Application of BP Neural Network in TBM Tunneling Performance Prediction

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***Abstract*—The tunneling performance of Tunnel Boring Machine (TBM) is the key factor to affect its excavation effect and efficiency. This paper is based on the TBM tunnel project of Minle parking lot of Shenzhen Metro Line 6 phase II, using BP neural network and selecting 30 groups of sample data from the project cases as the research aims to predict the tunneling performance of TBM. The prediction curves corresponding to penetration, cutterhead thrust and cutterhead torque are obtained respectively, and the existing change rules are analyzed. At the same time, the prediction results of BP neural network are compared with the results of regression analysis and field measurement to verify the rationality and applicability of the BP neural network prediction algorithm. The results show that: (1) the error of BP neural network prediction algorithm is less than 3%, the overall results show that the method is suitable for TBM tunneling parameters prediction; (2) compared with the prediction results of regression analysis, it has smaller error, thus to a certain extent, BP neural network prediction algorithm has higher accuracy, which can provide reference for the prediction of TBM tunneling performance under similar geological conditions test.**

***Index Terms*—Tunnel Boring Machine (TBM), tunneling performance, BP neural network, sample data, prediction algorithm**

I. INTRODUCTION

Full Face Tunnel Boring Machine has the advantages of fast excavation speed, high safety, good engineering quality, economic and environmental protection, so it is widely used in underground tunnel excavation engineering [1], especially for the construction of subway engineering in hard rock stratum. TBM has become the preferred equipment for rapid excavation of this kind of tunnels [2]. In recent years, with the construction of tunnel engineering, TBM has become more and more important construction machinery for tunnel excavation. In order to better apply TBM in engineering practice, it is necessary to have a comprehensive understanding of its tunneling performance. Therefore, domestic and foreign scholars have carried out various researches on it and established a variety of TBM performance prediction models.

TBM performance prediction model is mainly divided into empirical model and theoretical model [2]. The empirical model is represented by NTNU model of Norwegian University of Science and Technology, but it needs to obtain relevant parameters through complex experiments before inputting parameters, which is limited to a large extent. The theoretical model is represented by CSM model developed by Colorado Institute of Mining [3], which considers the rock breaking mechanism of hob, and also needs to obtain the tool balance equation based on the relevant experimental data, so as to complete the performance prediction of TBM. Of course, in addition to the above empirical model and theoretical model, Luo Hua et al established the prediction model of TBM tunneling rate based on the field data [4]. Yan Changbin et al successively established the prediction model of TBM net tunneling rate based on the surrounding rock mechanical parameters, rock mass index and tunneling parameters, using multiple regression analysis method [5,6]. At the same time, Gong Qiuming et al established the TBM utilization prediction model based on the rock mass classification system (RMR) [7]. Wang Jian et al established the TBM tunneling performance parameter prediction model based on the RMR [8]. Rostami J established a new TBM performance prediction model based on the RMR in order to improve the TBM performance evaluation accuracy and utilization [9]. Salimi A et al established a new TBM performance prediction model based on the RMR [10]. Discussed the influence of rock mass classification system (RMR) on TBM performance, and proposed a prediction model of hard rock TBM performance based on regression tree. So far, many scholars have studied the rock mass classification system and established an empirical model for TBM performance prediction. But with the development of the times, in recent years, support vector machine, neural network, particle swarm optimization and other intelligent algorithms gradually realize

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interdisciplinary, and continue to combine with the research of TBM performance prediction. For example, Mahdeveri S et al, Yagiz S et al and Adoko A C et al used support vector regression analysis, particle swarm optimization and Bayesian algorithm to predict the TBM driving speed of queenswater tunnel in New York City [11-13]. Xiong Fan et al predicted the TBM driving speed based on MATLAB and BP neural network successfully [14]. Hou Shaokang et al proposed a TBM driving parameter prediction model based on improved particle swarm optimization and BP neural network, and the prediction goodness of fit reached 0.85 [15]. The average absolute error is less than 12.68%. However, at present, the tunneling performance predicted by neural network mainly focuses on the tunneling rate, but the research on the prediction of penetration, cutterhead thrust and torque is still relatively less, so we should strengthen the relevant research on these contents combined with neural network.

BP neural network is the most widely used neural network, which has strong nonlinear mapping ability and is very effective for solving nonlinear prediction problems. Therefore, on the basis of previous research results, this paper uses BP neural network to predict the penetration, cutterhead thrust and cutterhead torque of TBM tunneling performance, and establishes a prediction model based on BP neural network algorithm with smaller error, which provides a reference for the adjustment of tunneling parameters in the process of engineering construction, and makes TBM have stronger ability to adapt to the current stratum during tunneling power.

II. BP Neural Network

There are randomness, nonlinearity and uncertainty in the process of interaction between TBM and rock. The parameters of TBM excavation are affected by many aspects. In addition to the influence of rock strength and integrity index, they are also related to TBM mechanical parameters and the angle between TBM excavation axis and axis, and there may be some relationship between each kind of data. Therefore, regression analysis method is used to predict them It is difficult to find the relationship between different types of data in time measurement, and machine learning algorithm is superior to regression analysis in this aspect. Artificial neural network (ANN) is a mathematical model based on the knowledge of network topology to simulate the human brain's processing of complex problems. It can achieve some functions similar to human brain.

In machine learning algorithm, BP neural network is the most adaptive and extensive learning algorithm, which has been successfully used in many aspects [16]. BP neural network is commonly known as back propagation network. The biggest difference between BP neural network and other neural network algorithms is forward propagation signal and back propagation error. Its structure is shown in Fig. 1. Its composition includes input layer, hidden layer and output layer. The number of each layer is selected according to the actual situation, as shown in Fig. 1. where, (x_1, x_2, x_3... x_n) is the number of input units, (y_1, y_2, y_3... y_n) is the number of output units, and V_{ij} and W_{jk} are the network connection weights. In the process of neural network operation, the signal is transmitted layer by layer through the input layer, and then transmitted to the output layer after passing through the hidden layer; in the process of error back transmission, the error is calculated according to the difference between the calculated result and the expected value, and then the interpolation is back transmitted layer by layer through the output layer, and the threshold and weight are updated and modified until the specified range of error is met. BP neural network is a typical "supervised" learning algorithm. If BP neural network is used for prediction analysis, it is necessary to create a network in advance, train a large number of data, find out the potential relationship between input data and output data, and then use it for prediction analysis.

The learning steps of BP neural network include the following points.

(1) Network initialization: including the initialization of input layer, hidden layer and output layer, as well as the initialization of network weights and thresholds in each stage. The initial values of weights and thresholds are generally random numbers in (- 1,1).

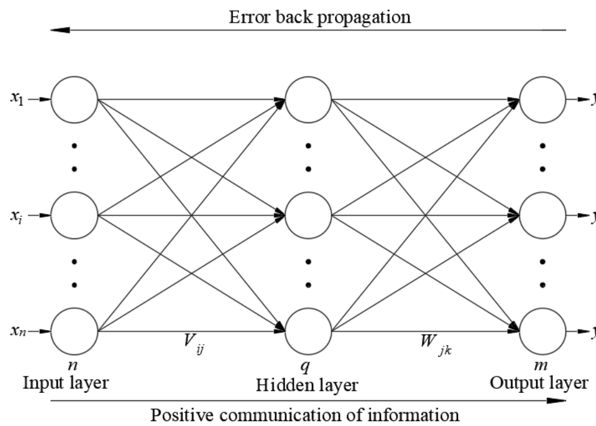

Figure 1. Structure of BP neural network.

(2) Hidden layer output value calculation: according to the output vector X of the input layer, the weight V_{ij} between the input layer and the hidden layer, and the threshold θ of the hidden layer, the hidden layer output value H is calculated by combining the activation function f.

$$H_j = f\left(\sum_{i=1}^{n} V_{ij} x_i - \theta_j\right) \qquad j = 1,2,\ldots q \cdot \tag{1}$$

Where q is the number of hidden layer nodes and f is the activation function.

(3) Output value calculation of output layer: according to the input vector H of hidden layer, the weight W_{jk} between hidden layer and output layer, and the threshold γ of output layer, the output value O of output layer is calculated by combining the activation function f.

$$O_k = f\left(\sum_{j=1}^{n_1} W_{jk} H_j - \gamma_k\right) \qquad k = 1,2,\ldots m \cdot \tag{2}$$

Where m is the number of output layer nodes.

(4) Error calculation: according to the output value O_k of network training and the real output value Y, the network error e and energy error E are calculated.

$$e_k = Y - O_k \qquad k = 1,2,\ldots m. \quad (3)$$

$$E_k = \frac{1}{2}\sum_{k=1}^{m} e_k^2 . \quad (4)$$

(5) Error back propagation, update of weights and thresholds: update the weights V_{ij} and W_{jk} and thresholds θ and γ according to the calculated error e_k and energy error E_k. The specific formula is as follows.

$$w_{ij} = w_{ij} + \Delta w_{ij} \qquad \Delta w_{ij} = \eta \frac{\partial E}{\partial w_{ij}} . \quad (5)$$

$$w_{jk} = w_{jk} + \Delta w_{jk} \qquad \Delta w_{jk} = \eta \frac{\partial E}{\partial w_{jk}} . \quad (6)$$

$$\theta_j = \theta_j + \Delta\theta_j \qquad \Delta\theta_j = \eta \frac{\partial E}{\partial \theta_j} . \quad (7)$$

$$\gamma_k = \gamma_k + \Delta\gamma_k \qquad \Delta\gamma_k = \eta \frac{\partial E}{\partial \gamma_k} . \quad (8)$$

(6) Judge whether the error meets the system requirements. If not, repeat step (2) until the required error meets the system requirements.

III. Sample Data Selection and Regression Analysis

Based on the TBM tunnel project of Minle parking lot in Shenzhen Metro Line 6 phase II, 30 groups of sample data are selected as shown in Table I.

Combined with the needs of regression analysis, the relevant data of 7 groups of stations corresponding to MRDK0+406, MRDK0+811, MRDK0+991, MRDK1+313, MRDK1+736, MRDK1+810 and MRDK2+299 are selected in turn, and the following formula is obtained based on linear regression method.

$$h = \left(\frac{F}{9412\text{In}\sigma_c - 2264\text{In}K_v - 4.097E_4}\right)^{-10.1\text{In}\sigma_c + 1.919\text{In}K_v + 48.68} . \quad (9)$$

$$h = \left(-3.722E - 4\sigma_c + 0.0162K_v + 0.02989\right)M + 1 . \quad (10)$$

TABLE I. List of Sample Data

Stake number	σ_c/MPa	K_v	F/kN	M/(kN · m)	h/(mm re v^{-1})
MRDK0+242	86.7	0.551	4857.12	666.93	4.092
MRDK0+370	86.9	0.425	8572.15	1279.52	7.4852
MRDK0+377	93.8	0.548	9538.45	1185.09	5.948
MRDK0+730	89.8	0.571	7498.63	986.55	9.485
MRDK0+782	86.5	0.503	6363.85	946.48	9.84568
MRDK0+801	86.3	0.496	6034.94	1226.75	6.7657
MRDK1+136	83.8	0.517	5391.51	1148.02	10.812
MRDK1+277	86.5	0.516	6501.66	1759.00	9.997
MRDK1+285	84.2	0.504	5548.56	1823.39	10.87356
MRDK1+320	88.8	0.555	6770.89	1778.33	12.404
MRDK1+353	85.1	0.516	6166.32	1179.55	12.5355
MRDK1+373	81.3	0.421	4962.49	822.20	8.4693
MRDK1+410	88.0	0.580	5895.12	956.95	6.15359
MRDK1+491	94.0	0.587	8460.84	1272.44	6.1679
MRDK1+703	90.4	0.514	7660.79	978.10	6.3553
MRDK1+733	89.0	0.561	6157.93	1222.68	5.329
MRDK1+901	83.1	0.493	5228.11	1322.40	9.38
MRDK2+083	85.4	0.512	6443.19	1753.28	9.2397
MRDK2+382	86.6	0.543	6566.45	1608.96	7.9366
MRDK2+393	94.9	0.528	10272.85	1649.68	4.7761
MRDK2+415	88.5	0.546	7219.28	1561.20	9.7508
MRDK2+435	89.0	0.527	7216.10	1478.18	6.9171
MRDK2+528	87.9	0.450	6135.36	1643.20	4.6942
MRDK2+572	88.4	0.528	7158.21	1837.57	7.8435
MRDK2+580	88.9	0.512	7574.12	1265.90	7.5453
MRDK2+646	83.8	0.521	5728.39	1253.06	11.6908
MRDK2+720	83.9	0.516	6049.61	1323.74	12.0965
MRDK2+725	96.6	0.587	11259.43	1748.49	6.9373
MRDK2+757	90.7	0.515	9080.18	1634.58	7.3537
MRDK2+771	90.2	0.512	8611.12	2072.93	8.4066

By using Eqs. 9 and 10, and combining with the actual data, the penetration of hob, the thrust of cutter head and the torque of cutter head are fitted, predicted and analyzed in turn. The results are shown in Figs. 2-4.

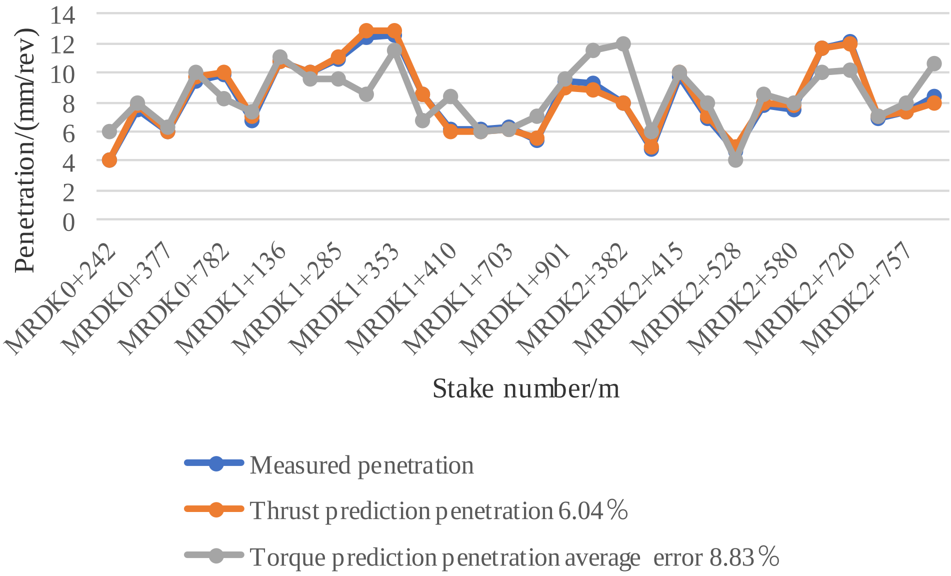

Figure 2. Prediction curve of hob penetration.

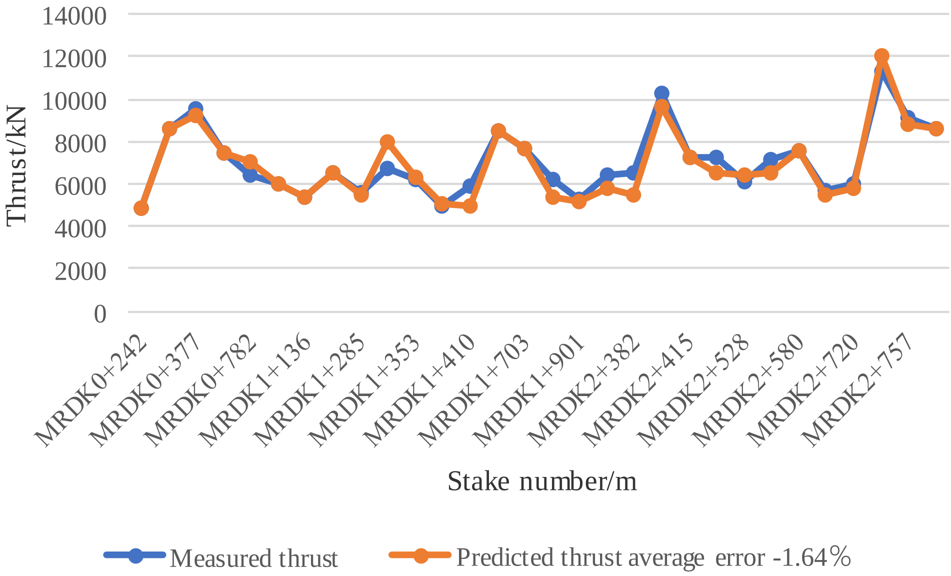

Figure 3. Prediction curve of cutter head thrust.

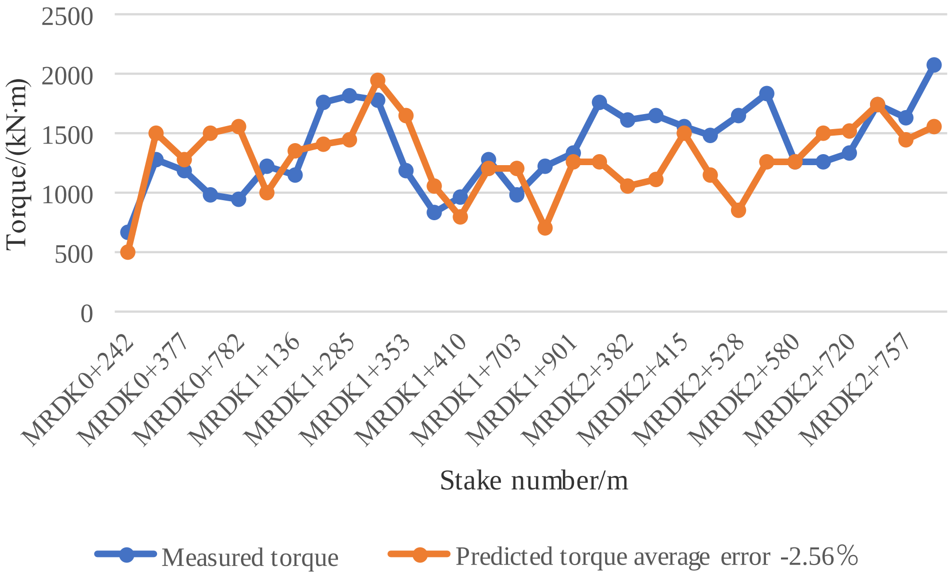

Figure 4. Prediction curve of cutter head torque.

It can be seen from Fig. 2 that in hard rock stratum, the effect of thrust prediction of penetration is better than that of torque prediction. The average error of thrust prediction of penetration is 6.04%, and the average error of torque prediction of penetration is 8.83%. It can be seen from Figs. 3 and 4 that the average error of predicting the cutter head thrust based on the measured penetration is -1.64%, and the average error of predicting the cutter head torque based on the measured penetration is -2.65% The influence of rock mass strength is also related to mechanical factors and the deviation angle of TBM driving axis.

To sum up, based on the above 30 groups of sample data, this paper uses the method of BP neural network in machine learning algorithm to predict it, in order to get better prediction results.

IV. Selection of Structure Parameters of BP Neural Network

According to the above basic operation steps of BP neural network, the parameters to be created in the construction process of BP neural network mainly include the number of input layer nodes, the number of output layer nodes, the number of hidden layer nodes, the number of network layers, the number of hidden layers, the activation function and the weight and threshold. The specific values of these parameters are as follows:

(1) Network layers and hidden layers

Generally speaking, three-layer network (i.e. input layer, hidden layer and output layer) can satisfy the mapping between two groups of numbers with any difficulty. Therefore, in this paper, when using BP neural network for prediction analysis, three layers are selected for the network layer, and the number of hidden layers is set to two.

(2) Number of input layer and output layer nodes

The number of nodes in the input layer and the output layer is selected according to their respective data categories. In order to ensure the smooth progress of TBM driving law prediction and analysis, the value of the input layer should take into account the rock compressive strength and integrity index; the value of the output layer should take into account the thrust, torque and penetration, so the number of nodes in the input layer is 2, and the number of nodes in the output layer is 3.

(3) Selection of hidden layer nodes

The selection of hidden layer nodes is the most difficult problem in BP neural network. If the number of hidden layers is too small, the fault-tolerant performance of the network becomes poor, and the output value of the network is not good. If the number of hidden layers is too large, the generalization ability of the network will be reduced and the phenomenon of over fitting will appear. Therefore, it is very important to choose the number of hidden layer nodes for the establishment of BP neural network. According to the results of previous studies, the selection of hidden layer nodes has the following empirical formula.

$$k < \sum_{i=0}^{n} C \begin{bmatrix} q \\ i \end{bmatrix}. \tag{11}$$

$$n_1 = \sqrt{n+m} + c. \tag{12}$$

$$q > \log_2 n. \tag{13}$$

Where k is the number of samples; n is the number of input nodes; m is the number of output nodes; q is the number of hidden layer nodes; c is the constant in the range 0-10.

In order to ensure the smooth and accurate analysis of prediction, 30 groups of samples, namely k=30, have been selected in this paper, which can be obtained after calculation and analysis by the above formula

$$\begin{cases} q = 11 \\ 4 \le q \le 13 \\ q > 2 \end{cases}. \tag{14}$$

In conclusion, the value range of q can be determined as [11,13]. After testing, it is found that when the number of hidden layers q=13, the overall error is the smallest and the calculation speed is fast, so the hidden layer q=13.

(1) Network transfer function, weight and threshold

The weight and threshold should be selected according to the random number allocated before each calculation, and the range is [- 1,1]. Transfer function is an important part of neural network, which mainly includes linear function, slope function, threshold function, S-type function, bipolar S-type function and so on. The most frequently used ones are S-type function and bipolar S-type function. The expressions of S-type function and bipolar S-type function are described as follows.

$$f(x) = \frac{1}{1+e^{-\alpha x}} \qquad (0 < f(x) < 1). \tag{15}$$

$$f(x) = \frac{2}{1+e^{-\alpha x}} - 1 \qquad (-1 < f(x) < 1). \tag{16}$$

In this paper, we choose S-type function, take the value of α is 1, then S-type function is called ordinary S-type function.

V. Prediction and Analysis of TBM Driving Performance

A. Normalization of Neural Network Parameters

Before the application of neural network, it is necessary to normalize the corresponding input and output parameters. The so-called normalization process is to map each data to the interval of [-1,1] or [0,1]. The reason is that the magnitude and range of different properties of data may vary greatly. In the process of neural network operation, it may lead to many problems, such as difficult convergence of neural network, long training time and so on. Therefore, it needs to be normalized. Since the activation function is an ordinary S-type function, the normalized interval is [0,1]. The results of normalization of input layer data and output layer data are shown in Table II.

B. Network Training Results and Analysis

The mathematical tool MATLAB is used to analyze the training of BP neural network. The network error is 0.01, the training step is 100000, and the momentum gradient descent algorithm traingdx with adaptive learning rate is used as the training function. The 20 samples of the above 30 samples are randomly selected for network learning. According to the training results, when the iteration step reaches 11010 steps, the training is completed, the target error meets the preset conditions, and there is a high linear correlation between the actual output value and the network training output value, which indicates that the BP neural network training results are effective and correct.

TABLE II. NORMALIZED DATA PROCESSING TABLE

Stake number	σ_c/MPa	K_v	F/kN	M/(kN·m)	h/(mm·rev^{-1})
MRDK0+242	0.3529	0.7831	0	0	0
MRDK0+370	0.3660	0.0241	0.5803	0.4357	0.4019
MRDK0+377	0.8170	0.7651	0.7312	0.3685	0.2198
MRDK0+730	0.5556	0.9036	0.4126	0.2273	0.6387
MRDK0+782	0.3399	0.4940	0.2353	0.1988	0.6814
MRDK0+801	0.3268	0.4518	0.1840	0.3982	0.3167
MRDK1+136	0.1634	0.5783	0.0835	0.3422	0.7959
MRDK1+277	0.3399	0.5723	0.2569	0.7767	0.6994
MRDK1+285	0.1895	0.5000	0.1080	0.8225	0.8032
MRDK1+320	0.4902	0.8072	0.2989	0.7905	0.9844
MRDK1+353	0.2484	0.5723	0.2045	0.3646	1.0000
MRDK1+373	0.0000	0.0000	0.0165	0.1104	0.5184
MRDK1+410	0.4379	0.9578	0.1621	0.2063	0.2442
MRDK1+491	0.8301	1.0000	0.5629	0.4307	0.2459
MRDK1+703	0.5948	0.5602	0.4379	0.2213	0.2681
MRDK1+733	0.5033	0.8434	0.2032	0.3953	0.1465
MRDK1+901	0.1176	0.4337	0.0579	0.4662	0.6263
MRDK2+083	0.2680	0.5482	0.2477	0.7727	0.6097
MRDK2+382	0.3464	0.7349	0.2670	0.6700	0.4553
MRDK2+393	0.8889	0.6446	0.8459	0.6990	0.0810
MRDK2+415	0.4706	0.7530	0.3690	0.6360	0.6702
MRDK2+435	0.5033	0.6386	0.3685	0.5770	0.3346
MRDK2+528	0.4314	0.1747	0.1997	0.6944	0.0713
MRDK2+572	0.4641	0.6446	0.3594	0.8326	0.4443
MRDK2+580	0.4967	0.5482	0.4244	0.4260	0.4090
MRDK2+646	0.1634	0.6024	0.1361	0.4169	0.9000
MRDK2+720	0.1699	0.5723	0.1863	0.4671	0.9480
MRDK2+725	1.0000	1.0000	1.0000	0.7692	0.3370
MRDK2+757	0.6144	0.5663	0.6596	0.6882	0.3863
MRDK2+771	0.5817	0.5482	0.5864	1.0000	0.5110

Due to the limited number of samples, in order to make the prediction results more universal, the trained neural network model is used to predict and analyze the TBM tunneling parameters of 30 groups of sample data (including 10 groups not used in the training) in the project. The comparison curves of penetration, thrust and torque predicted by BP neural network and the original data are shown in Figs. 5-7

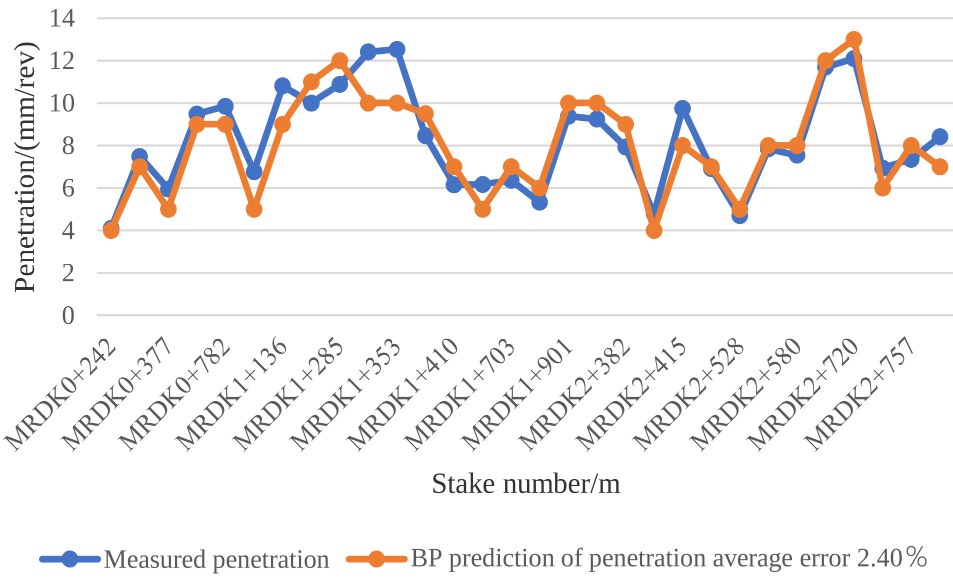

Figure 5. BP neural network penetration prediction curve.

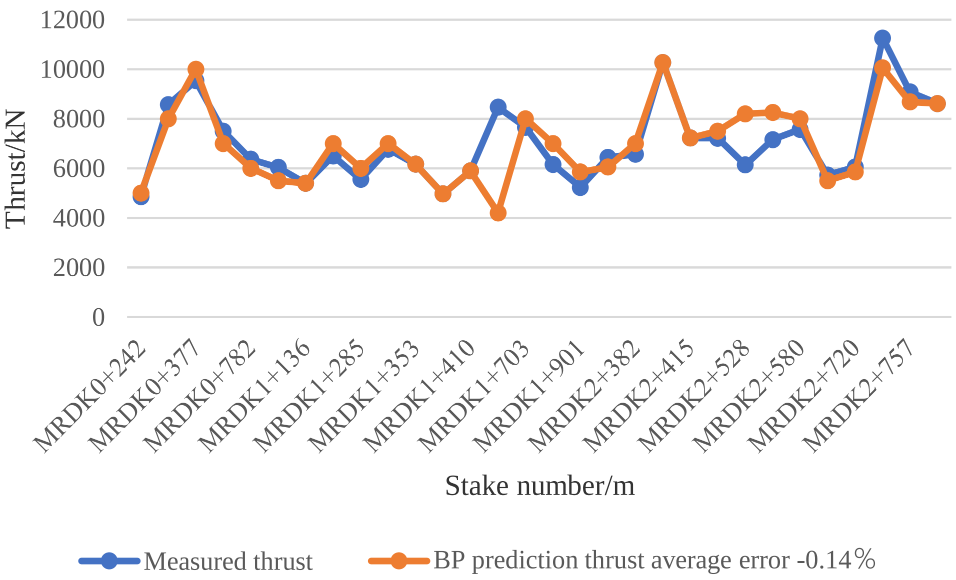

Figure 6. Thrust prediction curve of BP neural network.

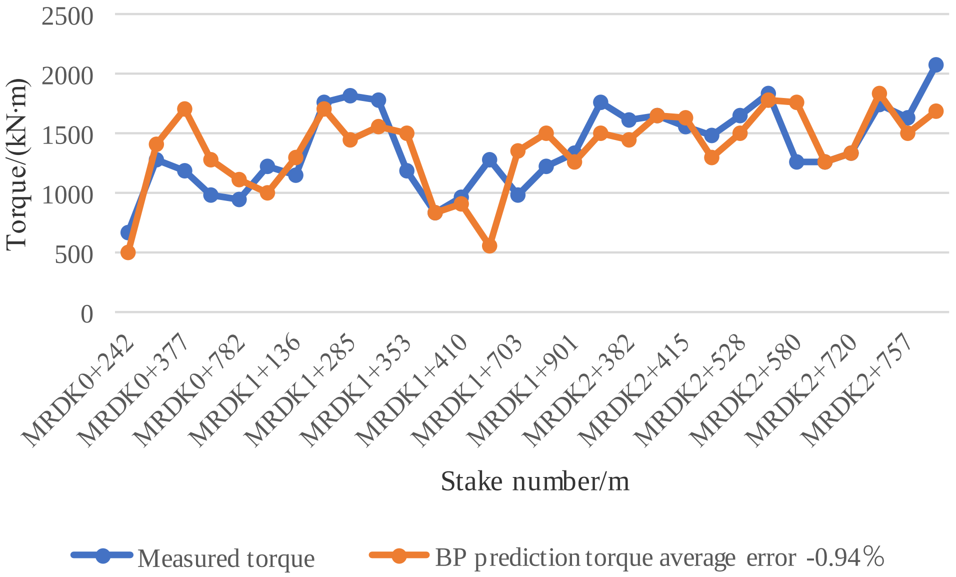

Figure 7. Torque prediction curve of BP neural network.

The results obtained from BP neural network show that the overall error of the cutter head thrust is -0.14%, the overall error of the cutter head torque is -0.94%, the overall error of the penetration of the cutter disc is 2.40%, which shows that the overall error of BP neural network prediction is less than 3%. Compared with the regression analysis method, the prediction accuracy is higher. The reason is that BP neural network has the function of implicit layer and error retransmission. The existence of hidden layer can explore the internal relationship between input and output parameters, rather than single mapping relationship like regression analysis. Meanwhile, the work of error retransmission can make the real error decrease continuously and approach the set value gradually within the set error range. It is because of the self-renewal and supervision mechanism of BP neural network that makes BP neural network successfully applied to the prediction of TBM driving parameters.

VI. Conclusions

Based on the Shenzhen Metro Line 6 project, the relevant data are selected as sample data, and the driving parameters of several stations are predicted based on BP neural network algorithm. The following conclusions can be obtained after comparing the predicted results with regression analysis results and measured results.

(1) The prediction results of TBM driving parameters by BP neural network show that the overall error of cutter head thrust is -0.14%, the overall error of cutter head torque is -0.94%, the overall error of cutter head penetration is 2.40%, and the error is controlled within 3%. The overall results show that the machine learning algorithm is feasible in the prediction of TBM driving parameters. This method can make TBM adjust the parameters of TBM driving continuously according to the rock data predicted in advance in the process of

excavation, so that TBM can better carry out the excavation of the strata in which it is located.

(2) In the regression analysis and BP neural network prediction of penetration, hob thrust and hob torque, the error of the prediction results is controlled within 10% and 3%, so both methods are applicable to the prediction of TBM driving parameters, but obviously the prediction accuracy of BP neural network method is higher. Therefore, in the actual project, if the equipment conditions permit, BP neural network method should be preferred as the method of parameter adjustment in the project implementation stage.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Chao Wang concuted the research; Chao Wang, Shifan Qiao and Hongzhong Liu analyzed the data; Chao Wang wrote the paper; all authors had approved the final version.

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