

## Research Article

# Station Stopping of Freight Trains with Pneumatic Braking

Yun Bai,<sup>1</sup> Baohua Mao,<sup>1</sup> Tinkin Ho,<sup>2</sup> Yu Feng,<sup>1</sup> and Shaokuan Chen<sup>1</sup>

<sup>1</sup>MOE Key Laboratory for Urban Transportation Complex Systems Theory and Technology, Beijing Jiaotong University, No. 3 Shangyuancun, Haidian District, Beijing 100044, China

<sup>2</sup>Department of Computer Science, Shantou University, 243 Daxue Road, Shantou 515063, China

Correspondence should be addressed to Yun Bai; [yunbai@bjtu.edu.cn](mailto:yunbai@bjtu.edu.cn)

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In Chinese mainline railway, freight trains need to stop within passenger stations at times because of the delayed passenger trains. Without any decision-support system, it is very difficult for drivers to stop trains within stations with consistency in one braking action. The reasons are that braking performance of train changes with the conditions of braking equipment and the drivers' subjective evaluations of track profiles and braking distance are vague and imprecise. This paper presents a fuzzy neural network (FNN), which is based on the historical datasets of train stops, to model the latest condition of train braking equipment and to attain the braking distance under a predefined braking rate, track profiles, and initial braking speed. The braking distance is used to find the initial braking position to advise the drivers on commencing braking action. Case studies confirm that it is feasible to stop trains within stations in one braking action by applying the proposed approach. Furthermore, the runtime and energy consumption of train movement are both reduced in comparison to the practical two-step action train stopping (TATS); that is, drivers stop trains before entering stations and remotor at a low speed before slowly stopping within stations.

## 1. Introduction

Railway plays a very important role in many countries. Its development goes very closely with the stringent requirements on safety, reliability, and environment impacts. In the last decade, many researchers focused on the optimization of train interstation runs, for energy saving [1–3], delay recovery [4], and automatic train control [5, 6]. However, station stopping is not as thoroughly studied as others but its importance for safety and efficiency of railways should not be underestimated [7].

The station stopping of freight trains aims to keep the number of changes of braking rate minimal to reduce dynamic longitudinal forces within trains, which may lead to the rupture of coupler yokes in heavy trains [8]. On the other hand, the practical demand of stopping margins, which is usually in tens of meters, must be satisfied. Due to the characteristics of pneumatic braking, freight train drivers can only keep or increase the braking rate during the braking process. In such case, it is quite difficult for drivers to stop trains with sufficient accuracy in one braking action. This is

because the braking performance of train changes with the use of braking equipment and drivers are not familiar with the condition of braking equipment as they are not always assigned to one specific train. Moreover, the influence of track profiles on braking distance is difficult for any drivers to accurately evaluate.

In practice, the driver usually adopts a practical two-step action train stopping (TATS) approach. The driver stops the train completely more than 100 m away from the station at first and then remotors the train at a low speed, usually within 5–10 km/h, before gradually stopping at the station. Because the train stops twice, the run-time and energy consumption both increase substantially. To this end, this paper aims to propose a control approach to assist drivers stop the train within stations in one braking action.

For station stopping of freight trains, there are two control variables to determine. One is the initial braking position where braking begins and the other is the braking rate, which is expressed as a percentage of the full braking force [9]. To minimize the longitudinal forces within the train, a constant braking rate is preferable. Therefore, it is better for freight

train drivers to select an initial braking position to match a predefined braking rate, which is usually 50% of the full braking rate in practice. Thus, the problem discussed in this paper is to find initial braking position according to the target stop point and the braking distance with a constant braking rate.

It is easy to specify the target stop point as freight trains should stop at the center of the station to allow maximum stopping margin. The key of train stopping control is to predict the braking distance under the given braking rate, track profiles, and initial braking speed, which means the train speed at the initial braking position.

Analytical models have been developed to calculate the braking distance under given control instructions and operation condition [10, 11]. However, these models do not take into account the tear-and-wear of train braking equipment, which directly affects train braking performance. Thus the stop error is continuously magnified with the excessive use of braking equipment.

Machine learning techniques have found applications in metro train stopping control [12, 13]. With a number of position and speed sensors installed at stations, real-time estimation of the current train braking performance becomes possible [14]. The initial braking rates applied are tuned at real-time at predefined positions according to the estimated train braking performance [15]. These methods achieve high accuracy but bring an increase on the operating cost. In addition, altering braking rates frequently gives rise to longitudinal forces within the train and leads to excessive tear-and-wear on braking equipment. Therefore, the methods in previous studies are not suitable for the problem discussed in this paper.

The historical datasets of train stops are able to reflect the latest condition of train braking equipment although the accuracy is not as high as real-time measurement. With historical data, train braking distance under any given operation condition can be attained by soft computing methods [16]. The inputs here are the initial braking speed and track profiles between the initial braking position and target stop point. The output is the braking distance. The historical data should be updated to the latest stop considering that the condition of the braking equipment is changing with use.

In recent years, artificial neural network (ANN), one of the common soft computing methods, is used in various fields such as pattern recognition, self-adaptation control, classification, decision optimization, prediction analysis, and knowledge processing [16]. Feed forward neural networks are widely applied at first and backpropagation (BP) is the most popular training algorithm. To improve the convergence speed and stability of neural networks, some new types of ANN, such as radial basis function (RBF) networks and recurrent neural networks, are presented [17, 18]. In this paper, feed forward neural network and BP algorithm are chosen for their simple implementation. To enhance the learning speed and training accuracy of feed forward neural networks, fuzzy inference is integrated to utilize the prior knowledge and experiences [19, 20]. The proposed approach is incorporated into existing train monitoring devices or a real-time decision support system to guide drivers in train

control. The main contribution of this paper is to provide an economical approach, without extra equipment investments, to assist drivers in train stopping control.

This paper is organized as follows. The proposed FNN model is presented in Section 2. Next, the fuzzy inference and the parameters learning of FNN are given in Sections 3 and 4, respectively. Thereafter, Section 5 validates the feasibility and effectiveness of the proposed approach. Finally, Section 6 draws conclusions and indicates some future research issues.

## 2. FNN Model

Train braking distance depends on the braking force, friction force, air resistance, resistance due to track grades, and centrifugal force due to curvatures. Assuming a train as a mass point, the station stopping process is described as follows:

$$\begin{aligned} \frac{dv}{dt} &= -f_b b(v, v_0) - \omega_0(v) - i_g, \\ ds &= v \cdot dt, \end{aligned} \quad (1)$$

where  $v$  is train speed;  $f_b$  is the braking rate;  $b(v, v_0)$  is the full braking force with the train speed  $v$  and initial braking speed  $v_0$ ;  $\omega_0(v)$  is the friction and air resistance;  $i_g$  represents the equivalent track gradient as a result of grade and curvature [3]:

$$i_g = i + \frac{600}{R} + 0.00013 \cdot L_s, \quad (2)$$

where  $i$  denotes the track gradient;  $R$  is the radius of curvature;  $L_s$  is the length of train in tunnel, if any. A negative value of  $i$  denotes a downhill run, and a positive value indicates an uphill run.

As the speed for a stopped train is zero, the braking distance is expressed as follows:

$$S = \int v dt = \frac{\int_{v_0}^0 v dv}{-f_b b(v, v_0) - \omega_0(v) - i_g}. \quad (3)$$

In general, the friction force acting upon the train varies linearly with train speed. Air resistance and centrifugal force are quadratic functions of train speed. The braking force is even more complicated. The full braking force changes nonlinearly with train speed and it is also influenced by initial braking speed and the condition of braking equipment. The wear of braking equipment is very hard to model. Therefore, it is impossible to build a precise mathematical model, taking into account all the factors, to directly attain train braking distance.

In (3), the braking rate is predefined as a constant value. The functions of braking force and resistance caused by friction and air are the same for trains of the same formation, regardless of the condition of the braking equipment. Thus, with a given train formation, the braking distance is determined by initial braking speed and the track profiles between the initial braking position and the target stop point, as expressed by (4):

$$S = f(v_0, i_g). \quad (4)$$

On most rail lines, the formations of freight trains are usually the same in each direction and the train may stop at a sequence of stations along the journey. The recent historical datasets of train stops, in terms of  $(S, v_0, i_g)$ , can be used to predict the current braking distance under given initial braking speed and track profiles by FNN, as the wear of braking equipment is rather slow.

FNN is commonly used for nonlinear function approximation, as it can approximate any function even if the function form is unknown [21]. A standard FNN model has five layers and one of them is the normalized layer to contain the range of output [22]. However, the upper limit of train braking distance is unrestricted here. To reduce computation effort, an enhanced two-input-and-one-output FNN model with four layers is presented in this study, as illustrated in Figure 1.

In the first layer, the neurons deliver the exact value of inputs, including initial braking speed  $v_0$  and track resistance  $i_g$ , to the next layer:

$$O_i^{(1)} = x_i^{(1)} \quad i = 1, 2, \quad (5)$$

where  $x_i^{(1)}$  and  $O_i^{(1)}$  are the inputs and output of the first layer.

In the second layer, the neurons denote the fuzzy subsets of inputs. Gaussian function is applied as the activation function of each neuron. The output of each neuron is the membership degree of the fuzzy subset:

$$O_{ij}^{(2)} = \mu_{ij} = \exp\left(-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}\right), \quad 1 \leq i \leq 2; \quad 1 \leq j \leq m_i, \quad (6)$$

where  $m_i$  denotes the number of fuzzy subsets of input  $x_i^{(1)}$ ;  $c_{ij}$  and  $\sigma_{ij}$  denote the expected value and standard deviation in the Gaussian function.

In the third layer, the neurons denote the outputs of fuzzy rules. In the fuzzy inference system, the output of logical operation ‘‘AND’’ is the product of the membership degree of all the antecedents. The output of each neuron is the membership degree of the rule, which is denoted by (7) as

$$O_j^{(3)} = \mu_j = \mu_{1a} \times \mu_{2b}, \quad 1 \leq j \leq k, \quad (7)$$

where  $a \in (1, 2, \dots, m_1)$ ;  $b \in (1, 2, \dots, m_2)$ . The number of neurons in this layer depends on the number of fuzzy rules.

In the fourth layer, there is only one neuron which denotes the exact output, that is, the braking distance. The output is the weighted sum of all fuzzy rules, which is calculated as follows:

$$O^{(4)} = S = \omega_1 O_1^{(3)} + \omega_2 O_2^{(3)} + \dots + \omega_k O_k^{(3)}, \quad (8)$$

where  $\omega_k$  is the weight coefficient.

It should be noted that the track between the initial braking position and target stop point may include more than one gradient grade. The track resistance acting upon the train may change during the braking process. In such case, the weighted average of equivalent track gradient according to the lengths of grades is taken as the input  $i_g$  of FNN model.

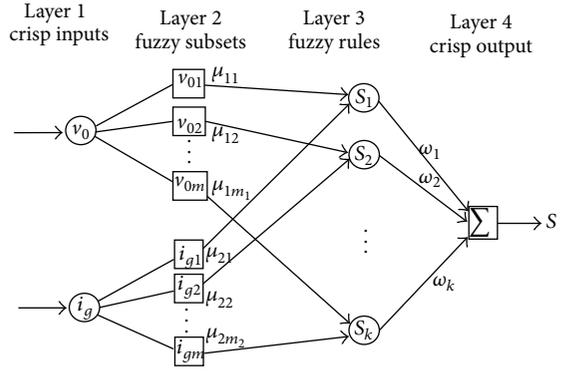


FIGURE 1: Fuzzy neural network model to attain train braking distance.

To attain the train braking distance,  $i_g$  is unknown at first since the initial braking point is not determined yet. The exact track resistance at the location of target stop point is selected as the initial  $i_g$  forwarded into the FNN model to attain train braking distance. Once the braking distance is attained, the initial braking position is determined and the corresponding  $i_g$  is known. If it is different from the initial one, the  $i_g$  forwarded into the FNN model should be updated to attain the new braking distance until the input  $i_g$  of FNN equals the weighted average of equivalent track gradient corresponding to the output  $S$  of FNN.

### 3. Fuzzy Inference in FNN Model

A fuzzy inference system, being capable of expressing the drivers’ experiences and modeling the uncertainties of track and train speed, is incorporated in ANN to enhance the learning speed and training accuracy. There are two kinds of methods to generate a fuzzy inference system. One is subtractive clustering, which originates from the mountain clustering method [23]. Its advantage is keeping the number of fuzzy rules minimal. The other one is grid partition, which is more applicable when the neurons have clear physical meanings. Grid partition will generate many fuzzy rules and a number of parameters need to be determined when there are many inputs in the FNN model. Therefore, it is not suitable for a multiple inputs problem. Considering the characteristics of the proposed FNN, the grid partition is applied here.

In this study, the complete fuzzy set of input  $v_0$  is divided into five fuzzy subsets, that is,  $\{S_2, S_1, M, B_1, B_2\}$ .  $i_g$  can be positive or negative and it is also divided into five fuzzy subsets, that is,  $\{NB, NS, ZO, PS, PB\}$ . The fuzzy term set of the output  $S$  is  $\{S_3, S_2, S_1, M, B_1, B_2, B_3\}$ . The subsets of inputs and output adopt Gaussian membership functions, as mentioned earlier.

The fuzzy rules are built by the relationship between inputs and output, expressed as follows:

$$R_i : \text{if } v_0 \text{ is } A_i \text{ and } i_g \text{ is } B_i, \text{ then } S \text{ is } C_i \quad i = 1, 2, \dots, n, \quad (9)$$

where  $R_i$  indicates the  $i$ th fuzzy rule;  $A_i$  and  $B_i$  are the fuzzy subsets of inputs;  $C_i$  is the fuzzy subset of output. The

TABLE 1: Fuzzy rules in FNN model.

$i_g$	S				
	$S_2$	$S_1$	$v_0$	$B_1$	$B_2$
NB	M	M	$B_1$	$B_2$	$B_3$
NS	$S_1$	M	M	$B_1$	$B_2$
ZO	$S_2$	$S_1$	M	$B_1$	$B_2$
PS	$S_2$	$S_2$	M	M	M
PB	$S_3$	$S_2$	$S_1$	$S_1$	M

rules bases, as shown in Table 1, are established according to drivers' experiences.

#### 4. Parameters Learning in FNN Model

There are three types of parameters that need to be determined in the proposed FNN model. The first type is the weight coefficients of fuzzy rules  $\omega_l$  ( $l = 1, 2, \dots, k$ ). The other two are the position and shape parameters in the Gaussian function, that is,  $c_{ij}$  and  $\sigma_{ij}$ . Considering that the proposed FNN is a multilayered neural network and the Gaussian function is differentiable, the classical BP algorithm could be used to attain the three kinds of parameters in the FNN model [24].

In the BP algorithm, the differences between actual and expected outputs are attributed to the errors of parameters of neuron activation function and the weight coefficients of fuzzy rules. Having propagated the errors backwards layer by layer from output to input, BP calculates the gradient of the error of each node regarding the modifiable parameters. This gradient is used in a simple stochastic gradient descent algorithm to find parameters that minimize the error. Since BP uses the gradient descent method, the derivative of the squared error function with respect to the parameters of the network has to be calculated. The square error function is defined as follows:

$$E' = \frac{1}{2}(O_d - O^{(4)})^2 = \frac{1}{2}(\bar{S} - S)^2, \quad (10)$$

where  $O^{(4)}$  and  $S$  are the actual outputs;  $O_d$  and  $\bar{S}$  are the expected outputs.

In the gradient descent method, the parameters are corrected in the direction with negative gradient direction. The corrections of the three kinds of parameters  $\Delta\omega_l$ ,  $\Delta c_{ij}$ , and  $\Delta\sigma_{ij}$  are calculated as follows:

$$\begin{aligned} \Delta\omega_l &= -\eta \cdot \frac{\partial E'}{\partial \omega_l} = -\eta \cdot \frac{\partial E'}{\partial O^{(4)}} \frac{\partial O^{(4)}}{\partial \omega_l} = \eta \cdot (\bar{S} - S) \cdot \prod_{i=1}^2 \mu_{ij} \\ &= \eta \cdot (\bar{S} - S) \cdot \prod_{i=1}^2 \exp\left(-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}\right), \end{aligned}$$

$$\begin{aligned} \Delta c_{ij} &= -\eta \cdot \frac{\partial E'}{\partial c_{ij}} = -\eta \cdot \frac{\partial E'}{\partial O^{(4)}} \frac{\partial O^{(4)}}{\partial O_j^{(3)}} \frac{\partial O_j^{(3)}}{\partial O_{ij}^{(2)}} \frac{\partial O_{ij}^{(2)}}{\partial c_{ij}} \\ &= \eta \cdot (\bar{S} - S) \cdot \omega_j \cdot \prod_{i=1, i \neq j}^2 \mu_{ij} \cdot 2 \exp\left(-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}\right) \\ &\quad \cdot \frac{x_i - c_{ij}}{\sigma_{ij}^2}, \\ \Delta\sigma_{ij} &= -\eta \cdot \frac{\partial E'}{\partial \sigma_{ij}} = -\eta \cdot \frac{\partial E'}{\partial O^{(4)}} \frac{\partial O^{(4)}}{\partial O_j^{(3)}} \frac{\partial O_j^{(3)}}{\partial O_{ij}^{(2)}} \frac{\partial O_{ij}^{(2)}}{\partial \sigma_{ij}} \\ &= \eta \cdot (\bar{S} - S) \cdot \omega_j \cdot \prod_{i=1, i \neq j}^2 \mu_{ij} \cdot 2 \exp\left(-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}\right) \\ &\quad \cdot \frac{(x_i - c_{ij})^2}{\sigma_{ij}^3}. \end{aligned} \quad (11)$$

In the above equations,  $\eta$  denotes the learning rate. The greater the learning rate is, the faster the neuron trains are. The lower the learning rate is, the more accurate the training can be.

#### 5. Case Studies

**5.1. Feasibility Analysis of the Proposed Approach.** The freight trains serviced on Ningxi rail line are employed here to test the feasibility of the proposed approach. The trains consist of a  $DF_{8B}$  locomotive and 50 heavy loaded wagons. The steepest grade near the stations is 5‰ and the speed limit is 80 km/h. The situations where the initial braking speed is lower than 10 km/h are excluded from this study since in these cases it is easy for drivers to stop trains within stations. In other words, the range of  $v_0$  and  $i_g$  in the proposed FNN is (10 km/h, 80 km/h) and  $(-5, 5)$ , respectively.

With a lack of sufficient field data, the historical datasets of train stops are attained by a train movement simulator [11]. To model the wear of train braking equipment in simulation, the braking force under the same operation condition is reduced by a random number within the range of (0, 0.001) after each stop, considering the wear characteristics of braking equipment of selected trains [25]. In practice, external factors like wind carry impact on friction and air resistance. The effects are usually very small, which is also assumed as a random number within the range of  $(-0.001, 0.001)$ . 320 datasets of train stops, covering the effective ranges of  $v_0$  and  $i_g$ , are attained by the simulator and illustrated in Figure 2. The 320 samples are forwarded into the FNN model to attain the three kinds of parameters of FNN.

The learning rates of all parameters are defined as 0.02 and the maximum number of training is set as 4,000. The initial position parameters of the Gaussian function  $c_{ij}$  are uniformly distributed within the effective range, and the initial shape parameters of the Gaussian function  $\sigma_{ij}$  and the

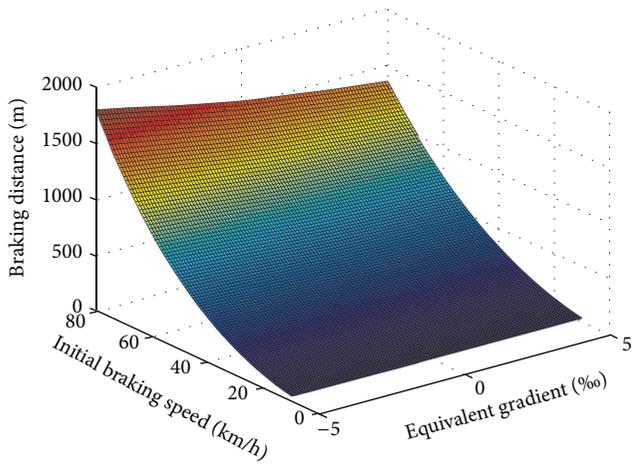


FIGURE 2: Relationships among braking distance, initial braking speed, and equivalent track gradient.

weight coefficients of fuzzy rules  $\omega_i$  are generated by a random number generator. To avoid that the training falls into local optimal solution, the initial parameters of  $\sigma_{ij}$  and  $\omega_i$  will be generated at random again and training is restarted, once the root-mean-square error converges at an unsatisfied level.

The training is conducted on a computer with a Pentium-M 2.8 GHz processor and 2 GB RAM. The training process only needs several seconds. In the process, the root-mean-square error decreases rapidly and it converges to 0.85 after 500 iterations in BP, as shown in Figure 3. According to the training results, the membership function of the two inputs, that is,  $i_g$  and  $v_0$ , is given in Figure 4. It is found that the fuzzy subsets are uniformly distributed within the effective range.

To test the accuracy of FNN, another 76 datasets of train stops are collected through simulations. To model the possible wear of train braking equipment, the braking force under the same operation condition in these 76 simulations is reduced by a random number within the range of (0, 0.001) from that in one of the previous 320 samples. The simulation results are compared to the calculated ones by FNN model. The errors are normally distributed as shown in Figure 5, in which a positive value indicates that the braking distance attained by FNN is larger than the simulated one and a negative value denotes the opposite case. Most of the errors are within 1 m. The average absolute error is 0.85 m and the maximum error is 4.05 m.

The 76 braking distances attained by FNN model are then used to attain the initial braking positions, which are forwarded into the simulator to verify the stop accuracy of the proposed approach. Time delay is unavoidable in such a real-time control problem [26, 27]. The stop errors with and without driver's reaction time are given in Figure 6. Regardless of driver's operation delay, the maximum stop error is limited within 5 m. In practice, the driver's reaction time is usually about 0.5 s, which may vary with different drivers but usually no more than 1 s. The maximum stop error in the situation of 1 s operation delay is limited within 25 m, which still satisfies the practical demand of stopping

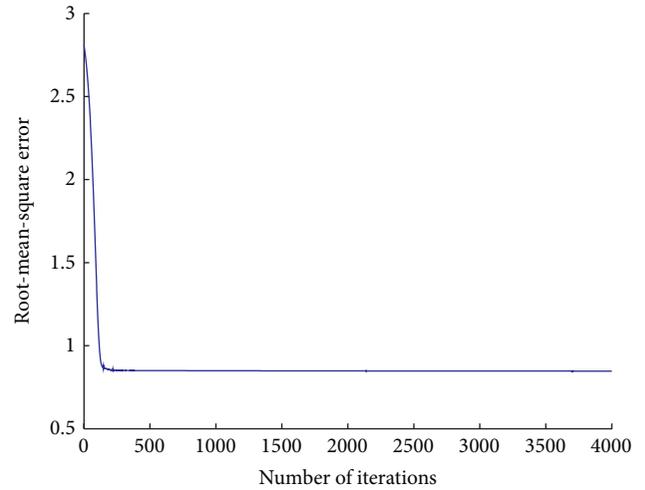


FIGURE 3: Root-mean-square errors with different steps of iterations in BP.

TABLE 2: Effectiveness of the proposed approach in comparison with TATS.

	Run-time (min)	Energy consumption (kg)	Stop error (m)
TATS	17.63	114.10	1.64
FNN	14.35	111.40	3.82
Saving	18.60%	2.40%	—

margins for freight trains. In other words, it is feasible to stop trains within a station by applying a constant braking rate on the train from the initial braking position attained by the proposed FNN model. Thus the number of changes of braking rate during one station stop is kept minimal, while the practical demand of stopping margins is satisfied.

**5.2. Run-Time and Energy Consumption Savings.** Another case study has been carried out to evaluate the run-time and energy savings of the proposed approach in comparison with a real-life train station stopping control which adopts TATS. The train runs in a section of 10.611 km from the same rail line adopted in the previous section. The train length and traction weight are 758 m and 4,174 tons, respectively. The train speed trajectories of FNN and TATS in the entire interstation run are given in Figure 7. The corresponding train run-time and energy consumption are given in Table 2. The driver's reaction time is not considered here since its influence on train run-time and energy consumption is negligible.

With TATS, the train stops at first and then moves at a very low speed to approach the target stop point. The train stop error is easy to control at a low initial braking speed. On the other hand, the train stops within the station at once by applying a predefined braking rate from the initial braking point attained by the proposed approach. The stop error is larger but it still satisfies the practical demand of freight train stops. More importantly, the run-time and energy

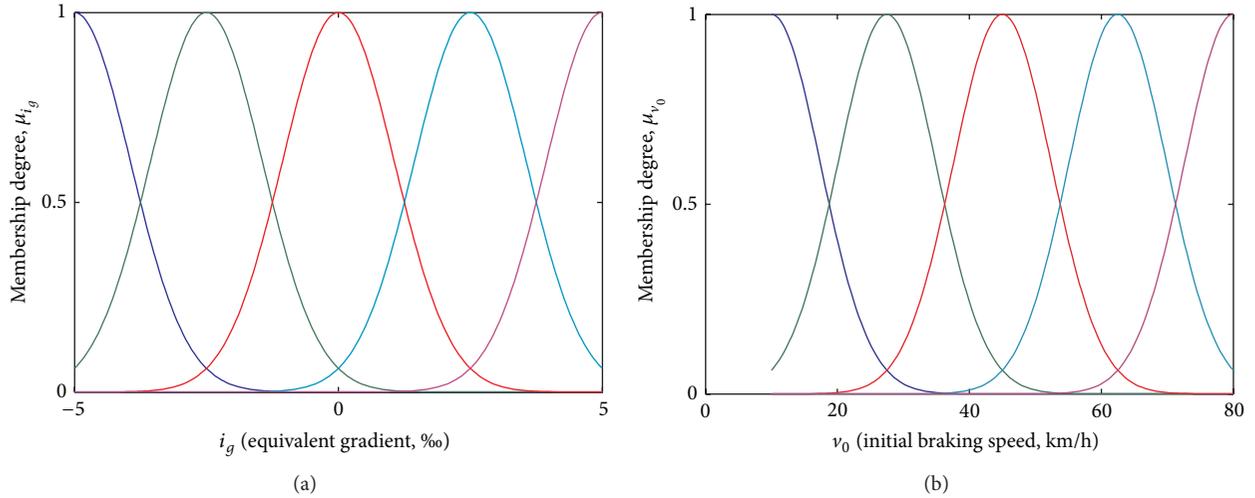


FIGURE 4: Membership functions of FNN inputs.

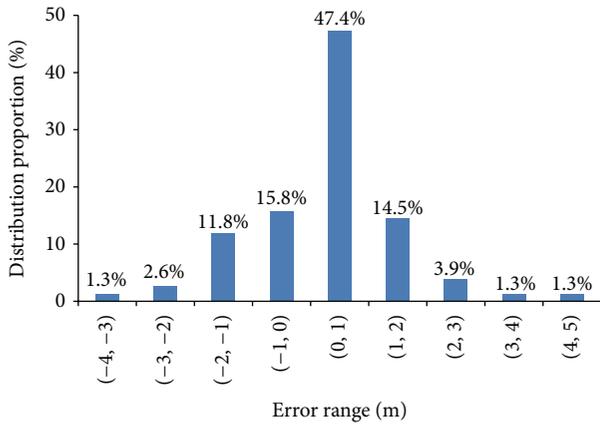


FIGURE 5: The errors distribution of FNN model.

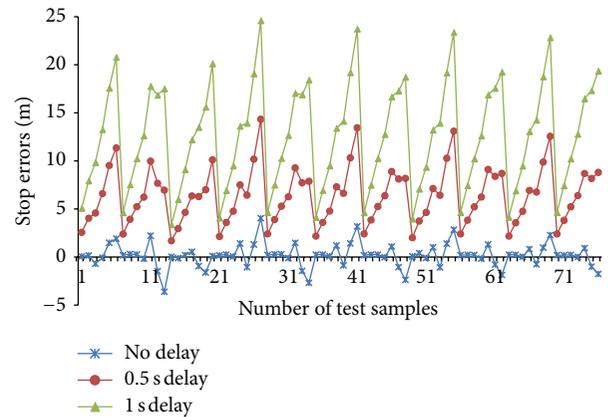


FIGURE 6: The stop errors in application of the proposed approach.

consumption are reduced by 18.60% and 2.40%, respectively. Time savings of freight train interstation run is regarded as a bonus as delayed trains have more margins to recover their delays.

## 6. Conclusions

In Chinese mainline railways, stopping freight trains within a station in one braking action is quite difficult for drivers, because the train braking performance changes with the use of braking equipment and the drivers' subjective evaluations of track profiles and braking distance are vague and imprecise. To minimize dynamic longitudinal forces within trains, the number of braking rate changes should be kept minimal. The machine learning approaches adopted previously, which need to adjust braking rate for several times in each station stop, are not suitable. In this paper, a FNN model, using the latest datasets of train stops to approximately model the current train braking performance, is proposed to attain the

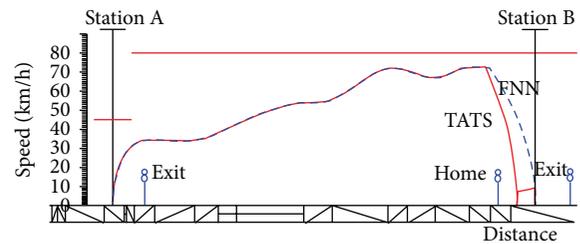


FIGURE 7: Comparison of train speed trajectories of FNN and TATS.

initial braking position under the given braking rate, track profiles, and initial braking speed.

Case studies show that the braking rate can be kept constant during the stop process by applying the predefined braking rate on the train from the initial braking position attained by the proposed approach, while the practical demand of stopping margins is satisfied. A further case study shows that the train run-time and energy consumption with the proposed control approach are reduced by 18.60% and

2.40%, respectively, in comparison with the practical TATS. The proposed approach is suitable for the rail lines on which the train formation is fixed. For other rail lines, the number and type of wagons should be regarded as the inputs of FNN model, as they imply different braking distances.

### Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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