to estimate the adhesion coefficient, and determines the dynamic creep speed adjustment coefficient through the interval type-2 fuzzy controller, and then combines with the whale optimization algorithm to realize the optimization of PID parameters, so as to improve the robustness and dynamic response performance of the adhesion control system. The main contributions of this paper are

1) The maximum adhesion point search method based on interval type-2 fuzzy controller is constructed;

2) Introducing WOA to realize the joint optimization of fuzzy and PID parameters;

3) The advantages of the method in adhesion utilization and speed tracking performance are verified through simulation.

2. **Adhesion of Wheel and Rail.** Measurements of adhesion coefficients were first made in the late 1800s. In the 1940s, two German men, Curtius and Kniffler, developed and published a standard for the measurement of the coefficient of adhesion (Figure 1). The adhesion coefficient standard provides an approximation of the adhesion coefficient under dry rail conditions. More general curves are needed to calculate the acceleration of the train for wet track and sanding conditions. However, when considering the actual wheel-rail traction behavior, the cohesion factor becomes the traction force factor. This is a more complicated situation, since the actual traction coefficient of the train depends

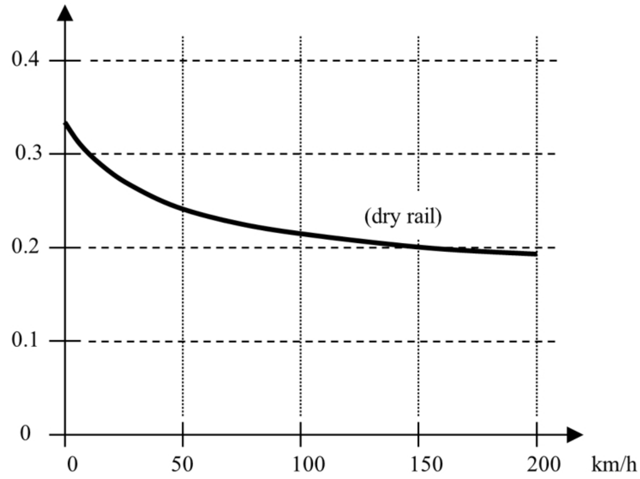


Figure 1. Adhesion coefficient with Curtius-Kniffle

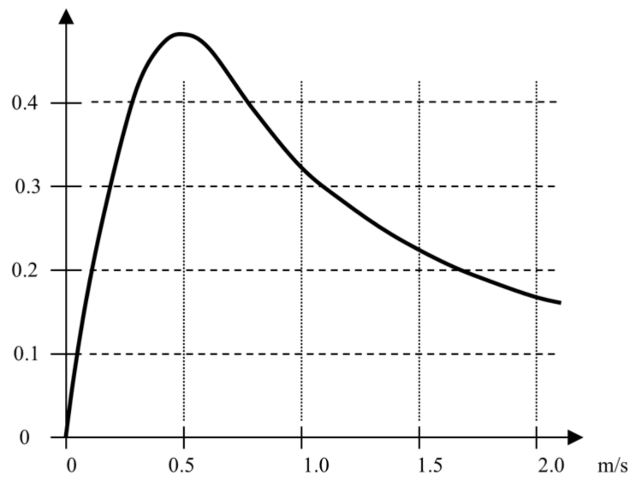


Figure 2. Traction force coefficient versus wheel-to-rail slip velocity

mainly on the creep-slip velocity between the wheel rails (Figure 2). Therefore, a certain amount of creep-slip has to exist between the wheels and rails in order to generate traction. Since the coefficient of adhesion has a maximum value in the adhesion characteristic curve, the goal of adhesion control is to enable the train to operate stably in the region near the peak of the adhesion force and as close to its peak as possible. The goal of existing slip control is to prevent wheel and rail wear by controlling creep and to achieve effective utilization of the adhesion force.

The hybrid slip control that is presented in Figure 3 is a general method in the field of adhesion control for railway vehicles. The control signals used are the slip velocity and the vehicle acceleration. The control system comprises three blocks which are train velocity estimation, acceleration criterion and slip velocity criterion. The block of train velocity estimate calculated a reference speed which is defined as (1) when the train is in acceleration or (2) when the train is in deceleration.

$$v_{ref} = \min(v_1, v_2, \ldots, v_n) \tag{1}$$

$$v_{ref} = \max(v_1, v_2, \ldots, v_n) \tag{2}$$

where v_i is the velocity of the axle.

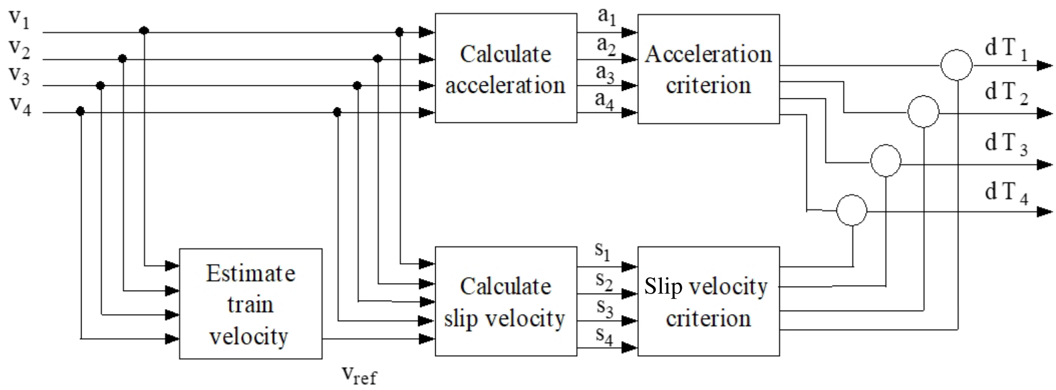


FIGURE 3. Hybrid slip control method

The slip velocity criterion used slip velocity to calculate the compensating torques. The slip velocity can be described by

$$v_{slip} = \omega r - v \tag{3}$$

where ω is the angular velocity of the wheel, r is the radius of the wheel, and v is the train speed. If the slip velocity exceeds the specific threshold, the wheel-slip is detected and the torque of the motor will be decreased and waited for a while. After the wheel slipping stops, the torque will be increased.

When all wheels are simultaneously slipping, the acceleration criterion will be activated. It reduces the torque if the specific threshold is exceeded.

3. **Design of Adhesion System Based on Interval Type-2 Fuzzy Control.** The overall design block diagram of the adhesion maximum point search method based on interval type-2 fuzzy control designed in this section is shown in Figure 4. It includes adhesion coefficient observer module, interval type-2 fuzzy control module, optimal creep speed search module and PID torque controller module based on whale optimization algorithm. The adhesion coefficient estimation module is used to estimate the adhesion coefficient in the current rail surface state in real time and input it into the fuzzy logic module. The fuzzy logic module is used to calculate the adjustment coefficient of the optimal creep speed search under the current rail surface and input it into the optimal creep speed search module. The optimal creep speed search module is used to calculate the reference creep speed under the current rail surface and input it into the PID torque controller module. The PID torque controller module is used to calculate the torque

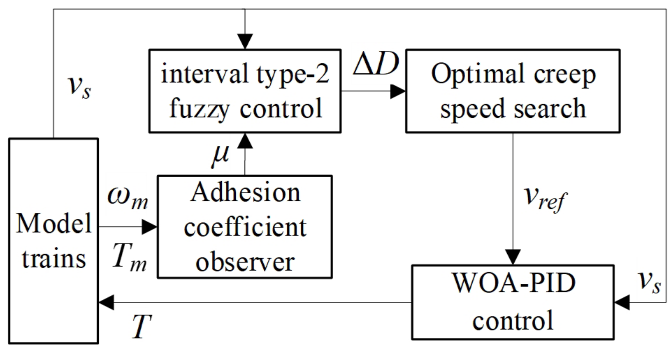


FIGURE 4. General design diagram of the adhesion system based on interval type-2 fuzzy control

control value of the locomotive, and output it to the locomotive dynamics model to form a closed-loop control, and finally realize the adhesion control of the heavy-duty locomotive.

3.1. **Interval fuzzy-2 controller structure.** The overall design of the interval type-2 fuzzy controller is shown in Figure 5. It can be seen from the design block diagram that the interval type-2 fuzzy controller also includes three stages: fuzzification, fuzzy rule reasoning and clarification. Compared with the type-1 fuzzy controller, in the clarity stage of the fuzzy controller, the interval type-2 fuzzy controller needs to reduce the interval type-2 fuzzy set to the type-1 fuzzy set, and then perform the defuzzification operation.

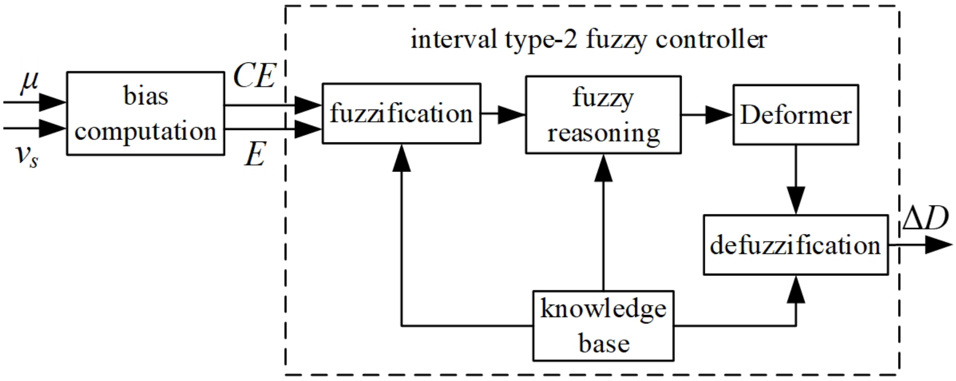


FIGURE 5. Block diagram of interval type-2 fuzzy controller design

According to the overall design of the adhesion system shown in Figure 4, first of all, it is necessary to calculate the deviation between the estimated adhesion coefficient and the actual creep speed of the locomotive, and obtain these two parameters as the input of the fuzzy controller, and then through the fuzzy logic operation, finally output the creep speed adjustment coefficient. The calculation formula of the slope value and the change value of the slope per unit time are as follows:

$$E = \frac{\mu(k) - \mu(k-1)}{v_s(k) - v_s(k-1)} \tag{4}$$

$$CE = E(k) - E(k-1) \tag{5}$$

where $\mu(k)$ and $v_s(k)$ are the sampling values of adhesion coefficient and creep speed of heavy haul locomotive at time, respectively.

3.2. **Design of interval type-2 fuzzy controller.** In this paper, the input variables $E(k)$, $CE(k)$ and output variable ΔD are partitioned into five fuzzy subsets, respectively. They are described by the statements "Positive Large (PL), Positive Small (PS), Zero (ZE), Negative Small (NS), Negative Large (NL)", namely

$$E(k) = \{NL, NS, ZE, PS, PL\} \tag{6}$$

$$CE(k) = \{NL, NS, ZE, PS, PL\} \tag{7}$$

$$\Delta D = \{NL, NS, ZE, PS, PL\} \tag{8}$$

Set the domain of $E(k)$ to $[-1, 1]$; set the domain of $CE(k)$ similarly to $[-1, 1]$; and set the domain of ΔD to $(-1, -0.5, 0, 0.5, 1)$.

In this paper, according to the requirements of control and the characteristics of high-speed trains in operation, the input variables of the fuzzy controller (deviation and actual creep speed) are respectively in the form of triangular affiliation functions as shown in Figure 6 and Figure 7.

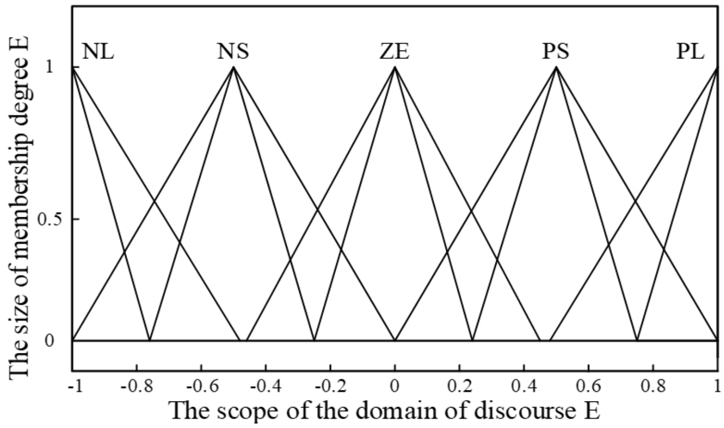


Figure 6. Affiliation function for “E”

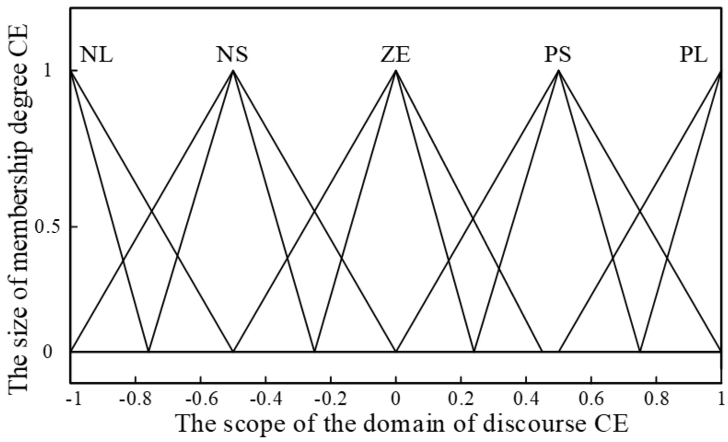


Figure 7. Affiliation function for “CE”

Fuzzy logic rules are in the form of IF A AND B THEN C. The rule base on which the fuzzy inference machine works is in the form of T-S. The rules of the T-S fuzzy system are

$$R^l: \text{ IF } x_1 \text{ is } A_1^l \text{ AND } \cdots \text{ AND } x_n \text{ is } A_n^l$$
$$\text{THEN } y \text{ is } f(x_1, \ldots, x_n)$$

There are 25 fuzzy rules and the fuzzy rules are shown in Table 1.

Table 1. Fuzzy rule inference table

	CE				
E	NL	NS	ZE	PS	PL
NL	NL	NS	ZE	PS	PS
NS	NL	NS	ZE	PS	PS
ZE	ZE	ZE	ZE	ZE	ZE
PS	PL	PS	ZE	NS	NS
PL	PL	PL	ZE	NL	NS

The reduced-order method uses the Enhanced KM Algorithm (EKA).

The type-2 fuzzy set is reduced to a type-1 fuzzy set, and the center of mass of the reduced set is found and obtained by weighted average method. For a type-1 fuzzy set A in discrete domain, its center of mass can be expressed as

$$C_A = \frac{\sum_{i=1}^{N} x_i \mu_A(x_i)}{\sum_{i=1}^{N} \mu_A(x_i)} \tag{9}$$

4. **PID Controller Parameter Tuning Based on WOA.** Australian swarm intelligence algorithm experts converted the hunting behavior of whales into a mathematical model by studying the hunting behavior of humpback whales [20]. In 2016, the WOA (Whale Optimization Algorithm) was proposed. The basic idea of the WOA is to imitate the hunting behavior of humpback whales, regard the optimization problem as a prey, and find the optimal solution by constantly chasing and capturing. The predation behavior is shown in Figure 8.

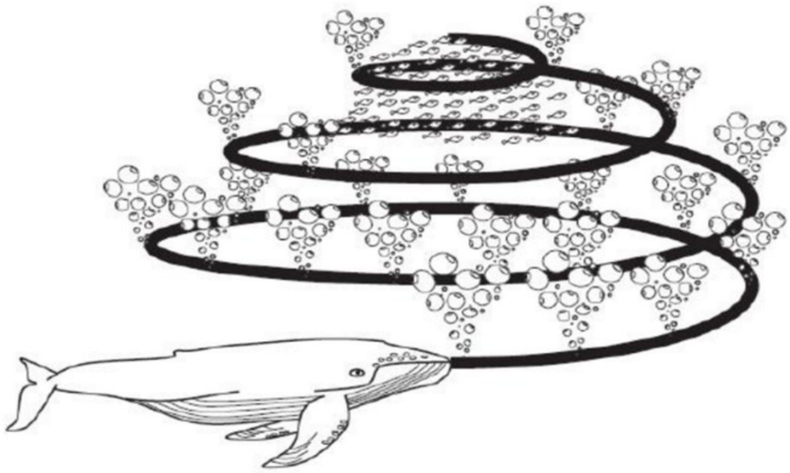


FIGURE 8. Schematic diagram of humpback whale feeding behavior

Combine the whale optimization algorithm with the PID control theory, and use WOA to adjust the PID controller parameters. The whale optimization algorithm proposed in this paper optimizes the locomotive PID torque controller parameters, and the optimization process is

1) Set the size of the population, because the optimization parameters are K_p, K_i, K_d, the dimension of the individuals in the population is set as a 3-dimensional vector, set the upper and lower limits of the variables, and set the maximum number of loop iterations, etc.

2) Find the fitness value according to the objective function.

3) Optimize the individuals using the whale optimization algorithm, record the optimal solution and the optimal fitness value this time, determine the location of the optimal solution in the space, and then import it into the controller.

4) Enter the main loop of the algorithm, determine which stage the algorithm enters according to the size of the random parameter and the coefficient vector, and continuously update the position vector of each individual.

5) When the number of iterations reaches the maximum value or meets the termination conditions, the algorithm ends, at which time the optimal solution and the corresponding objective function value are output; conversely, go to step 3 and continue to iterate to update the optimal value.

5. **Simulation Analysis.** In order to verify the practical significance of the adhesion control method designed in this paper, this section builds a four-axis dynamic model of heavy-duty locomotive based on the Modeling Tech platform developed by NI to verify the

feasibility of the adhesion maximum point optimization search method based on interval type-2 fuzzy controller.

5.1. **Modeling of multi-axle locomotives considering axle weight transfer.** When the heavy-duty locomotive generates traction, because the traction force and the coupler force are not in a straight line, coupled with the body structure, line conditions, driving speed and other factors, the center of gravity of the locomotive moves, so that the axle load distribution of each axle of the locomotive changes. In this paper, the simplified model of locomotive dynamics is adopted, and the dynamic model of single-axle locomotive is extended to the dynamic model of four-axle locomotive, and the influence of axle load transfer is considered.

$$\dot{\omega}_{di} = \frac{1}{J}\left(-Wg\mu_i - B\omega_{di} + \frac{R_g T_{mi}}{r}\right) \tag{10}$$

$$\dot{v}_t = \frac{Wg}{M}\sum_{i=1}^{n}\mu_i - \frac{f_v}{M} \tag{11}$$

where ω_{di} represents the wheel speed of the i axle, T_{mi} is the motor torque of the i axle, $Wg = \sum W_i g$ and $W_i g$ is the axle weight of the i axle, R_g is the transmission ratio, r is the radius of the wheels, v_t is the longitudinal speed of the locomotive as a whole, μ_i is the adhesive force of the i axle, f_v is the running resistance of the locomotive and

$$f_v = \left(1.2 + 0.0003 \cdot v_t + 0.00038 \cdot v_t^2\right)/M \tag{12}$$

5.2. **Comparison of interval type-2 fuzzy controller and conventional fuzzy controller simulation results.** The simulation results of simulink-based traditional fuzzy controller and interval type-2 fuzzy controller are shown in Figures 9-12. The locomotive starts in the dry rail surface state at $t < 15$ s, enters the wet rail surface at $15 \leq t \leq 30$ s, and returns to the dry rail surface again at $t > 30$ s.

The basic control ideas of the adhesion control method based on traditional fuzzy control and the adhesion control method based on interval type-2 fuzzy control are similar, and the essential difference lies in the difference of fuzzy controller. Therefore, it can be seen from the results that both control methods can realize the tracking control of the adhesion maximum point under the changing rail surface state, and the control effect is close. Since

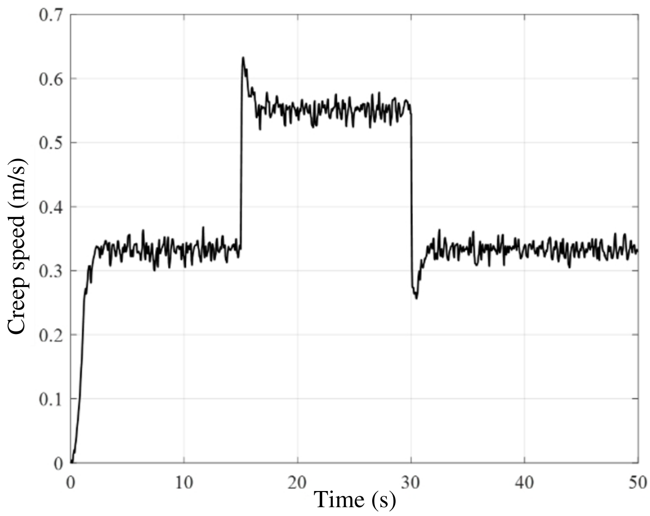


FIGURE 9. Creep speed profile of conventional fuzzy control based adhesion control method

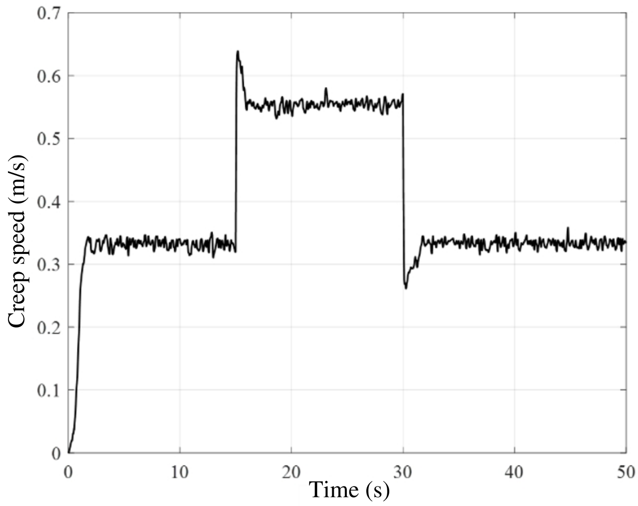


Figure 10. Creep speed profile of adhesion control method based on interval type-2 fuzzy control

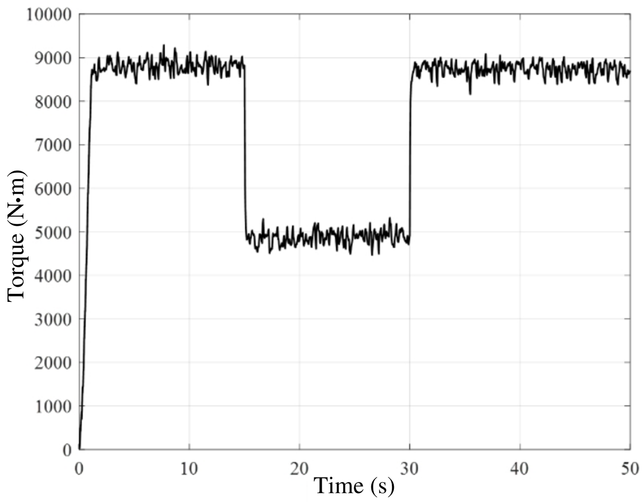


Figure 11. Control torque profile of conventional fuzzy control based viscous control method

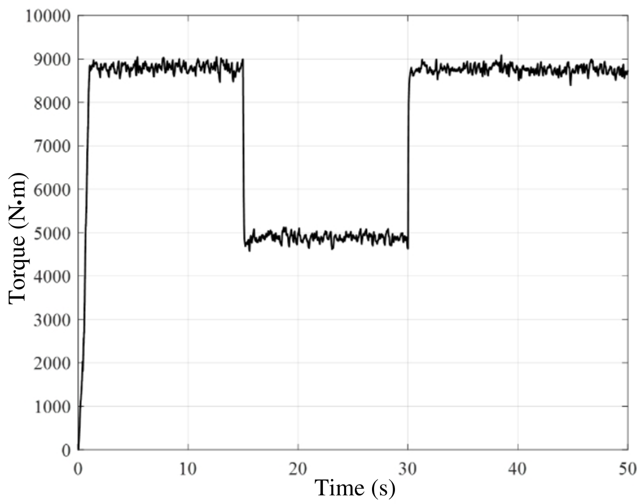


Figure 12. Control torque profile of viscous control method based on interval type-2 fuzzy control

the interval type-2 fuzzy controller is more effective than the traditional fuzzy in dealing with the nonlinear system, the noise interference can be better suppressed through the parameter setting of the interval type-2 fuzzy controller, and the adhesion control method based on the interval type-2 fuzzy control can better suppress the jitter and reach the steady state faster than the adhesion control method based on the traditional fuzzy control under the consideration of the influence of the noise interference, and ultimately achieve the purpose of better control effect.

5.3. **Simulation and analysis of adhesion control based on semi-physical platforms.** The whole hardware-in-the-loop simulation platform is shown in Figure 13. The mapping input and output module in StarSim defines the adapter plate to simulate the output pin, and then connects the oscilloscope to observe the traction torque and creep speed of each axle of the locomotive. The output voltage of the analog pin of Modeling Tech is 0-10 V. Before the start of the simulation, the signal to be observed is connected to the corresponding oscilloscope port, and the output voltage value is set on the signal adapter board. The simulation output signal settings for the four axes of the locomotive are shown in Table 2.

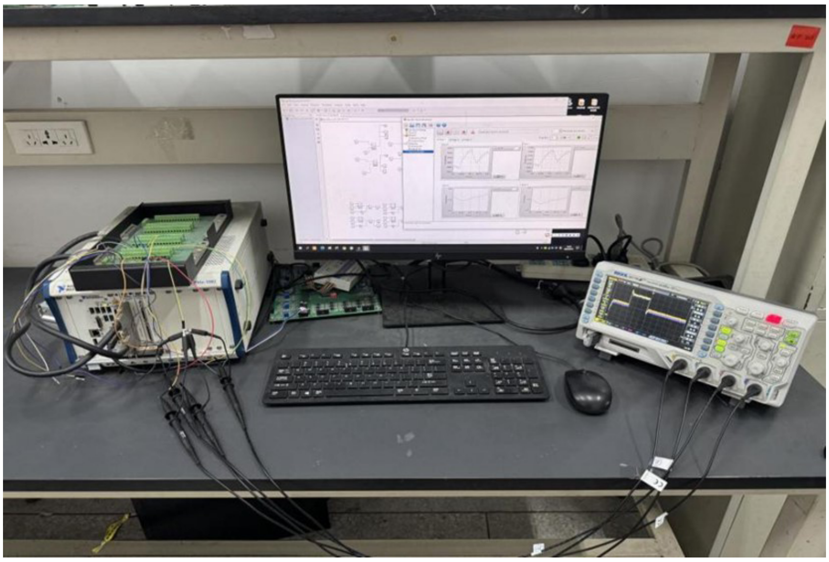


FIGURE 13. Semi-physical simulation platform

TABLE 2. Output signal parameter settings

Signal	Motor torque	Creep and slide speed
Analog Output Channel	1	2
Scale factor	1/1000	10
Offset	0	0
Maximum Output Voltage (V)	10	10

In this paper, two rail surface states of dry and wet are set. The total simulation time is 60 s. It is preset that the locomotive runs on the dry rail surface at $t < 15$ s and $t > 30$ s runs on the wet rail surface at 15-30 s. The parameters of the traction system of a certain type of heavy haul locomotive are shown in Table 3, and the results are observed and analyzed on the oscilloscope.

The results of the oscilloscope output are shown in the following figure, in which Figure 15 shows the control torque of each axis output from the locomotive motor, Figure 16

Table 3. The parameters of the traction system of a certain type of heavy haul locomotive

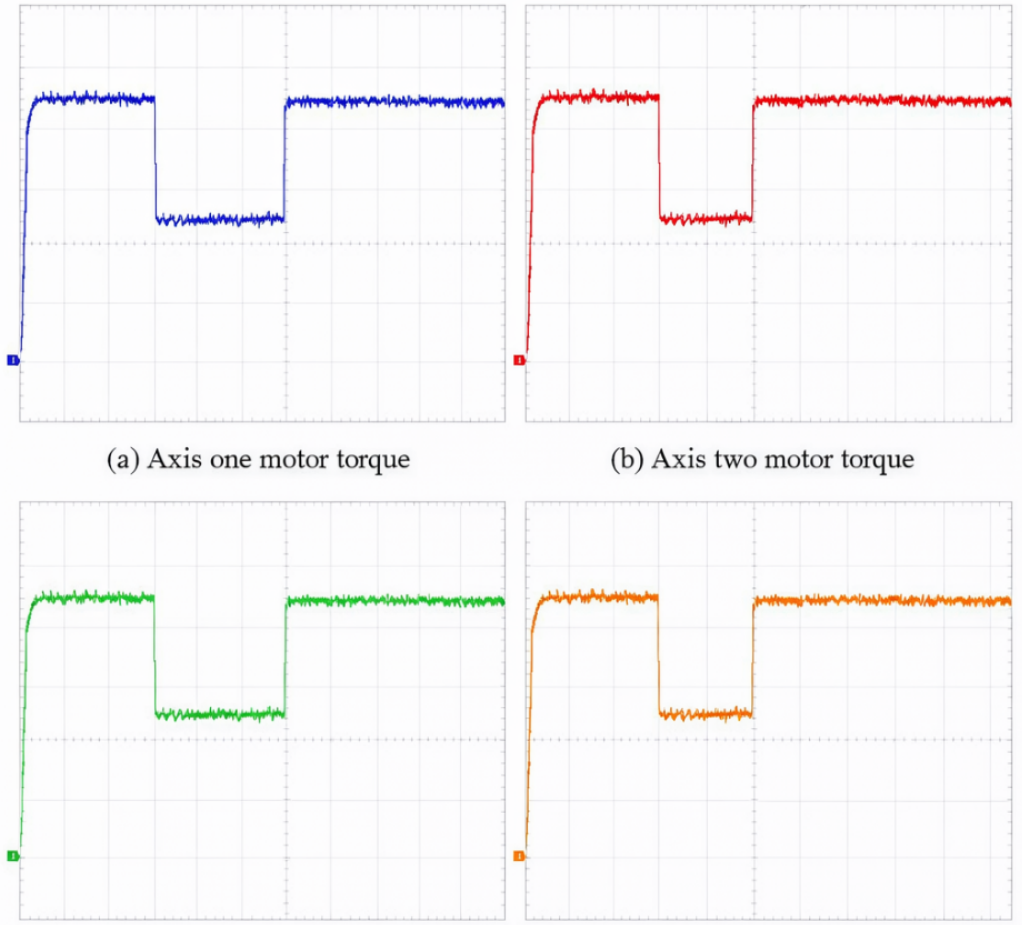
Parameters	Numerical value
Vehicle weight M	200 t
Shaft weight W	25 t
Running velocity	0-120 km/h
Power of test locomotive	9600 kW
Wheel arrangement	$2(B_0 - B_0)$
Starting traction force	760 kN
Continuous traction force	532 kN
Maximum braking force	461 kN
Wheel radius r	0.625 m
Gear speed ratio R_g	6.24
Bogie center distance L	19 m
Bogie wheelbase l	2.56 m
Hitch height H	1.2 m
Traction point height h	0.23 m

Figure 14. Test locomotive

shows the control torque of the four axes, Figure 17 shows the actual creep-slip speed of each axis of the locomotive, and Figure 18 shows the creep-slip speed of the four axes. For a multi-axle heavy-duty locomotive considering the phenomenon of axle weight transfer, the time for each axis to reach the adhesion maximum point is different, so the search algorithm's speed of searching for the adhesion maximum point should also be different.

In order to analyze the data on the oscilloscope, the analog output signals are scaled. In Figures 15 and 16, the scaling factor of the oscilloscope is set to 1/1000, with each vertical frame indicating 2000 and each horizontal frame indicating 5; in Figures 17 and 18, the scaling factor of the oscilloscope is set to 10, with each vertical frame indicating 0.1 and each horizontal frame indicating 5.

The locomotive starts to run from the dry track surface, and it can be seen from Figure 15 that the torque of each axis of the locomotive rises rapidly to the optimal traction



(a) Axis one motor torque (b) Axis two motor torque

(c) Axis three motor torque (d) Axis four motor torque

FIGURE 15. Control torque for each axis

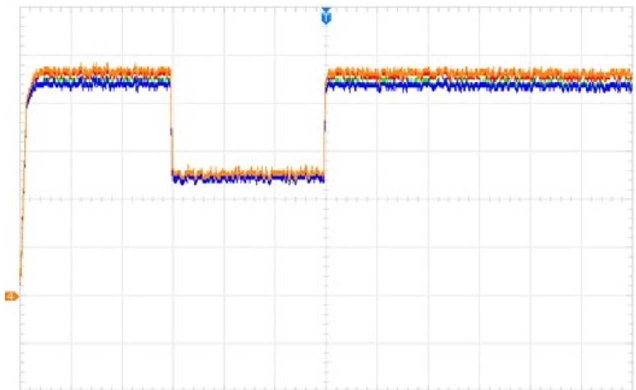


FIGURE 16. Four-axis control torque

torque under the current track surface condition. Due to the influence of the axle weight transfer, the optimal traction torque of axle one under the dry track surface is about 9400, axle two is about 9600, axle three is about 9500, and axle four is about 9700. After 15 s of operation, the locomotive enters the wet track surface, in order to inhibit idling, the torque of each axle decreases rapidly to the optimal traction torque under the wet track surface, at this time, the torque of axle 1 is about 4400, axle 2 is about 4500, axle 3 is about 4400, and axle 4 is about 4500. After continuing to run on the wet track surface

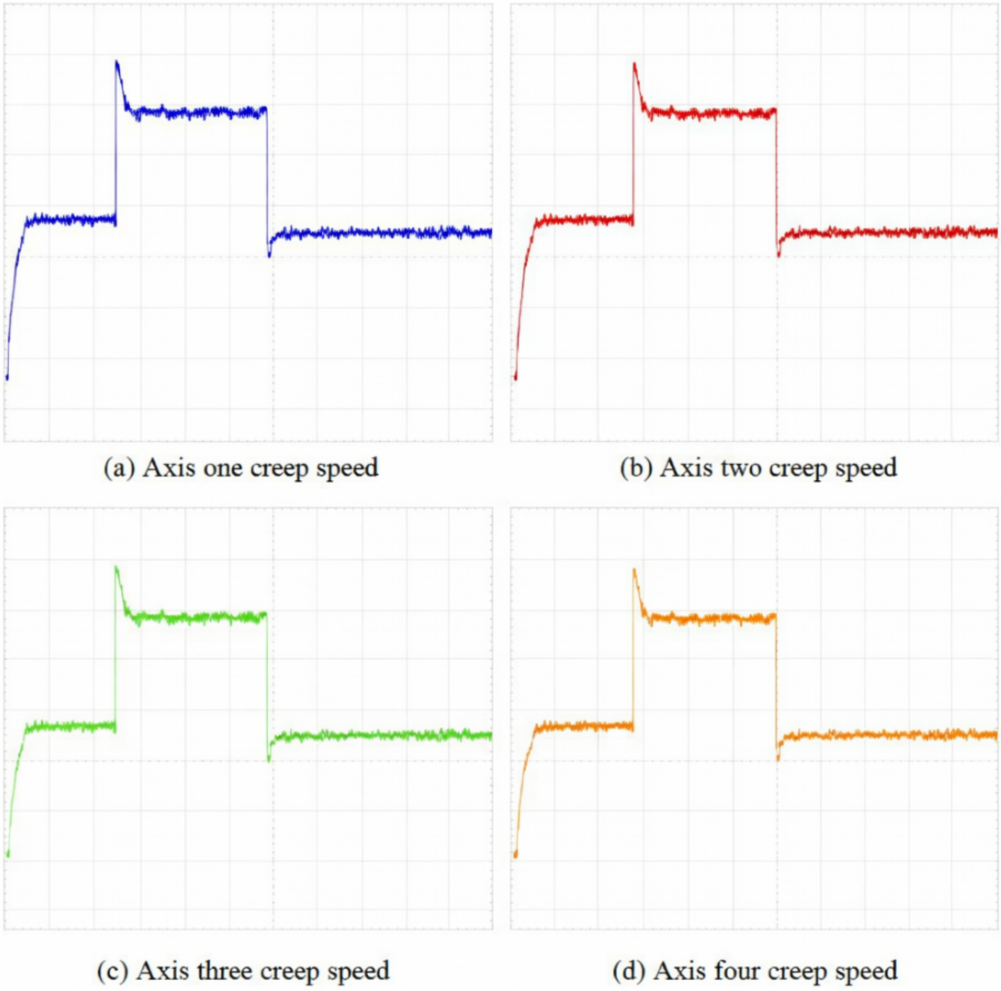


FIGURE 17. Actual creep speed of each axis

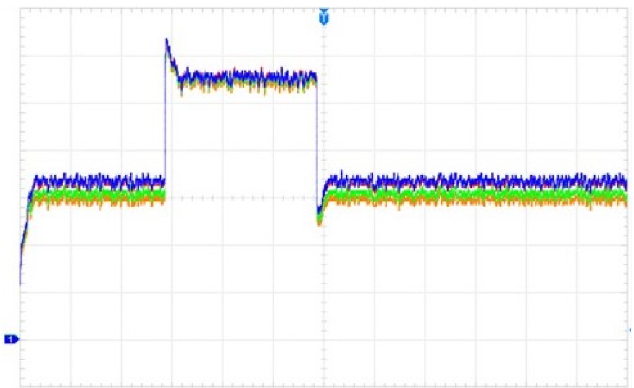


FIGURE 18. Four-axis creep speed

for 15 years and returning to the dry track surface again, the torque of each axis of the locomotive quickly returns to the optimal traction torque under the dry track surface condition, at this time, the torque of axis 1 is about 9400, axle 2 is about 9600, axle 3 is about 9500, and axle 4 is about 9700.

As can be seen in Figure 17, when the locomotive is started, the search algorithm also starts to search for the optimal creep speed under the current rail surface condition. Due to the influence of the axle weight transfer, the optimal creep speed of each axle of the locomotive under the dry rail surface is also different, which is about 0.34 for axle one, 0.33 for axle two, 0.32 for axle three, and 0.31 for axle four. The theoretical optimal creep speed of dry rail surface in the preset model of adhesion curve is 0.34, and the simulation results show that the actual creep speed can quickly track the theoretical optimal value and stabilize in its vicinity. After running 15 into the wet track surface, the search algorithm quickly searches for the optimal creep speed value in the wet track surface state, and the actual creep speed can also be successfully tracked to the optimal value under the action of the adhesion controller. At this time, axis one is about 0.56, axis two is about 0.56, axis three is about 0.55, and axis four is about 0.55. After the locomotive continues to run on the wet track for 15 minutes and then returns to the dry track again, the creep speed of each axle is restored to the optimal value under the dry track condition.

In summary, when the locomotive operates under the track conditions of switching between dry and wet rails, compared with the traditional fuzzy control, the adhesion utilization rate is improved by 5%, the system response speed is improved by 20%-40% compared with the traditional fuzzy control, the system jitter is reduced, and the robustness is improved, the optimal searching control of the maximum attachment point can be realized, and the optimal searching method of the maximum attachment point based on the interval type-2 fuzzy control is verified. The feasibility of the optimal search method for maximum attachment point based on interval type-2 fuzzy control is verified.

6. **Conclusions.** In this paper, a heavy-duty locomotive adhesion control method based on interval type-2 fuzzy controller is proposed. Compared with the traditional type-1 fuzzy control method, interval type-2 fuzzy controller reduces the jitter in the control, improves the dynamic response speed of the system as well as the adhesion utilization rate, and the overall control performance of the locomotive is improved. Aiming at the problem of difficult manual adjustment of PID control parameters in complex control systems, the self-tuning method of PID control parameters based on whale optimization algorithm is adopted.

The optimal creep speed search method based on interval type-2 fuzzy controller mentioned in this paper can quickly search the optimal creep speed under different rail surfaces and realize the most adhesion control of locomotives. However, there are still some limitations in this study, and the simulation mainly focuses on the dry/wet rail surface condition, which has not yet fully covered the more complex operating environment and extreme rail surface conditions. In the future, further research will be carried out for more rail surface conditions (such as ice, snow, oil, and fallen leaves) and the real-time optimization capability of the algorithm, in order to meet the real-time control requirements of trains under complex line conditions.

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REFERENCES

[1] N. Lin, A. Kanellopoulos, R. Akkerman, J. Zhang and J. Ruan, Vehicle routing in precooling logistics with dynamic temperature-dependent product quality decay, *European Journal of Operational Research*, vol.321, no.2, pp.407-427, 2025.

[2] H. Li and Z. Hu, Analysis of factors affecting operation performance of locomotives, *Electric Drive for Locomotive*, no.3, pp.53-54, 2010.

[3] Z. Ni, B. Wu, G. Xiao, Q. Shen and L. Yao, Wheel-rail adhesion control model by integrating neural network and direct torque control during traction under low adhesion, *Journal of Vibration and Control*, vol.31, nos.11-12, pp.2328-2339, 2025.

[4] J. Li, J. Ma and H. Peng, Basic principle and methods of adhesion control of locomotive, *Electric Drive for Locomotive*, no.6, pp.4-8, 2002.

[5] H. Yamazaki, M. Nagai and T. Kamada, A study of adhesion force model for wheel slip prevention control, *JSME International Journal*, vol.47, no.2, pp.496-501, 2004.

[6] W. Aribowo, H. Suryoatmojo and F. A. Pamuji, A novel modified osprey optimization algorithm for tuning droop control parameters in DC microgrid, *International Journal of Innovative Computing, Information and Control*, vol.20, no.4, pp.1105-1124, 2024.

[7] H. Pedram and S. M. Ali, Intelligent-PID controller design for speed track in automatic train operation system with heuristic algorithms, *Journal of Rail Transport Planning & Management*, vol.22, 2022.

[8] Y. Fan, Y. Zhang and B. Wen, Research on virtual coupling trains cooperative control method based on improved artificial potential field, *International Journal of Innovative Computing, Information and Control*, vol.20, no.4, pp.1185-1197, 2024.

[9] X. Fang, S. Lin, Z. Yang, F. Lin, H. Sun and L. Hu, Adhesion control strategy based on the wheel-rail adhesion state observation for high-speed trains, *Electronics*, vol.7, no.5, 2018.

[10] K. Zhao, Y. Li, C. Zhang, J. He and P. Li, Optimal adhesion control for heavy-haul locomotive based on extremum seeking with sliding mode, *Journal of Electronic Measurement and Instrumentation*, vol.32, no.3, pp.88-95, 2018.

[11] W. Li, H. Du and W. Li, A new torque distribution strategy for blended anti-lock braking systems of electric vehicles based on road conditions and driver's intentions, *SAE International Journal of Passenger Cars Mechanical Systems*, vol.9, no.1, pp.107-115, 2016.

[12] W. Gan, Y. Wu, Z. Bai, Y. Hu, Z. Hou, X. Li and K. Chen, Research and application of adhesion optimization control in the traction system of permanent magnet high-speed EMU trains, *Transportation Safety and Environment*, vol.7, no.1, pp.54-61, 2025.

[13] Y. Ma, J. Zhao, H. Zhao, C. Lu and H. Chen, MPC-based slip ratio control for electric vehicle considering road roughness, *IEEE Access*, vol.7, pp.52405-52413, 2019.

[14] J.-H. Ewering, C. Schwarz, S. F. G. Ehlers, H.-G. Jacob, T. Seel and A. Heckmann, Integrated model predictive control of high-speed railway running gears with driven independently rotating wheels, *IEEE Transactions on Vehicular Technology*, vol.73, no.6, pp.7852-7865, 2024.

[15] Y. Wu, X. Zhao, L. Yu and K. Li, Research on adhesion control based on optimal creep identification of high-speed train, *Electric Drive for Locomotives*, no.2, pp.12-16, 2020.

[16] B. Moaveni, F. R. Fathabadi and A. Molavi, Fuzzy control system design for wheel slip prevention and tracking of desired speed profile in electric trains, *Asian Journal of Control*, vol.24, no.1, pp.388-400, 2022.

[17] G. Shi, J. Xiao, Y. Zhang and L. Chen, Adhesion control of locomotive based on virtual prototype and type-2 fuzzy logic system, *Automation Information*, no.12, pp.41-44, 2011.

[18] A. Amirkhani, M. Shirzadeh and M. Molaie, An indirect type-2 fuzzy neural network optimized by the grasshopper algorithm for vehicle ABS controller, *IEEE Access*, vol.10, pp.58736-58751, 2022.

[19] J. Li, C. Ma and Y. Jiang, Fuzzy neural network PID-based constant deceleration control for automated mine electric vehicles using EMB system, *Sensors*, vol.24, no.7, 2129, 2024.

[20] M. Seyedali and L. Andrew, The whale optimization algorithm, *Advances in Engineering Software*, vol.95, pp.51-67, 2016.

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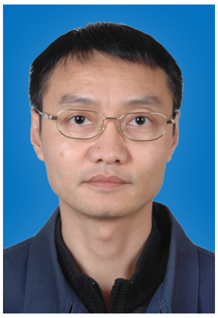

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