IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received April 12, 2020, accepted April 23, 2020, date of publication April 29, 2020, date of current version June 8, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2991300

An Intelligent Coupling 3-Grade Fuzzy Comprehensive Evaluation Approach With AHP for Selection of Levitation Controller of Maglev Trains

YOUGANG SUN[1], LUKUN WANG[2], JUNQI XU[1], AND GUOBIN LIN[1]

[1]College of Transportation Engineering, National Maglev Transportation Engineering Research and Development Center, Tongji University, Shanghai 201804, China

[2]Department of Information Engineering, Shandong University of science and Technology, Taian 271019, China

Corresponding author: Lukun Wang (wanglukun@sdust.edu.cn)

This work was supported by the National Natural Science Foundation of China under Grant 51905380, in part by the China Postdoctoral Science Foundation under Grant 2019M651582, in part by the National Natural Science Foundation of Shandong Province under Grant ZR2018BF005, and in part by the Research on Key Technologies of high-speed maglev for advanced rail transit in the 13th five year plan under Grant 2016YFB1200602.

ABSTRACT During recent years, maglev transportation has made great progress, and as a result, many intelligent levitation control algorithms have emerged. However, enterprises often find it difficult to make a choice when faced with the selection of a controller. The main reason is that the performance evaluation of control algorithms is a complex, multiple-criteria, multifactor coupling problem that cannot be represented by a precise mathematic model. In this paper, a novel artificial intelligent evaluation method for the selection of a levitation controller is developed based on a 3-grade fuzzy method and analytic hierarchy process (AHP). Three kinds of intelligent levitation control algorithms are applied to a full-size test maglev train to collect experimental results with real data. The proposed artificial intelligence method to develop a 3-grade fuzzy multicriteria approach is used to select the best levitation controller for the maglev train. This method can then provide information consultation services to maglev train firms. To the best of our knowledge, for maglev trains, this is the first intelligent evaluation approach with real experimental data. The proposed method can also be applied to other information consultation and decision making systems with appropriate modifications.

INDEX TERMS Information consultation, intelligent evaluation approach, 3-grade fuzzy method, maglev train.

I. INTRODUCTION

With the rapid improvement of the worldwide economic situation and, in particular, urbanization, urban traffic has many difficult problems Examples include traffic accidents, and more so, latterly, exhaust pollution. Although the use of subways can minimize these problems, the noise and, in particular, subway vibration not only affects passengers but, depending on foundation quality, can also affect the state of surrounding buildings and consequently their residents. In such circumstances, an environmentally friendly, comfortable, safe and intelligent transportation method is urgently needed. The maglev train, as shown in Fig. 1, is a new type of urban transportation method [1]–[3]. It can travel faster than 500 km/h and has such advantages as riding comfort, safety, low maintenance relative to other transportation methods and also contributes to environmental protection. In the light of the above, maglev transportation is further developing and spreading vigorously worldwide [4].

The levitation control system, which determines the performance of a maglev train, is the core element. The characteristics of this system include such as strong nonlinearity, open loop instability, time-varying parameters and external disturbances, all of which challenge the control design. Currently, the traditional control algorithm is classic linear control, such as the PID controller. Increasingly,

The associate editor coordinating the review of this manuscript and approving it for publication was Mengchu Zhou.

FIGURE 1. Maglev train lines: (a) Incheon line, (b) Changsha line, (c) Shanghai line, and (d) Emsland line.

alongside, the development of artificial intelligence technology many intelligent control algorithms have been proposed. An active levitation controller with a virtual energy harvester designed by Li *et al.* [5] is used to suppress vehicle-guideway coupling vibration. Sun *et al.* [6] proposed an adaptive sliding mode control of the maglev system, based on the radial basis function (RBF) neural network and an adaptive learning law for network weights, which can approximate unknown parameters effectively. Zhou *et al.* [7] designed an active control method with a finite impulse response (FIR) filter for a magnetic levitation system, which can suppress the vibration caused by the track irregularity. Qian and Fan [8] utilized RBF neural network to approximate the uncertainties, which can solve the load frequency control problem for the renewable power system. Fuzzy control approaches had, already, proved to be successful in various applications [9]–[15]. Sun *et al.* [9] established a Takagi-Sugeno (T-S) fuzzy model of a maglev vehicle-guideway with global nonlinearity. This greatly greatly facilitates stability analysis and control law design. Ding *et al.* [10] proposed a novel method to analyze the stability of the hybrid systems with fuzziness. The effectiveness of the method presented in this Paper is verified by the successful application to a differential-drive two-wheeled mobile robot. Precup *et al.* [11] presented a fuzzy logic control algorithm to stabilize the Rössler chaotic dynamic system with sufficient satisfactory simulation results. Sun *et al.* [12] designed a fuzzy PID controller to address vehicle-rail coupling vibration problems. Radgolchin and Moeenfard [13] developed an adaptive supervised multi-level fuzzy controller to control the deflection of an electrostatically actuated microplate. The simulation results show that the proposed controller can effectively stabilize the microplate beyond the pull-in instability limit. Sun *et al.* [15] proposed a nonlinear robust control law with an adaptive fuzzy logic approximator. Although these levitation control algorithms have their own advantages and disadvantages, there is still no method for evaluating them, despite the fact that many maglev train companies want to choose new intelligent control algorithms, but in the face of the variety of control algorithms, it is difficult to determine which one is the most suitable. Currently there is an urgent need to comprehensively evaluate control effects, based on artificial intelligence algorithms and to hence be able to advise enterprises regarding suitable decisions.

The purpose of a levitation intelligent control algorithm evaluation system is the selection and evaluation of the control scheme using artificial intelligence (AI) algorithms. In expert systems and AI, many rules and criteria cannot be accurately described [16]–[18], hence, fuzzy mathematic methods are used to do so. If the systems contain a relatively complicated and large amount of knowledge and associated experience, the results obtained by the fuzzy methods are more realistic. The evaluation of levitation control is a typical example. The values of the evaluation factors, which cannot be accurately described by mathematics, are based on multiple-criteria decision making. In recent years, AI analysis methods including, such as Bayesian networks, accident trees, fuzzy comprehensive evaluation, fatality analysis, gray theory and other evaluation methods, have been widely applied to consultations and decision-making and to find information,. Yao *et al.* [19] proposed a constrained parameter evolutionary learning (CPEL) algorithm for Bayesian network parameter learning to analyze the decision-making related to UAV autonomous missions. Lakehal and Harouz [20] presented a novel method, based on a fault tree and a BN to enable simpler information processing. The method has been successfully applied to turbo compressor analysis. Dong *et al.* [21] utilized a 2-tuple fuzzy linguistic approach in the analytic hierarchy process to improve the selection of the individual numerical scale and prioritization. Wang *et al.* [22] proposed a fuzzy case-based reasoning method based on a design thinking process and extracted the key form features by utilizing a fuzzy analytic hierarchy process. Abdel-Basset *et al.* [23] proposed a new method based on a neutrosophic analytical hierarchy process to evaluate risks in the supply chain. Mouronte-López *et al.* [24] utilized an analytic hierarchy process, neural networks, and software agents to improve the spare parts management process in a telecommunications' operation. Xu and Xu [25] developed a new method for the probability-hesitant analytic hierarchy process. Han *et al.* [26] proposed a fuzzy comprehensive evaluation method, which is effective and applicable for power grid enterprises in the assessment of the efficiency of a power plant program, The inconsistent elements can be rapidly and accurately detected with the proposed method. Thus, it appears that the factors that affect controllers are numerous and coupled. However, traditional methods, such as the equal weight method, statistical experiment method, variable weight method and set-valued statistical iteration method, often yield little differences in those evaluation values, which cause decision-making difficulties, or require a deep understanding of the problems in applied mathematics. Thus, to evaluate and compare the performance of different levitation controllers in a one-dimensional space, it is important to scientifically and objectively synthesize a multi index problem into a single index form and subsequently be used by maglev trains companies to select new intelligent control algorithms.

The evaluation and analysis methods for maglev traffic have not yet been reported, however, the application of these intelligent analysis methods, in other aspects, provides a suggested method to evaluate the controllers. However, the evaluation is complicated, in that it involves such as control accuracy, dynamic performance, anti-disturbance ability, response speed. For example, some algorithms have quick response speed, but are sensitive to disturbances, causing overshoot. Additionally, there is an analysis deficiency if only a single mathematical analysis method is used. When fault tree analysis alone, (FTA) is used, it is difficult to determine the importance of each basic event from the top event, in the cases, in which the probability of each, cannot be accurately counted. When the analytic hierarchy process (AHP) alone, is used, there is some subjectivity, because the judgment matrix is constructed by an experts' understanding of the whole system. In addition, only when the random consistency index CR<0.1 is the consistency of the judgment matrix considered to meet the requirement. Otherwise, it must be readjusted. Therefore, to analyze and evaluate the levitation control algorithm, which can provide consulting services for enterprises to select the control algorithms, a new 3-grade fuzzy comprehensive evaluation approach with AHP method is proposed. The main contributions are summarized as follows:

1. In comparison with traditional methods, the designed 3-grade fuzzy comprehensive evaluation approach, with AHP, is able to provide a more comprehensive and effective evaluation.

2. The proposed method, to evaluate the performance of different levitation controllers in one dimension space, is able to synthesize a multi index problem into a single index form.

3. As far as we know, this is the first intelligent evaluation approach for maglev trains using real experimental data.

The rest of this paper is organized as follows: in Section 2, the preliminary knowledge is given. In Section 3, three intelligent levitation control algorithms are introduced. In Sec. 4, intelligent comprehensive levitation control algorithm evaluations are given. The paper concludes with conclusions and the future outlook.

II. PRELIMINARY KNOWLEDGE

A. ANALYTIC HIERARCHY PROCESS (AHP)

The analytic hierarchical process takes the target of the research as a problem that requires systematic analysis, and decomposes the complex problems associated with the target layer by layer [23]–[27]. The factors in the same layer are compared, discriminated and calculated.

The numerical scale of AHP consists of 17 values and can be described as follows:

$$\left\{\frac{1}{f}, f_1, f_i\right\}, \quad i = 2, 3, \ldots, 9$$

where, $f_1 = 1$ and $f_{i+1} > f_i > 1$. The value of $f_i\,(i = 1, 2, \ldots, 9)$ corresponds to the ith grade of the AHP linguistic scale. By choosing different values for $f_i\,(i = 1, 2, \ldots, 9)$, different numerical scales can be obtained.

Let $A = \left(a_{ij}\right)_{n\times n}$, where $a_{ij} > 0$ and $a_{ij} \times a_{ji} = 1$, be a reciprocal numerical pairwise comparison matrix. The priority vector can be derived from A.

TABLE 1. Linguistic scale.

Grade	AHP linguistic scale
1	equally important
2	weakly more important
3	moderately more important
4	moderately plus more important
5	strongly more important
6	strongly plus more important
7	demonstratedly more important
8	very, very strongly more important
9	extremely more important

The AHP linguistic scale has nine gradations [23]–[27], which are listed in Table 1 as follows.

The additive normalization method is a prioritization method; it can be expressed as follows:

$$\omega_i = \frac{1}{n}\sum_{j=1}^{n}\frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}}, \qquad i = 1, 2, \ldots, n \tag{1}$$

The principal eigenvector of A as the desired priority vector **W** can be obtained by solving the linear system

$$A\mathbf{W} = \lambda\mathbf{W}, \quad e^T\mathbf{W} = 1 \tag{2}$$

where, λ is the principal eigenvalue of matrix A.

$\lambda_{\max}$ is the maximum eigenvalue of the judgment matrix. The consistency criterion of the judgment matrix can be written as follows:

$$\eta_\lambda = \frac{\lambda_{\max} - n}{n-1} \tag{3}$$

R is the average random consistency index value and η_R can be calculated as follows:

$$\eta_R = \frac{\eta_\lambda}{R} \tag{4}$$

where, $\eta_R < 0.1$ and the pairwise comparison matrix is generally considered to have complete consistency; otherwise, the matrix needs to be readjusted until it has satisfactory consistency.

B. COMBINATION WITH FUZZY COMPREHENSIVE EVAIUATION

The method combined with fuzzy comprehensive evaluation approach [21], [22], [28] can be described as follow.

1) Establish indicator set $\mathbf{U} = \{u_1, u_2, \cdots, u_n\}$. Divide $\mathbf{U}$ into k first-level indicators $\mathbf{U} = \{U_1, U_2, \cdots, U_k\}$ such that $\mathbf{U} = \bigcup_{i=1}^{k} U_i$, $U_i \cap U_j = \emptyset (i \neq j)$, and each first-level indicator is divided as follows: $\mathbf{U_i} = \left\{u_{i1}, u_{i2}, \cdots, u_{in_i}\right\}(i = 1, 2, \cdots, k)$, where $n_1 + n_2 + \cdots + n_k = \sum_{i=1}^{k} n_i = n$.

2) Construct a priority vector according to the improvement AHP. The priority vector corresponding to **U** can be written as follows:

$$\bar{\mathbf{W}} = (a_1, a_2, \cdots, a_n) \quad i = 1, 2, \cdots, n \tag{5}$$

The priority vector corresponding to U_i can be obtained as follows:

$$\bar{\mathbf{W}}_i = (a_{i1}, a_{i2}, \cdots, a_{ij}, \cdots, a_{im}) \quad i = 1, 2, \cdots, m \tag{6}$$

3) To determine the rating level as $\mathbf{V} = (v_1, v_2, \cdots, v_n)$, we use the comment set to rank items into 3 levels (*i.e., $n =$* 3), excellent, average, and poor.

4) The single factor fuzzy evaluation is carried out and the single factor evaluation matrix can be obtained as follows.

$$\mathbf{R} = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{mm} \end{pmatrix}, \quad 0 \le r_{ij} \le 1 \tag{7}$$

5) Let the fuzzy synthetic decision model be ($\mathbf{U}$, $\mathbf{V}$, $\mathbf{R}$), the priority vector be $\bar{\mathbf{W}}$, and the corresponding comprehensive evaluation can be $\mathbf{B} = \bar{\mathbf{W}} \circ \mathbf{R}$. The multi-grade fuzzy evaluation model can be designed, in accordance with the complexity of the model. At present, most are two-grade fuzzy comprehensive evaluation models.

III. INTELLIGENT LEVITATION CONTROL ALGORITHMS

Firstly, it is necessary to determine which controllers will participate in the evaluation. The fuzzy PID controller [11], the adaptive neural-fuzzy sliding mode controller (ANF-SMC) [15], and the RBF neural network sliding mode controller with the minimum parameter learning method [6] were subsequently chosen as examples. For the design of the fuzzy, neuro-fuzzy and sliding mode controllers, refer to [6], [12] and [15]. The three kinds of levitation controllers are to be comprehensively evaluated and compared based on the proposed intelligent evaluation approach.

1) FUZZY PID CONTROL ALGORITHM

The fuzzy PID controller can be expressed as follows:

$$\begin{cases} k_p = k_{p0} + \Delta k_p \\ k_i = k_{i0} + \Delta k_i \\ k_d = k_{d0} + \Delta k_d \end{cases} \tag{8}$$

$$u(t) = k_p error(t) + k_i \int_0^t error(t)dt + k_d \frac{derror(t)}{dt} \tag{9}$$

The meaning of the symbols is found in [12]. The control schematic diagram of the fuzzy PID is illustrated in Fig. 2.

The maglev system fuzzy control rules tables are listed in Tables. 2- 4. More detailed information about the fuzzy PID controller is given [12].

2) ADAPTIVE NEURAL-FUZZY SLIDING MODE CONTROL ALGORITHM

The adaptive neural-fuzzy sliding mode controller (ANF-SMC) is described below.

$$u_{eq} = -\left[\hat{g}(\boldsymbol{\eta}) + \Delta g(\boldsymbol{\eta}, \boldsymbol{\theta}_{\Delta g})\right]^{-1} \cdot \left[\hat{f}(\boldsymbol{\eta}) + \Delta f(\boldsymbol{\eta}, \boldsymbol{\theta}_{\Delta f}) + c_1\eta_2(t) + c_2\eta_3(t) + c_0 e(t)\right]$$

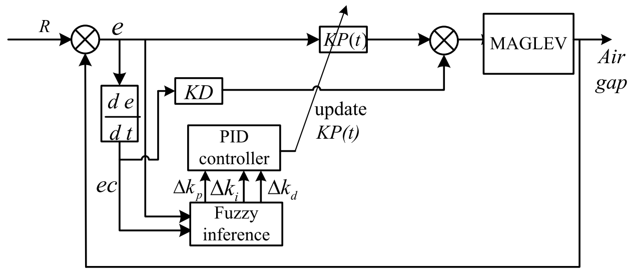

FIGURE 2. Schematic diagram of the fuzzy PID.

TABLE 2. Fuzzy inference rules Of ΔK_P.

ΔK_p	e: NB	NM	NS	ZO	PS	PM	PB
e_c NB	PB	PB	PM	PM	PS	ZO	ZO
NM	PB	PB	PM	PM	ZO	ZO	PS
NS	PB	PB	PM	PS	NS	NM	NM
ZO	PB	PB	PM	ZO	NM	NB	NB
PS	PM	PM	PS	PS	NM	NB	NB
PM	PS	ZO	ZO	NS	NM	NB	NB
PB	ZO	ZO	NS	NM	NM	NB	NB

TABLE 3. Fuzzy inference rules of ΔK_i.

ΔK_i	e: NB	NM	NS	ZO	PS	PM	PB
e_c NB	NB	NM	NM	PS	PS	ZO	ZO
NM	NM	NM	NM	PS	ZO	ZO	ZO
NS	NM	NS	NS	ZO	ZO	ZO	PS
ZO	NS	NS	ZO	ZO	ZO	PS	PS
PS	NS	ZO	ZO	ZO	PS	PS	PM
PM	ZO	ZO	ZO	NS	PM	PM	PM
PB	ZO	ZO	NS	NS	PM	PM	PB

TABLE 4. Fuzzy inference rules of ΔK_d.

ΔK_d	e: NB	NM	NS	ZO	PS	PM	PB
e_c NB	PS	PS	ZO	NS	ZO	PS	PS
NM	NB	NB	NM	NS	PM	PB	PB
NS	NB	NB	NM	NS	PS	PS	PM
ZO	NS	NS	NS	NS	ZO	PS	PM
PS	NB	NB	NM	NS	PS	PB	PB
PM	NB	NB	NM	NS	PM	PB	PB
PB	PS	PS	ZO	ZO	ZO	PS	PS

$$u_{sw} = -\left[\hat{g}(\boldsymbol{\eta}) + \Delta g(\boldsymbol{\eta}, \boldsymbol{\theta}_{\Delta g})\right]^{-1} \cdot \left[W sgn(S) + \kappa\left(c_1 e + c_2\eta_2 + \eta_3 + c_0 \int_0^t e(t)dt\right)\right]$$

$$\begin{cases} \dot{\boldsymbol{\theta}}_{\Delta f} = -r_{\Delta f} S \xi_f(\boldsymbol{\eta}) \\ \dot{\boldsymbol{\theta}}_{\Delta g} = -r_{\Delta g} S u_{eq} \xi_g(\boldsymbol{\eta}) \end{cases} \tag{10}$$

The meanings of the symbols are given in [15]. The structure of the neural network fuzzy system used in ANFSMC is shown in Fig. 3.

The detail of how to train, test and validate the neural network and the architecture is given in [15].

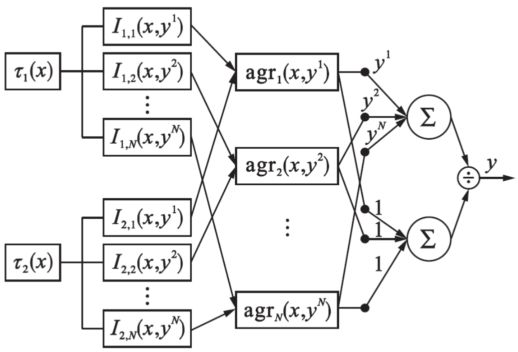

FIGURE 3. Structure of the neural network fuzzy system.

FIGURE 4. Full-scale IoT-based maglev train system.

3) RBF NEURAL NETWORK SLIDING MODE CONTROL ALGORITHM

The RBF sliding mode controller [30-31] is described as follows:

$$u_m(\boldsymbol{x}, t) = \frac{1}{1/2s\hat{\varphi}\boldsymbol{h}_g^T\boldsymbol{h}_g}\left[-\frac{1}{2}s\hat{\phi}\boldsymbol{h}_f^T\boldsymbol{h}_f + r - c_1\dot{e} - c_2\ddot{e} - \eta sgn(s) - \mu s\right]$$

$$\dot{\hat{\phi}} = \frac{\gamma_1}{2}s^2\boldsymbol{h}_f^T\boldsymbol{h}_f - \Omega_1\gamma_1\hat{\phi} \tag{11}$$

$$\dot{\hat{\varphi}} = \frac{\gamma_2}{2}s^2\boldsymbol{h}_g^T\boldsymbol{h}_g u_m - \Omega_2\gamma_2\hat{\varphi} \tag{12}$$

The meaning of these symbols and RBF neural network details can be found in [6].

These control algorithms are programmed and tested on a full-size maglev test vehicle, as shown in Fig. 4, and experimental data can be collected for later analysis and evaluation.

IV. INTELLIGENT COMPREHENSIVE EVALUATION OF THE LEVITATION CONTROL ALGORITHMS

To evaluate the levitation controller, is a complicated system engineering problem. The factors that affect controllers are numerous and complicated. The influence of each factor is correspondingly different, and there are particular relationships between them. The boundary between a good and bad performance is also quite vague, and hence difficult to describe by using classical mathematics. Fuzzy mathematic is a better choice when solving such complex large-scale problems. To comprehensively evaluate more factors and thereby overcome the difficulty of the weight distribution caused by the interlinkage of factors, to evaluate the controllers, an intelligent comprehensive evaluation approach, based on a 3-grade fuzzy method and AHP is proposed. The main steps of the proposed algorithm are given in Tab. 5.

TABLE 5. Scheme for the proposed method.

Algorithm： 3-grade fuzzy method with AHP
Input: The pairwise comparison matrixes $\mathbf{A}_i$
$\lambda_{\max}$ ， η_R
$\beta_1(\zeta)$ ， $\beta_2(\zeta)$ ， $\beta_3(\zeta)$
comprehensive judgment: $\boldsymbol{R}$, $\bar{\mathbf{W}}$
Output: comprehensive evaluation result $\boldsymbol{B}$
1: Selection of evaluation index
2: Experimental data for candidate controllers
3: Determine the comparison matrixes $\mathbf{A}_{ij}$
4: Desired priority vector $\mathbf{W}$
5: Calculate principal eigenvalue： λ
6: Judge consistency criterion ($\lambda_{\max}$ ， η_R)
yes→step 7; no→step 3;
7: Determine membership function between 3-grade index and the evaluation set: $\beta_i(\zeta)$, $i = 1,2,3$;
8: Update single factor evaluation matrixes.
9: Fuzzy comprehensive decision model as (**U, V, R**)
comprehensive judgment: $\boldsymbol{R} = (r_{ij})_{n\times m}$
$\bar{\mathbf{W}} = [a_1 \quad a_2 \quad \cdots \quad a_n]^T$
11: Output calculation $\boldsymbol{B} = \bar{\mathbf{W}} \circ \boldsymbol{R}$
where, $\circ$ denotes Principal factor determinant mode
$b_j = \overset{n}{\underset{i=1}{\vee}}(a_i \bullet r_{ij}) \quad (j = 1,2,\cdots,m)$

A. SELECTION OF THE EVALUATION INDEX AND EVALUATION SET

Firstly, the selection of an evaluation index and evaluation set was made. The control performance is evaluated in terms of the carrying capacity and anti-disturbance capacity. The carrying capacity involves no load, full load and overload. The anti-disturbance capability includes high-frequency square wave input, low-frequency square wave input, high-frequency harmonic input and low-frequency harmonic input. The evaluation indices include two first-grade indexes, seven second-grade indexes and twenty third-grade indexes, as shown in Fig. 5. The first-grade indexes are the carrying capacity and anti-disturbance capacity. The second-grade indexes are the no-load, full-load, overload, high-frequency square wave input, low-frequency square wave input, high-frequency harmonic input and low-frequency harmonic input. The third-grade indexes are different indicators of the control performance. The evaluation set of a maglev train can be denoted as $\mathbf{U} = \{u_1, u_2, \cdots, u_{20}\}$.

During the experiment, the different disturbance signals are artificially added at the sensor inputs of. The high-frequency square wave input signal refers to a square wave signal with a period of 0.5 s and amplitude of 1.5 mm. The low-frequency square wave input signal is a square wave signal with a period

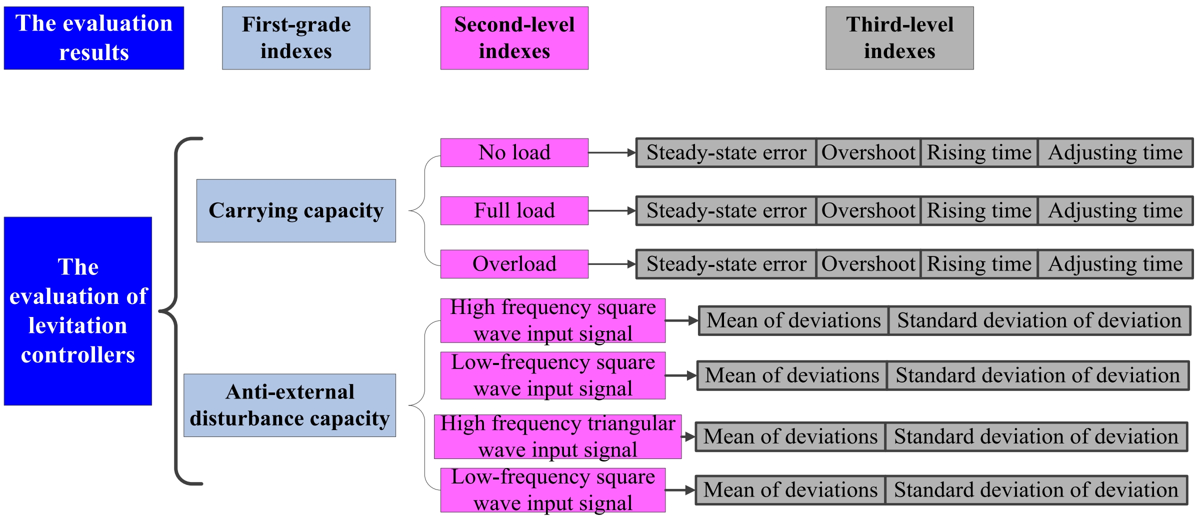

FIGURE 5. Evaluation index of levitation controllers for maglev train.

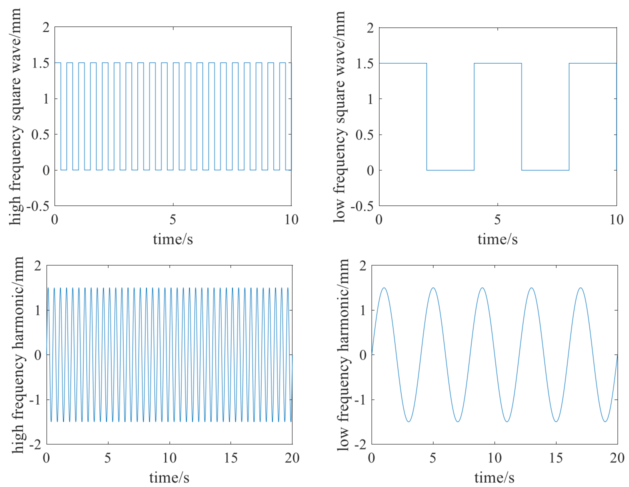

FIGURE 6. Different disturbance signals.

of 4 s and amplitude of 1.5 mm. The high-frequency harmonic input signal generates a harmonic signal with a period of 0.5 s and amplitude of 1.5 mm. The low-frequency harmonic input signal generates a harmonic signal with a period of 4 s and amplitude of 1.5 mm. The sampling period of all signals is 0.01 s. The different disturbance signals are shown in Fig. 6.

B. EVALUATION INDEX VALUES OF REAL DATA IN EXPERIMENTS

After selecting the evaluation index, experimental data for candidate controllers should be provided. Based on the data collected in the experiments, a trusted database is built according to the Apriori algorithm [29]. The relevant data are analyzed and extracted to form the required evaluation index values. The evaluation index values of the three controllers are listed in Tables 6-7.

TABLE 6. Evaluation index values of fuzzy PID.

Carrying capacity	Steady-state error (mm)	Over-shoot (%)	Rising time (s)	Adjusting time (s)
No load	0.0961	0.8859	0.0325	0.0426
Full load	0.0962	6.9429	0.0325	0.0849
Overload	0.0961	12.678	0.0355	0.0997
Anti-distub	Mean of deviation		Standard of deviation	
High-.sq.	0.0166		0.1352	
Low-sq.	0.5546		0.2516	
High-har.	0.0000		0.5001	
Low-har.	0.0777		0.5111	

TABLE 7. Evaluation index values of ANFSMC.

Carrying capacity	Steady-state error (mm)	Over-shoot (%)	Rising time (s)	Adjusting time (s)
No load	0.4532	0.8702	0.0586	0.0714
Full load	0.4522	6.9973	0.0507	0.1375
Overload	0.4533	12.180	0.0507	0.1575
Anti-distub	Mean of deviation		Standard of deviation	
High-.sq.	0.0368		0.0891	
Low-sq.	0.0368		0.0891	
High-har.	0.0012		0.0179	
Low-har.	0.0047		0.0023	

C. DETERMINATION OF INTELLIGENT PRIORITY

The intelligent priority should be determined following the steps below:

First, the hierarchical structure of various control indices of the maglev train is established as shown in Fig. 5.

Second, the pairwise comparison matrix of the levitation system for the maglev train is constructed.

TABLE 8. Evaluation index values of the RBF controller.

Carrying capacity	Steady-state error (mm)	Over-shoot (%)	Rising time (s)	Adjusting time (s)
No load	0.0283	1.5247	0.0400	0.0670
Full load	0.0280	21.0541	0.0420	0.2039
Overload	0.0272	39.0386	0.0449	0.2669
Anti-distub	Mean of deviation		Standard of deviation	
High-.sq.	0.0029		0.02710	
Low-sq.	0.0030		0.0091	
High-har.	0.0000		0.0000	
Low-har.	0.0000		0.0000	

According to the pairwise comparison of factors of the same grade with respect to the importance of a factor of the previous grade, the pairwise comparison matrix is obtained as follows.

1) The importance pairwise comparison matrix in the criterion layer 1 relative to the target layer.

Based on Table 1 and expert experience, the pairwise comparison matrix of $\mathbf{U}_1$ and $\mathbf{U}_2$ to $\mathbf{U}$ is $\mathbf{A} = \begin{bmatrix} 1 & 4 \\ 1/4 & 1 \end{bmatrix}$.

2) The importance pairwise comparison matrix of criterion layer 2 relative to criterion layer 1.

The pairwise comparison of $\mathbf{U}_{11}$, $\mathbf{U}_{12}$, and $\mathbf{U}_{13}$ to $\mathbf{U}_1$ is

$$\mathbf{A}_1 = \begin{bmatrix} 1 & 1/5 & 1/2 \\ 5 & 1 & 4 \\ 2 & 1/4 & 1 \end{bmatrix}.$$

The pairwise comparison matrix of $\mathbf{U}_{21}$, $\mathbf{U}_{22}$, $\mathbf{U}_{23}$ and $\mathbf{U}_{24}$ to $\mathbf{U}_2$ is

$$\mathbf{A}_2 = \begin{bmatrix} 1 & 1/2 & 4 & 3 \\ 2 & 1 & 6 & 4 \\ 1/4 & 1/6 & 1 & 1/2 \\ 1/3 & 1/4 & 2 & 1 \end{bmatrix}.$$

3) The importance pairwise comparison matrix of scheme layers relative to criterion layer 2.

The pairwise comparison matrixes of $\mathbf{U}_{111}$, $\mathbf{U}_{112}$, $\mathbf{U}_{113}$ and $\mathbf{U}_{114}$ to $\mathbf{U}_{11}$, and $\mathbf{U}_{121}$, $\mathbf{U}_{122}$, $\mathbf{U}_{123}$ and $\mathbf{U}_{124}$ to $\mathbf{U}_{12}$, and $\mathbf{U}_{131}$, $\mathbf{U}_{132}$, $\mathbf{U}_{133}$ and $\mathbf{U}_{134}$ to $\mathbf{U}_{13}$ are:

$$\mathbf{A}_{11} = \mathbf{A}_{12} = \mathbf{A}_{13} = \begin{bmatrix} 1 & 8 & 5 & 6 \\ 1/8 & 1 & 1/5 & 1/3 \\ 1/5 & 5 & 1 & 3 \\ 1/6 & 3 & 1/3 & 1 \end{bmatrix}$$

Similarly, the pairwise comparison matrixes of $\mathbf{U}_{211}$ and $\mathbf{U}_{212}$ to $\mathbf{U}_{11}$, $\mathbf{U}_{221}$ and $\mathbf{U}_{222}$ to $\mathbf{U}_{22}$, $\mathbf{U}_{231}$ and $\mathbf{U}_{232}$ to $\mathbf{U}_{23}$, $\mathbf{U}_{241}$ and $\mathbf{U}_{242}$ to $\mathbf{U}_{24}$ are:

$$\mathbf{A}_{21} = \mathbf{A}_{22} = \mathbf{A}_{23} = \mathbf{A}_{24} = \begin{bmatrix} 1 & 3 \\ 1/3 & 1 \end{bmatrix}.$$

Third, the weight of each layer is calculated, and a consistency check of the weights is conducted. Because the same calculated method is used, only matrix $\mathbf{A}_2$ is developed in detail here.

$$\mathbf{A}_2 = \begin{bmatrix} 1 & 1/2 & 4 & 3 \\ 2 & 1 & 6 & 4 \\ 1/4 & 1/6 & 1 & 1/2 \\ 1/3 & 1/4 & 2 & 1 \end{bmatrix} \xrightarrow{Column\ normalize} \begin{bmatrix} 0.279 & 0.261 & 0.308 & 0.353 \\ 0.558 & 0.522 & 0.462 & 0.471 \\ 0.070 & 0.087 & 0.077 & 0.059 \\ 0.093 & 0.130 & 0.154 & 0.118 \end{bmatrix} \xrightarrow{row\ sum} \begin{bmatrix} 1.201 \\ 2.013 \\ 0.293 \\ 0.495 \end{bmatrix} \xrightarrow{normalized} \begin{bmatrix} 0.300 \\ 0.503 \\ 0.073 \\ 0.124 \end{bmatrix}$$

Then, the eigenvector is $\mathbf{W} = \begin{bmatrix} 0.3 & 0.503 & 0.073 & 0.124 \end{bmatrix}^T$

Due to $\mathbf{A}_2\mathbf{W} = \begin{bmatrix} 1.216 & 2.037 & 0.294 & 0.496 \end{bmatrix}^T$, the maximum eigenvalue is:

$$\lambda_{\max} = \sum_{i=1}^{4} \frac{(\mathbf{PW})_i}{4W_i} = 4.0326 \tag{13}$$

The consistency indicator is calculated as follows:

$$\eta_\lambda = (\lambda_{\max} - n)/(n-1) = 0.0109 \tag{14}$$

The random consistency ratio is as below.

$$\eta_R = \eta_\lambda / R = 0.0121 < 0.1 \tag{15}$$

It is learned that $\eta_R < 0.1$, so the priority vector of $\mathbf{U}_{21}$, $\mathbf{U}_{22}$, $\mathbf{U}_{23}$ and $\mathbf{U}_{24}$ is $\bar{\mathbf{W}}_2 = \begin{bmatrix} 0.3 & 0.503 & 0.073 & 0.124 \end{bmatrix}^T$.

The same method can be utilized to obtain other priority vectors as follows:

$$\bar{\mathbf{W}} = [0.8, 0.2]^T, \quad \bar{\mathbf{W}}_1 = [0.111, 0.64, 0.249]^T,$$
$$\bar{\mathbf{W}}_{11} = \bar{\mathbf{W}}_{12} = \bar{\mathbf{W}}_{13} = [0.622, 0.051, 0.218, 0.109]^T,$$
$$\bar{\mathbf{W}}_{21} = \bar{\mathbf{W}}_{22} = \bar{\mathbf{W}}_{23} = \bar{\mathbf{W}}_{24} = [0.75, 0.25]^T$$

D. FUZZY COMPREHENSIVE EVALUATION OF LEVITATION CONTROL ALGORITHMS

The fuzzy comprehensive evaluation approach can be implemented as follows:

First, the membership function between the 3-grade index and the evaluation set is determined. To express the fuzzy mapping of the factors set to the evaluations set, the trapezoidal distribution is used as the membership function of "excellent", "average" and "poor".

The membership function of the "excellent" controller can be expressed as follows:

$$\beta_1(\zeta) = \begin{cases} 1, & \zeta \le \gamma_1, \\ \dfrac{\gamma_2 - \zeta}{\gamma_2 - \gamma_1}, & \gamma_1 < \zeta < \gamma_2, \\ 0, & \zeta \ge \gamma_2, \end{cases} \tag{16}$$

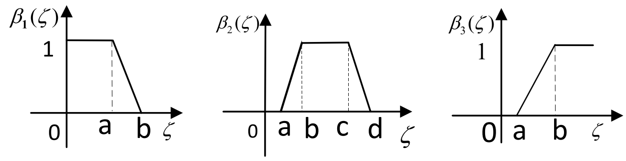

FIGURE 7. Membership function of evaluation set.

TABLE 9. Reference point value of the levitation control system.

Membership function	Steady-state error (mm)	Over-shoot (%)	Rise Time (s)	Adjust time (s)	Absolute error (mm)	Standard error (mm)
"excellent"	a=0.02 b=0.1	a=0.1 b=1	a=0.01 b=1	a=0.1 b=1	a=0.001 b=0.1	a=0.001 b=1
"average"	a=0.02 b=0.04 c=0.06 d=0.1	a=0.1 b=0.2 c=0.4 d=1	a=0.01 b=0.04 c=0.06 d=1	a=0.1 b=0.4 c=0.6 d=1	a=0.001 b=0.004 c=0.006 d=0.1	a=0.001 b=0.004 c=0.006 d=1
"poor"	a=0.02 b=0.1	a=0.1 b=1	a=0.01 b=1	a=0.1 b=1	a=0.001 b=1	a=0.001 b=1

The membership function of the "average" controller can be obtained as follows:

$$\beta_2(\zeta) = \begin{cases} 0, & \zeta \leq \gamma_1, \\ \dfrac{\zeta - \gamma_1}{\gamma_2 - \gamma_1}, & \gamma_1 < \zeta < \gamma_2, \\ 1, & \gamma_2 \leq \zeta \leq \gamma_3, \\ \dfrac{\gamma_4 - \zeta}{\gamma_4 - \gamma_3}, & \gamma_3 < \zeta < \gamma_4, \\ 0, & \zeta \geq \gamma_2, \end{cases} \tag{17}$$

The membership function of the "poor" controller is:

$$\beta_3(\zeta) = \begin{cases} 0, & 0 \leq \zeta \leq \gamma_1, \\ \dfrac{\zeta - \gamma_1}{\gamma_2 - \gamma_1}, & \gamma_1 < \zeta < \gamma_2, \\ 1, & \zeta \geq \gamma_2, \end{cases} \tag{18}$$

where, ζ denotes the control performance index value of the maglev levitation control system. $\gamma_1, \gamma_2, \gamma_3$ and γ_4 represent the membership function reference points. The membership function is described in Fig. 7.

The reference point values of the levitation control system are reported in Table 9.

Second, the original data are standardized, and a single factor evaluation of the third-grade index is conducted to obtain a single factor evaluation matrix.

Let the fuzzy comprehensive decision model be $(\boldsymbol{U}, \boldsymbol{V}, \boldsymbol{R})$ and the priority vector be $\bar{\mathbf{W}}$. The corresponding comprehensive evaluation is $\boldsymbol{B} = \bar{\mathbf{W}} \circ \boldsymbol{R}$, where $\bar{\mathbf{W}} = \left[\, a_1 \ a_2 \ \cdots \ a_n \,\right]^T$ and $\boldsymbol{R} = (r_{ij})_{n\times m}$(*i.e.*, comprehensive judgment). The principal factor determinant mode $b_j = \overset{n}{\underset{i=1}{\vee}} (a_i \cdot r_{ij})$ $(j = 1, 2, \cdots, m)$ is utilized to obtain the comprehensive evaluation matrix as $B = \left[\, b_1 \ b_2 \ \cdots \ b_m \,\right]$.

The results of the third-grade comprehensive evaluation are listed as follows:

$$B_{11} = [0.128, 0.218, 0.513], \quad B_{12} = [0.1, 0.124, 0.56],$$
$$B_{13} = [0.08, 0.622, 0.622], \quad B_{21} = [0.6, 0.626, 0.035],$$
$$B_{22} = [0.19, 0.75, 0.42], \quad B_{23} = [0.72, 0.75, 0.126],$$

and $B_{24} = [0.13, 0.138, 0.13]$

Third, the second-grade factor sets are comprehensively evaluated, and the second-grade evaluation matrix can be obtained as follows:

$$R_1 = \begin{pmatrix} B_{11} \\ B_{12} \\ B_{13} \end{pmatrix} = \begin{pmatrix} 0.12772 & 0.2177 & 0.5132 \\ 0.0991 & 0.1244 & 0.5598 \\ 0.0793 & 0.6220 & 0.622 \end{pmatrix}$$
$$R_2 = \begin{pmatrix} B_{21} \\ B_{22} \\ B_{23} \\ B_{24} \end{pmatrix} = \begin{pmatrix} 0.5939 & 0.6255 & 0.0351 \\ 0.1864 & 0.75 & 0.42117 \\ 0.7197 & 0.75 & 0.12613 \\ 0.131 & 0.138 & 0.12888 \end{pmatrix}$$

The priority vectors $\bar{\mathbf{W}}_{ij}$ are expressed in (16). The second-grade comprehensive evaluation results are $B_1 = [0.063, 0.155, 0.358]$ and $B_2 = [0.178, 0.377, 0.212]$.

Fourth, the first-grade factors sets are comprehensively evaluated, and the overall evaluation matrix is obtained as follows:

$$R = \begin{bmatrix} B_1 \\ B_2 \end{bmatrix} = \begin{bmatrix} 0.063 & 0.155 & 0.358 \\ 0.178 & 0.377 & 0.212 \end{bmatrix} \tag{19}$$

The priority vector is $\bar{\mathbf{W}} = [0.8, 0.2]^T$. The overall system comprehensive evaluation result is represented as $B = [0.051, 0.124, 0.287]$.

From the principle of maximum membership, it is concluded that the fuzzy PID is a "poor" controller, and the membership of "poor" is 0.287.

Additionally, the evaluation results for the ANFSMC and RBF neural network sliding mode controllers can be obtained in the same manner and are as follows:

$$B_{ANFSMC} = [0.287, 0.126, 0.056]$$
$$B_{RBF} = [0.056, 0.318, 0.318]$$

The results suggest that the ANFSMC is the best controller among the three controllers. This is consistent with the long-term experimental results from a national maglev transportation engineering R&D center.

Utilizing the classic AHP method, we can also obtain the weight vector of the three controllers for the total target is [0.214, 0.425, 0.361]. The greater value in the weight vector indicates better control effect. However, the results show that the difference between the evaluations is very small. Besides, once a new control algorithm is introduced for evaluation, the results of all control algorithms need to be recalculated. The proposed method in this work not only produces more comprehensive evaluation, but also only a single calculation is needed when a new control algorithm is introduced for evaluation. Therefore, the new method also can save a lot of computation time.

V. CONCLUSIONS

Proposed In the study, presented in this paper, is the provision of information consultation services for maglev train companies, and an intelligent comprehensive evaluation method for the selection of levitation controllers. To the best of our knowledge, the proposed method, herein, is the first artificial intelligence evaluation method enabling the selection of maglev levitation controllers capable of utilizing a 3-grade fuzzy multicriteria approach. The experimental results of three kinds of levitation controllers are provided for comprehensive evaluation, based on the proposed intelligent coupling 3-grade fuzzy comprehensive evaluation approach with AHP. The results show that the membership of ''good'' for the fuzzy PID, is 0.051. The membership of ''good'' for the RBF neural network sliding mode controller, is 0.056 and that for the ANFSMC, is 0.287. The ANFSMC is the best controller among the proposed three controllers. The evaluation results are consistent with the long-term experimental results. It should be noted that this result only relates to the evaluation of three controllers and under specific control parameters. Thus it is possible that different controller parameter values may produce different results. Additionally, the different importance levels selection (the pairwise comparison control indices matrix) also obtained different evaluation results. This can be determined by the companies according to the market rating. Focus, next, must be on the rules related to the selection of a numerical scale and the selection of a prioritization method for the proposed method, such that it can be extended to other systems for convenient evaluation and consultation.

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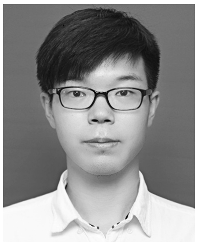
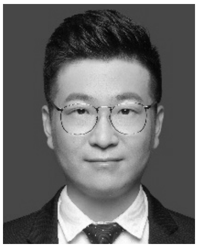


YOUGANG SUN received the B.S. degree in material formation and control engineering from Soochow University, China, in 2011, the M.S. degree (Hons.) in mechatronics engineering from Shanghai Maritime University, China, in 2013, and the Ph.D. degree in mechatronics engineering from Tongji University, Shanghai, China, in 2017.

From 2013 to 2018, he was a Mechatronics Engineer with Shanghai Maritime University. Since 2018, he has been a Postdoctoral Fellow with the National Maglev Transportation Engineering Research and Development Center, Tongji University. His current research interests include maglev trains, offshore cranes, quay cranes, and nonlinear control with applications to mechatronic systems.



LUKUN WANG received the B.S. degree from the Shandong University of Science and Technology, in 2006, and the M.S. degree from the Dalian University of Technology, in 2009, and the Ph.D. degree in computer science from the Ocean University of China, in 2016. His current research interests include artificial intelligence, image processing and pattern recognition, machine learning, control theory and applications, and sensor networks.

JUNQI XU received the B.S. degree in industrial automation from Lanzhou Jiaotong University, Lanzhou, China, in 2000, and the M.S. degree in power electronics and power transmission from Southwest Jiaotong University, Chengdu, China, in 2003. He is currently pursuing the Ph.D. degree with Southwest Jiaotong University.

From 2003 to 2012, he was an Electrical and Control Engineer with the Shanghai Maglev Transportation Engineering Research and Development Center. He is currently working with the National Maglev Transportation Engineering Research and Development Center, Tongji University, Shanghai, China. His research interests include levitation control technology of maglev train and coupling vibration between maglev train and track.

GUOBIN LIN received the B.S. degree in electric machine from Zhejiang University, Hangzhou, China, in 1986, and the M.S. degree in electrical engineering from Southwest Jiaotong University, Sichunan, China, in 1989.

He is currently a Professor and the Deputy Director of the National Maglev Transportation Engineering Research and Development Center, Tongji University. His research interests include maglev vehicle and linear drive research.

Dr. Lin has been a member of the Steering Committee of the International Maglev System and Linear Drive Conference, since 2014.