The research on train resistance prediction of low vacuum pipeline based on different neural network algorithms

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Abstract. In order to obtain the maximum aerodynamic resistance of low-vacuum pipeline train under different working conditions, this paper uses different neural network algorithms to predict the maximum aerodynamic resistance. First, it calculates 85 groups of maximum resistance values of trains under different operation speeds, pipeline pressure and blocking ratios. Then, it takes 81 groups of data as training samples, establishing and training RBF neural network models, which are based on three different functions, and a linear neural network model as a comparison. Finally, it verifies those models with four groups of randomly selected verification data. The results show that the RBF network prediction model based on Newrbe function has the best prediction effect. It is superior to the other two RBF models in prediction accuracy. The prediction error of the linear neural network model for the maximum resistance of the train is large, and the prediction accuracy is far lower than that of the radial basis function neural network model.

1. Introduction

At present, high-speed rail travel plays a most important role in people's work and life. With the urgent demand for travel efficiency, train speed has become a research focus in recent years. The research shows that when a train's running speed is more than 400km/h, aerodynamic resistance accounts for 4/5 of the total resistance [1]. Based on this premise, the train running assumption of low vacuum pipeline is put forward.

Although research on the train operation scheme of low vacuum pipeline is still in the initial stage, the concept of vacuum pipeline transportation has already been put forward a long time ago. Earlier, an American scholar Robert David proposed transport by vacuum pipeline, and a Swiss scholar proposed the low-vacuum high-speed maglev subway system. In 2017, the Hyperloop One company conducted a whole-system test in the vacuum pipeline [2]. At present, it is more economical and convenient to study the maglev train with low-vacuum pipeline by numerical simulation [3]. Domestic scholars have also carried out model tests on the maglev system with low vacuum pipeline. Peng Xu studied the aerodynamic characteristics and changing rules of piston wind in the vacuum transportation system [4]. Based on dynamic grid technology, Mi Baigang, Zhan Hao, Zhu Jun et al. analyzed the relationship between resistance, blocking ratio and vacuum degree of high-speed trains in vacuum pipeline under two-dimensional conditions [5]. Liu Jiali, Zhang Jiye et al. conducted a simulation study on the aerodynamic resistance of vacuum pipeline trains, and analyzed the relationship between the aerodynamic resistance of trains and the blocking ratio, running speed and pipeline pressure respectively [6-7]. Huang Zundi, Liang Xifeng and Chang Ning calculated
Knudsen’s number according to the minimum space size to judge the fluid flow state in the vacuum pipeline, considered the three-dimensional steady compressible effect, and based on sliding grid technology, they have analyzed the impact of train operation speed, pipeline vacuum degree, blocking ratio and ambient temperature on the aerodynamic resistance of the train [8]. Wang Zhifei and Na Risu et al. proposed a parameter design method based on numerical simulation and orthogonal theory, and analyzed the influence trend of running speed, blocking ratio and pipeline pressure on train aerodynamic resistance and the influence significance of each factor [9]. The train has a large slenderness ratio, and the simulation calculation of all working conditions is time-consuming and labor-consuming. A certain maximum resistance of the train is obtained through the simulation calculation, the prediction model is trained by the intelligent algorithm and the aerodynamic resistance of the train is predicted, which provides an idea for the research of the train with low vacuum pipeline.

The factors affecting the operation of pipeline trains include running speed, pipeline pressure and vacuum degree. Firstly, based on these three factors, this paper simulates a variety of train operating conditions and records the maximum aerodynamic resistance. Then, the RBF neural network and linear neural network was used to construct predictive model, with the RBF network using three different functions. Finally, in order to verify the prediction accuracy of each model, the prediction data and simulation data are compared respectively.

2. Network model

2.1. RBF neural network model

As shown in Figure 1, RBF neural network is a three-layer forward network. The input layer consists of multiple source nodes. The hidden layer is responsible for connecting the input and output, giving different weights to different inputs. The output layer responds to the previously transmitted input. The RBF function is used as the hidden layer unit transformation function [10-12].

As a basis function, there are many forms. The most commonly used is Gaussian function, and the formula [10] is as follows.

$$R_i(x) = \exp \left[ -\frac{||x-c_i||^2}{2e_i^2} \right] \quad i = 1, 2, ..., m$$

(1)

Where $i$ indicates $n$ dimension input vector, $c_i$ indicates the center of the $i$ basis function, it has the same dimension as $x$, $e_i$ indicates the variable of the hidden layer node $i$, which determines the width of the basis function around the center point, and the value can be freely selected, $m$ indicates the number of nodes in the hidden layer, $||x-c_i||$ indicates the norm of vector $x-c_i$, the distance between $x$ and $c_i$.

As Figure 1 shows, the first two layers $x \rightarrow r_i(x)$ are mapped nonlinearly, the last two layers $r_i(x) \rightarrow y_l$ are linearly mapped, the calculation formula [10] is as follows.

$$y_k = \sum_{i=1}^{m} w_{ik}r_i(x) \quad (k = 1, 2, ..., p)$$

(2)
Where $y_k$ indicates the output of the output node $k$, $w_{ik}$ indicates connection weight of hidden node $i$ and output node $k$, $p$ indicates number of output nodes.

2.2. **Linear neural network model**

The current linear neural network mainly refers to the adaptive linear neural network [13], the linear neural network structure is shown in Figure 2. The neuron transfer function is purelin, the input vector is $R$, the number of hidden neurons is $S$. The purpose of network training is achieved by adjusting the appropriate weight value $w$ and threshold value $b$. Using the determined input and output values, the linear neural network with the minimum mean square deviation is designed directly [14-16].

![Figure 2. structure of linear neural network.](image)

3. **Model establishment and prediction verification**

3.1. **Sample preparation**

The high-speed train model was established, and the pipeline model was built with different blocking ratios respectively. Among them, the blocking ratio is the main factor determining the inner diameter of the pipeline and one of the factors affecting the aerodynamic resistance of the pipeline train, which is defined as the ratio of the cross-sectional area of the train to the cross-sectional area of the pipeline [17]. In simulation condition, the blocking ratio is from 0.1 to 0.4, and the interval is 0.1, the train runs at a speed of 600-1000km/h with an interval of 100, the vacuum degree is from 600pa to 1000pa, the interval is 100. The maximum aerodynamic resistance of 85 groups of trains was recorded by simulation under different operating speeds, pipeline pressures and blocking ratios, taking 81 sets of data as training samples and selecting 4 sets of data randomly as verification samples. When building the model, the three parameters of running speed, pipeline pressure and blocking ratio are used as input, and the maximum resistance is used as output. The 4 selected sets of validation data are shown in Table 1 below.

| Number | Blocking ratio | Speed (km/h) | Vacuum (pa) | Simulate results (N) |
|--------|----------------|--------------|-------------|----------------------|
| 1      | 0.1            | 600          | 700         | 1252.51              |
| 2      | 0.2            | 700          | 800         | 3928.73              |
| 3      | 0.3            | 800          | 900         | 10104.88             |
| 4      | 0.4            | 800          | 1000        | 15229.46             |
3.2. Model establishment and training

3.2.1. RBF model. MATLAB Neural Network Toolbox provides a large number of functions that can be used to build different networks. Different RBF prediction models are established by using these building functions. We can use different functions to establish neural network models in MATLAB. As shown in Table 2, there are three kinds functions that can be used to establish radial basis neural network[18].

| Number | Name  | Function                                                      |
|--------|-------|---------------------------------------------------------------|
| 1      | newrb | The radial basis neural network function is established       |
| 2      | newrbe| Establish strict radial basis neural network function         |
| 3      | newgrnn| The generalized regression radial basis neural network function is established |

The established model can not be used directly for prediction and needs training. For the neural network established by different functions, it is important to determine the input vector, output vector and the appropriate expansion speed of radial basis function. The neural network that established by Newrb function are also need to determine the maximum number of neurons and the mean square error.

3.2.2. Linear network model. Using the toolbox function of linear neural network and newlind function, a specific linear neural network is established directly. Its weight matrix and threshold matrix can ensure the minimum mean square deviation [18].

3.2.3. Prediction result analysis. The comparison between the predicted value and the simulated value of the RBF neural network established by three different functions is shown in Figure 3. The prediction effect of the network model established by the Newrbe function is the best, and the deviation between the predicted value and the simulated value is the smallest; the deviation of the predicted value of the network model established by the Newrb function is large, the prediction model established by the Newgrnn function cannot predict the validation samples well.

Figure 4 shows the comparison between the predicted value and the simulated value by using the linear neural network model. The second and third groups of predicted values are similar to the simulated value, the fourth group of predicted values is lower than the simulated value and has a large deviation, and the first group of predicted values has a negative value.

Figure 5 shows the error percentage of two neural network prediction values. It is obvious that the prediction value error of RBF neural network model established by Newrbe function is better than that of linear neural network. The linear neural network model cannot accurately describe the relationship between the input and output of a given sample.
(a) Newrb function model  
(b) Newrb function model  
(c) Newgrnn function model

**Figure 3.** Comparison of prediction values of RBF network established by different functions.

**Figure 4.** Prediction value of linear neural network.
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(a) RBF neural network model based on Newrb function

(b) Linear neural network model

Figure 5. Error percentage of predicted values of different models.

4. Conclusion
In this paper, the maximum resistance of low vacuum pipeline train under different operating conditions is taken as the sample, and the RBF and linear neural networks are used to establish a prediction model of the maximum resistance of the train. Among them, three different functions are used to establish the RBF neural network model. The conclusion is as follows:

1. Among RBF network models, the model established by Newrb function has the highest prediction accuracy and the best prediction effect.

2. The prediction effect of linear neural network model is not good, because it cannot accurately describe the relationship between the input and output of a given sample.

3. On the whole, the prediction accuracy of RBF neural network is better than that of linear neural network.

In this paper, only the neural network is used to construct the prediction model, it is necessary to find a better prediction model and improve the prediction accuracy by using other advanced algorithms to build models and optimize them.

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