Performance Evaluation of Asphalt Pavement Based on BP Neural Network

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ABSTRACT

Asphalt pavement is widely used in road pavement because of its high temperature stability, low temperature crack resistance, water stability, fatigue resistance and many other advantages. However, with the increase of the service time, and the long-term effects of the surrounding environment and traffic loads, it is easy to cause cracks, subsidence, and water damage on the asphalt pavement, which brings enormous financial pressure to maintenance. For this reason, this study proposes an evaluation and prediction model of pavement performance based on BP artificial neural network through the analysis of the characteristics of pavement performance evaluation and use of the multi-factor fuzzy computing capability of artificial neural network algorithm, and adopts this model to predict the rut depth and flatness of asphalt pavements. The results show that the prediction data is in good agreement with the actual measured data, with high accuracy and small errors, which proves that the model has extremely high operability. This provides a theoretical basis for the prediction of asphalt pavement performance, which is of great practical significance to reduce the cost of asphalt pavement maintenance and improve the performance of asphalt pavement.

Key Words: Asphalt Pavement, Performance Evaluation, BP Neural Network, Prediction Model

DOI Number: 10.14704/nq.2018.16.6.1547 **NeuroQuantology 2018; 16(6):537-545**

Introduction

After the reform and opening up, China has witnessed a soaring progress, and China's roads has developed into a fast-moving highway transportation network extending in all directions driven by the strong economy. By the end of 2017, the total highway mileage in China has reached 4,773,500 kilometers, the highway density has reached 49.72 kilometers/100 square kilometers, and the highway maintenance mileage has reached 4,674,600 kilometers, accounting for 97.9% of the total highway mileage.

According to the different usages and technical and economic indexes of the highway, the road of lower grade adopts the gallet pavement, gravel pavement or soil pavement, while the road of higher grade mostly adopts the asphalt pavement. The pavement grade and the surface layer type are shown in Table 1. This is mainly because the asphalt pavement belongs to the flexible seamless continuous pavement, with such the advantages as high temperature stability, low temperature crack resistance, water stability, fatigue resistance, good mechanical performance, no dust, simple construction, smooth for running, etc (Guillaumot *et al.*, 2004; Yang *et al.*, 2005; Dubovsky *et al.*, 1999). In China, about 90% of highways adopt asphalt pavements.

As the service time increases, being affected by the vehicle load and the environment factor for a long time, the highway asphalt pavement is prone to have the problems such as crack, subsidence, frost heave, looseness and water damage, and a large amount of capital is needed for its maintenance (Giustozzi *et al.*, 2012;

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Relevant conflicts of interest/financial disclosures: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.
Received: 1 March 2018; **Accepted:** 2 May 2018

Table 1. Pavement grade and surface type

Pavement grade	Surface type	Applicable highway
Senior	Cement concrete pavement; asphalt concrete pavement; black gravel road; neat stone or stone pavement.	Senior highways, first or second grade highways
Secondary Senior	Bituminous gravel pavement; bituminous stone pavement; asphalt surface treatment; semi neat stone pavement.	second or third grade highways
Intermediate	Gravel gravel pavement; lime, asphalt, cement stabilized soil road; lime soil road; irregular pavement.	Third or fourth grade highways
Elementary	Strengthening the pavement with granular material and improving the soil pavement	Fourth grade highways

Duffuaa *et al.*, 1999; Lin *et al.*, 2016; Yu *et al.*, 2012). China's road construction has shifted to the road maintenance management stage, but the annual maintenance tax (50 billion yuan) is far less than the annual maintenance cost (100 billion yuan). A large amount of capital gap urges the pavement maintenance management department to study the maintenance method and transform the passive maintenance to the active and preventive maintenance so as to slow down the pavement damage and reduce the capital waste of pavement maintenance. The new pavement performance evaluation methods as how to prolong the service life of pavement, reduce the maintenance cost of pavement and improve the technical index of pavement, have become the important basis for pavement maintenance with low cost and high efficiency.

Since the causes of asphalt pavement damage are complex and changeable, it is difficult to predict and evaluate the performance of asphalt pavement accurately by using the conventional prediction model. The BP artificial neural network is a neural network structure that mimics the human brain's nervous system, which have behavior pattern recognition, system combination optimization, and prediction assessment effects, thus developing a nonlinear adaptive information processing capability. In the complex scenario, the neural network has extraordinary advantages. However, there are few researches on the performance of asphalt pavement based on neural network in China (Wong *et al.*, 1999; Wong *et al.*, 2002; Evdorides *et al.*, 2015).

Therefore, in view of the characteristics of the existing pavements in China and the technical problems in the maintenance process, this study proposes a prediction model for the asphalt pavement performance using the BP artificial neural network and adopts the model to predict the asphalt pavement maintenance, so as to improve the ability for choosing and determining the time and measures for pavement maintenance, and to provide theoretical basis for the performance evaluation of asphalt pavement, which is of great practical significance to reduce the maintenance cost of asphalt pavement, slow down the damage to it and improve its performance.

Analysis of performance evaluation indexes of asphalt pavement

Due to the impact of vehicle load and the environment, the performance of asphalt pavement is degraded, and in severe cases it even fails to meet the requirements for use. Therefore, it is necessary to master the performance of asphalt pavement in time, take proper maintenance measures and evaluate the performance of asphalt pavement regularly.

The comprehensive evaluation of asphalt pavement performance means the overall evaluation of pavement use status, which is mainly achieved mainly through the evaluation of the following four single evaluation indexes (Shekharan, 1998; Lou *et al.*, 2001; Fwa *et al.*, 1998), surface strength index (SSI) for evaluation of bearing capacity, running quality index(RQI) for evaluation of flatness, side force coefficient for anti-sliding evaluation, British pendulum number (BPN), Pavement Condition Index (PCI) for pavement damage evaluation. The specific evaluation system is shown in Figure 1.

In the highway technical condition evaluation system of China, pavement quality index (PQI) is evaluated through the following five single indexes, including pavement condition index (PCI), running quality index (RQI), rut depth index (RDI), skid resistance index (SRI), and pavement structure strength index (PSSI), as shown in Figure 2.

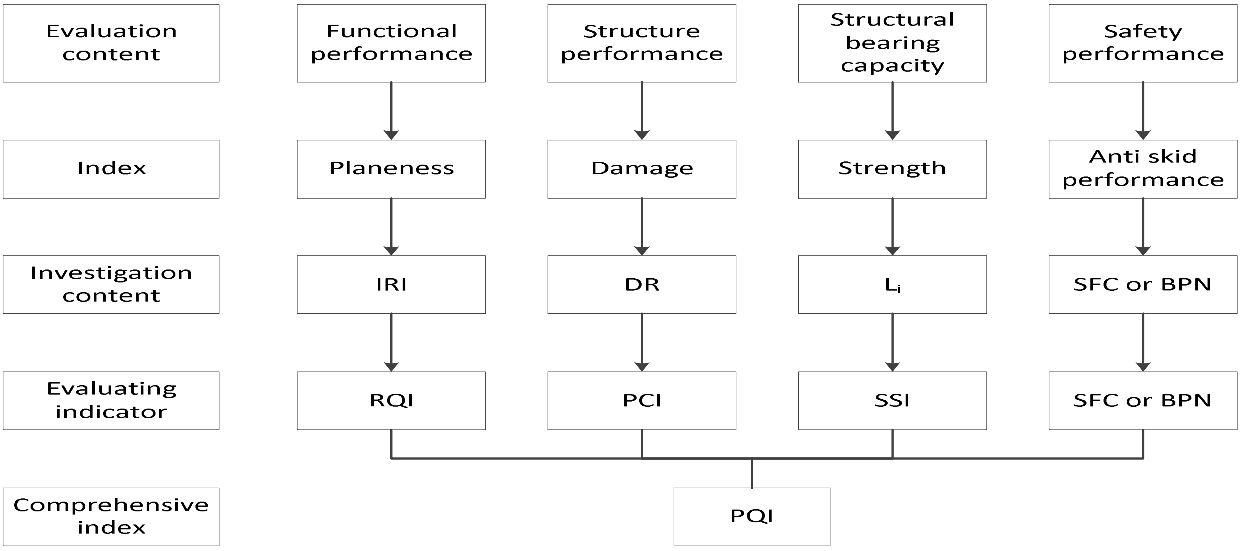

Figure 1. Evaluation system of pavement performance

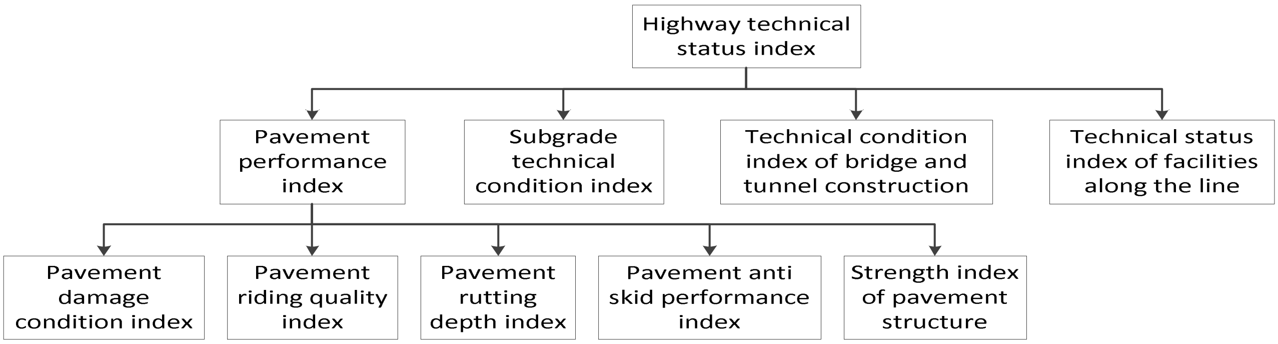

Figure 2. Evaluation system of highway technical condition

(1) RQI calculation formula:

$$RQI = \frac{100}{1+a_0 e^{a_1 IRI}} \quad (1)$$

where, a_0 and a_1 are calibration coefficients
(2) PCI calculation formula:

$$PCI = 100 - a_0 DR^{a_1} \quad (2)$$

where, DR is the comprehensive damage rate of pavement

(3) PSSI calculation formula:

$$PSSI = \frac{100}{1+a_0 e^{a_1 SSI}} \quad (3)$$

(4) SRI calculation formula:

$$SRI = \frac{100 - SRI_{min}}{1+a_0 e^{a_1 SFC}} + SRI_{min} \quad (4)$$

(5) RDI calculation formula:

$$RDI = \begin{cases} 100 - a_0 RD \ (RD \le RD_a) \\ 60 - a_1 (RD - RD_a)(RD_a \le RD \le RD_b) \\ 0 (RD \ge RD_b) \end{cases} \quad (5)$$

where, RD is rut depth (mm)

(6) PQI calculation formula:

$$PQI = w_{PCI} PCI + w_{RQI} RQI + w_{RDI} RDI + w_{SSI} SRI \quad (6)$$

In addition, as the comprehensive reflection of pavement damage, PQI is able to analyze the integrity of pavement, but fails to show the degree of individual item damage. When the comprehensive evaluation index indicates that the pavement is in a good condition, the individual index may indicate the unqualified state, leading to the failure of the preventive maintenance index system, so it is necessary to consider the single pavement indexes in addition to the comprehensive indexes.

Pavement performance prediction model based on BP neural network

Influencing factors of pavement performance

The use environment of asphalt pavement is complex, and there are many factors affecting its performance. These influencing factors are classified as shown in Figure 3.

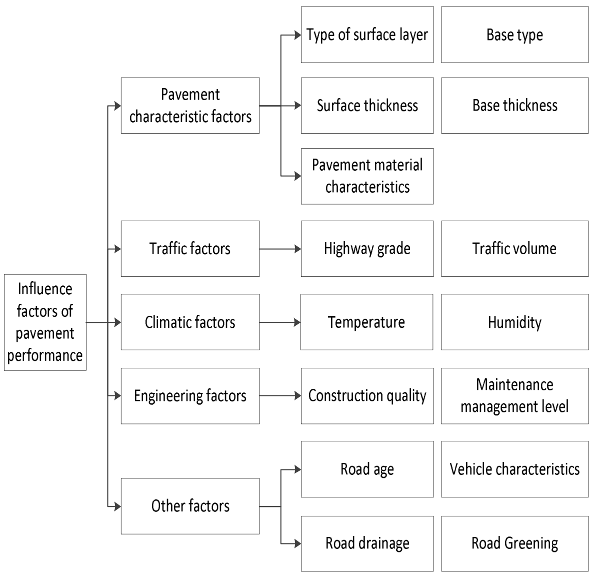

Figure 3. Influencing factors of pavement performance

Wherein, the pavement characteristic factors mainly include subgrade types, subgrade thickness and pavement materials, etc., which reflect the bearing capacity of the pavement structure under the factors of vehicle load and surrounding environment. The traffic factor mainly refers to the influence of traffic load on pavement damage. The bigger the load is, the more serious the damage will be. The climatic factors mainly refer to the influences of temperature and humidity on the pavement. The change of humidity will reduce the strength of the pavement, and the temperature will affect the creep of the material, resulting in permanent deformation or cracks. The engineering factors are mainly the construction quality and maintenance government level. Particularly in the early stage, the construction quality is the most important factor to determine the pavement performance. And the other factors such as the vehicle, the pavement service life, the greening condition, are also the factors that need to be considered in the evaluation and prediction of the pavement service performance.

Pavement performance prediction model

(1) Prediction model

Among the four pavement performance indexes, including flatness, rut depth, crack rate, and skid resistance, rut depth and flatness are selected to predict the pavement performance according to the existing data.

(2) Selection of influencing factors

Without increasing the prediction difficulties of neural network, the factors are to be selected to ensure that the prediction result is as accurate as possible. The influencing factors of pavement performance are divided into project-level influencing factors and network-level influencing factors, and the former include traffic volume, temperature and humidity; while the latter include modulus of resilience of subgrade, thickness of surface layer, road age, dry and wet condition of subgrade, traffic volume, humidity and temperature, etc. Every specific situation is analyzed individually according to the actual situation.

(3) Model structure

The specific parameters and indexes of BP neural network are as follows:

Hidden layer number selection: In order to improve the performance of BP neural network, double hidden layers are selected. More hidden nodes are set in the first layer and fewer hidden nodes set in the second layer.

Hidden node number: In order to enhance the network's acquisition ability and high-speed calculation, the selection is based on the number of training samples, noise, and the complexity of the rules.

Network learning rate: In order to stabilize the network system and improve the learning efficiency, relevant algorithms are used to constantly correct the errors during the training process so as to select the best learning efficiency.

(4) Data processing

In order to ensure that the two indexes, rut depth and flatness of different dimensions, have the same status, the data are processed, and its mathematical expression is as follows:

$$D_r^0 = \frac{D_{r(max)} - D_r}{D_{r(max)} - D_{r(min)}} \tag{7}$$

$$IRI^0 = \frac{IRI_{r(max)} - IRI}{IRI_{(max)} - IRI_{(min)}} \tag{8}$$

Where, D_r is the rut depth and IRI is the flatness.

The cumulative production method is used to process variable data such as temperature, humidity and traffic volume, because the effects of these variables are superimposed and their damage to pavement performance is a long-term result. The method can weaken the randomness of the original data to form regular data. The mathematical expression of the cumulative production method is:

$$X = \{x^{(!)}, x^{(!)}(2), \dots, x^{(!)}n\} = \{x^{(0)}(1), \sum_{k=1}^{2} x^{(0)}(k), \dots, \sum_{k=1}^{n} x^{(0)}(k)\} \quad (9)$$

(5) Neural network function

The functions, including newff (), tansig (), learngdm (), trainlm (), and mse () are selected as the functions of the BP neural network model.

Prediction of pavement performance

Prediction of influencing factor variables

As the impact of the influencing factors on pavement performance is a long-term result, the attribute values of the influencing factors need to be predicted as historical data.

(1) Prediction of attribute values of influencing factors of permanent deformation

The actual values and predicted values of the rut factor are shown in Table 2. The values of first four years are the training samples, and the cumulative values of the fifth year are the prediction samples, which are compared with the actual value to verify the feasibility of the model.

For the attribute values of temperature, humidity and traffic volume, the daily maximum temperature conversion number of days CD is adopted to represent the temperature attribute, the humidity attribute is expressed by the annual precipitation AW, and the annual average daily traffic volume AADT is used to represent the traffic volume attribute. According to the literature on the relationship between permanent deformation and temperature (Arifovic *et al.*, 2001; Gupta *et al.*, 1999; Blanco *et al.*, 2001), as well as the study on high-temperature rut, the concept of CD is used to analyze and predict the attribute values of permanent deformation influencing factors.

The mathematical expression of CD is:

$$CD = \sum_{i=1}^{n_0} e^{a_0(T_i - T_0)} \quad (10)$$

In order to simplify the neural network model solution process, the data is quantized and placed in the interval of [0, 1]. The quantitative formulas of CD', AW' and AADT' are as follows:

$$CD' = \frac{CD}{CD_{max}} \quad (11)$$

$$AW' = \frac{AW}{AW_{max}} \quad (12)$$

$$AADT' = \frac{AADT}{AADT_{max}} \quad (13)$$

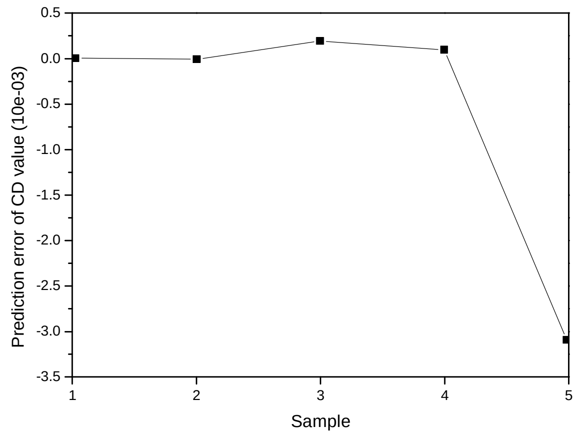

Figure 4. Prediction error curve of CD value

Table 2. Rutting prediction factors, attributes, measured values and predicted values

Year	First years	Second years	Third year	Fourth years	Fifth years	Sixth years	Seventh years	Eighth years	Ninth years
CD (day)	94	68	95	104	102	90	81	60	94
Accumulative value (day)	94	164	261	367	471	564	646	717	813
Predicted value (day)					471	563	646	717	807
AW (mm)	429	730	265	369	337	368	443	482	409
Accumulative value (mm)	429	1161	1428	1799	2138	2508	2953	3437	3848
Predicted value (mm)					2166	2506	2953	3432	3848
AADT (x10^4)	1.34	1.47	1.64	1.79	1.97	2.1	2.37	2.6	2.88
Accumulative value (x10^4)	1.34	2.81	4.45	6.24	8.21	10.36	12.73	15.33	18.21
Predicted value (x10^4)					8.53	10.37	12.7	15.29	18.15

Table 3. The measured values and predicted values of LT

Year	First years	Second years	Third year	Fourth years	Fifth years	Sixth years	Seventh years	Eighth years	Ninth years
LT (°C)	-7.7	-8.1	-6.4	-10.3	-9.1	-6	-7.3	-6.4	-6.3
Accumulative value (°C)	-7.7	-16	-22.6	-33.1	-42.4	-48.6	-56.1	-62.7	-69.2
Predicted value (°C)					-43.7	-48.6	-56.2	-62.3	-68.7

The quantized CD value is trained and calculated by BP neural network model, and the number of hidden layer nodes is set as 8. The prediction error curve of the CD value is shown in Figure 4.

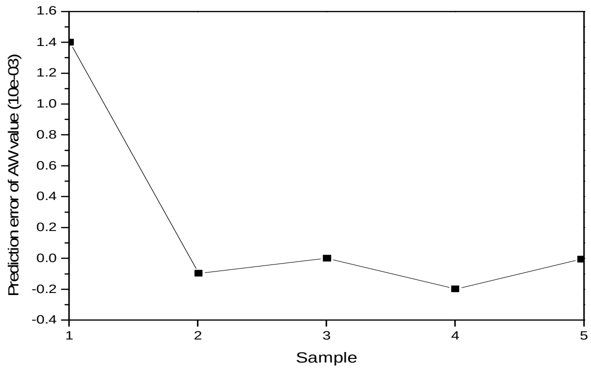

Figure 5. Prediction error curve of AW value

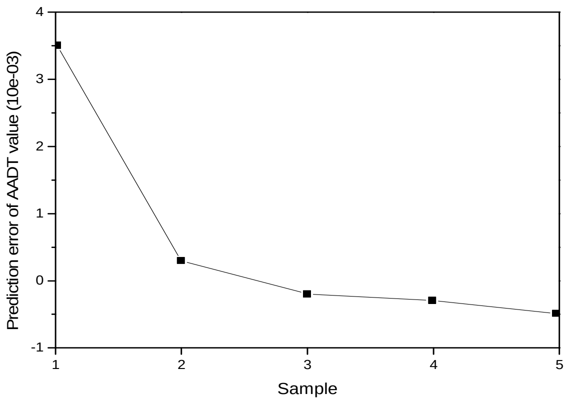

Figure 6. Prediction error curve of AADT value

The quantized AW value is trained and calculated by BP neural network model, and the number of hidden layer nodes is set as 11. The prediction error curve of AW value is shown in Figure 5.

The quantized AADT value is trained and calculated by BP neural network model, and the number of hidden layer nodes is set as 19. The prediction error curve of AADT value is shown in Figure 6.

(2) Flatness attribute value prediction

Here, for the attribute values of the temperature and humidity and the traffic volume, the monthly lowest average temperature LT is used to represent the temperature attribute, the annual precipitation AW is used to denote the humidity attribute, and the annual average daily traffic volume AADT is used to represent the traffic volume attribute. The measured and predicted values of AW and AADT are shown in Table 2, and those of LT are shown in Table 3.

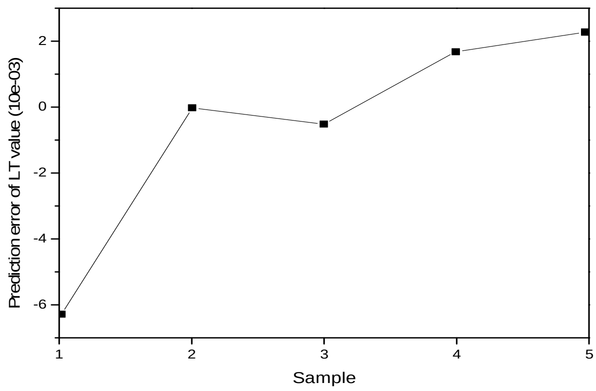

Figure 7. Prediction error curve of LT value

In order to simplify the neural network model solution process, the data is quantized and placed in the interval of [0, 1]. The formula of LT is as follows:

$$LT' = \frac{LT}{LT_{min}} \tag{14}$$

The quantized LT value is trained and calculated by BP neural network model, and the number of hidden layer nodes is set as 7. The prediction error curve of LT value is shown in Figure 7.

Pavement performance model prediction

(1) Prediction of rut depth

The 1-9 year rut depth measured data are selected for training and prediction of BP neural network model, in which the data of the first 7 years are training samples, and the data of the 8th and 9th years are the prediction samples, as shown in Table 4.

Table 4. Measured value and prediction value of rutting depth

Sample		**Training sample**					**Prediction sample**			
Year		First years	Second years	Third year	Fourth years	Fifth years	Sixth years	Seventh years	Eighth years	Ninth years
Measured input	CD Accumulative value (day)	94	164	261	367	471	564	646	717	807
	AW Accumulative value (mm)	429	1161	1428	1799	2138	2508	2953	3432	3848
	AADT Accumulative value (10^4)	1.31	2.79	4.42	6.21	8.18	10.34	12.71	15.29	18.15
Measured output	D_r (mm)	3.4	7.2	11.7	15.4	18.5	20.8	22.6	24	25.4
Predictive output	D_r' (mm)	3.4	7.2	11.1	15.4	18.5	20.8	22.6	24	25.2

D_r(max)=50mm and D_r(min)=0mm are selected. After the rut depth measurement data is quantized by the formula, the BP neural network road performance evaluation model is used for sample training, and the hidden node is calculated to be 9. The prediction error curves of the training samples and the prediction samples are obtained as shown in Figures 8 and 9.

As can be seen from Table 4, Figures 8 and 9, the actual measured data of the rut depth is highly consistent with the predicted values, and the training sample error is 2.17×10^{-5}, and the prediction error of the prediction sample is 8.49×10^{-6}, which shows that the evaluation model of asphalt pavement performance based on BP neural network has good feasibility and operability for the rut depth prediction.

(2) Prediction of flatness

The 1-9 year flatness measured data are selected for training and prediction of BP neural network model, in which the data of the first 7 years are training samples, and the data of the 8th and 9th years are the prediction samples, as shown in Table 5.

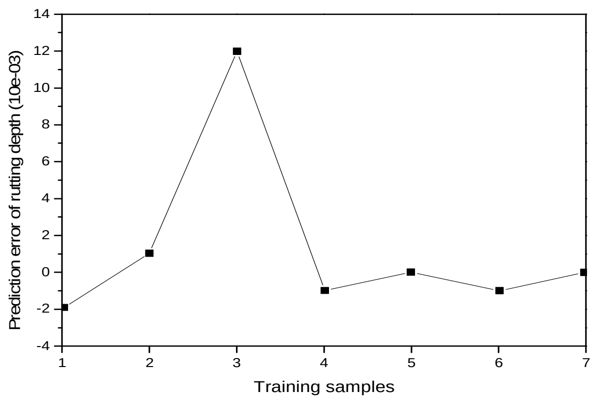

Figure 8. Prediction error curve of training samples (D_r)

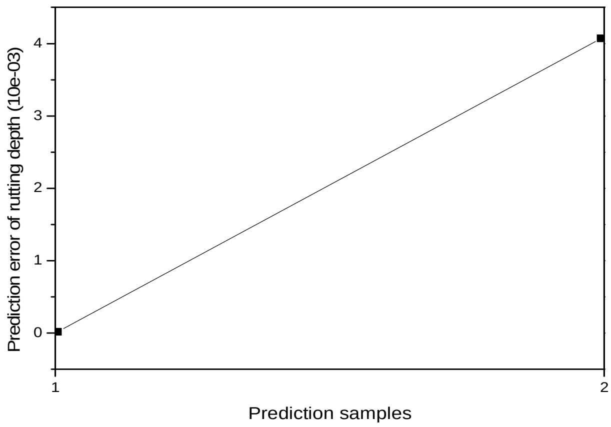

Figure 9. The prediction error curve of the test sample (D_r)

IRI(max)=10m/km and IRI (min)=0m/km are selected. After the flatness data is quantized through the formula, the BP neural network road performance evaluation model is used for sample training, and the hidden node is calculated to be 9. The prediction error curves of the training samples and the prediction samples are obtained as shown in Figures 10 and 11.

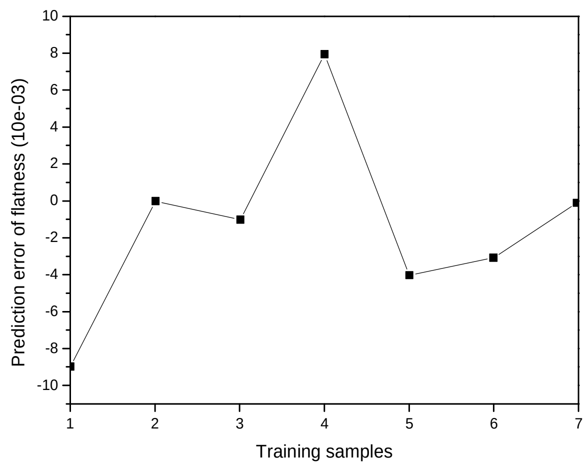

Figure 10. Prediction error curve of training samples (IRI)

Table 5. Measured value and prediction value of flatness

Sample		Training sample							Prediction sample	
Year		First years	Second years	Third year	Fourth years	Fifth years	Sixth years	Seventh years	Eighth years	Ninth years
Measured input	CD Accumulative value (day)	-7.7	-16	-22.6	-33.1	-42.4	-48.6	-56.1	-62.3	-68.7
	AW Accumulative value (mm)	429	1161	1428	1799	2138	2508	2953	3432	3848
	AADT Accumulative value (10^4)	1.31	2.79	4.42	6.21	8.18	10.34	12.71	15.29	18.15
Measured output	IRI (mm)	1.5	1.85	2.11	2.67	3.19	3.52	3.99	4.48	4.94
Predictive output	IRI (mm)	1.59	1.85	2.11	2.59	3.22	3.54	3.99	4.49	4.89

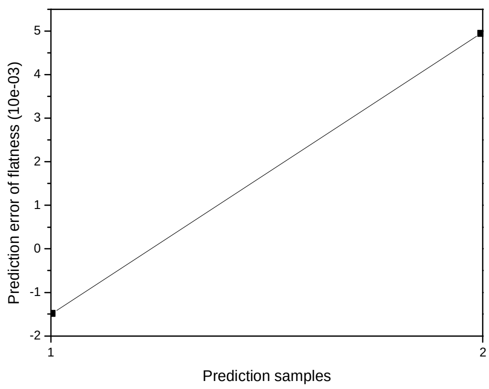

Figure 11. Prediction error curve of prediction sample (IRI)

As can be seen from Table 5, Figures 10 and 11, the actual measured data of the flatness is highly consistent with the predicted values, and the training sample error is 2.48x10^{-5}, and the prediction error of the prediction sample is 1.39x10^{-5}, which shows that the evaluation model of asphalt pavement performance based on BP neural network has good feasibility and operability for the prediction of flatness.

Conclusions

With the rapid economic development, the number of highways under construction in China is also increasing year by year. Asphalt pavement is widely used in road pavement because of its high temperature stability, low temperature crack resistance, water stability, fatigue resistance and many other advantages. However, with the increase of the service time, and the long-term effects of the surrounding environment and traffic loads, it is easy to cause cracks, subsidence, and water damage on the asphalt pavement, which brings enormous financial pressure to maintenance. With a view to reducing the maintenance cost of the asphalt pavement, slowing down the damage to it, and improving its performance, this study proposes an evaluation and prediction model of pavement performance based on BP artificial neural network, and uses the model to predict asphalt pavement maintenance, which improves the ability for choosing and determining the time and measures for pavement maintenance, and provides theoretical basis for the performance evaluation of asphalt pavement.

1) In this study, the evaluation indexes of pavement are analyzed and individual indexes, flatness and rut depth, representing pavement quality and rut depth are selected to evaluate the performance of the asphalt pavement.

2) In light of the advantages of artificial neural network and the characteristics of pavement performance evaluation, this study proposes a model of asphalt pavement performance evaluation and prediction based on BP neural network model.

3) The algorithm of BP network model and network capability are used to predict and analyze the rut depth and flatness indexes of asphalt pavement, through which it is found that the prediction data is in highly consistent with the actual measured data, with high precision and small error, which proves that the model has extremely high operability.

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