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Back-Propagation Network Modeling for Concrete Pavement Faulting Using LTPP Data

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Abstract: A reliable pavement performance prediction model is essential for long-term pavement maintenance and rehabilitation planning. There are many factors affecting joint faulting such as heavy traffic, pavement structure, climatic conditions, pavement age, etc. Design features including dowel, base type, pavement thickness, joint spacing, drainage system, shoulder type are also important factors for faulting. So the factors selection has a big effect on the modeling. In this paper, the adaptability of the widely used Back-Propagation Network (BPN) pavement prediction method, using actual joint faulting data is studied. Prediction models with different factors, including 10-factor model, 8-factor model, 6-factor model and 4-factor model, are established and the prediction results are compared. Research outcomes show that the factors that choosing affect the prediction capability and 8-factor model is most effective. Then the proposed factor selection method can effectively support model development.

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***Key words**: Back-propagation network, Faulting, Impact factors, Modeling.*

Introduction

Joint faulting is one of the major distresses of cement concrete pavement. Rough roads caused by faulting lead to user discomfort, increased travel times, and higher vehicle operating costs. Therefore, it is significant that predicting pavement condition provides a basis for decision making for maintaining and repairing damaged pavement based on the on-site road usage. There are some researches focusing on the prediction of concrete pavement performance [1-6]. Khazanovich presented a summary of the procedures used to model the effects of transverse joint faulting in the design of jointed plain concrete pavements [7]. Robinson described the development of distress prediction models for Portland cement concrete pavements in Texas for the Texas Department of Transportation's pavement management information system [8]. Solminihac presented rehabilitation performance prediction models of concrete pavements in incremental form [9]. Also, there is much research related to BPN modeling. However, there is no explicit study about factor selection method in back-propagation network prediction modeling. This paper presents a method to select the faulting factors for using the BPN method. Actual joint plain concrete faulting condition data collected from the LTPP program in the GPS-3 database is used for this study. Suggestions for BPN modeling improvement based on actual performance data are discussed.

Back-Propagation Network

Back-Propagation Network (BPN) is a common method for artificial neural networks training. BPN is a one-way communication multilayer feed-forward network [10]. Its layered structure is shown as shown in Fig. 1. Each layer consists of units that receive their input from units from a layer directly below and send their output to units in a layer directly above the unit. There are no connections within a layer. BPN is a neural network with three or more layers, including the input layer, hidden layer, and output layer.

Data Preparation

This paper uses 4 different types of network structures to create 4 different prediction models to analyze the accuracy of the prediction model. 49 sections and nearly 90 data points are selected as a training set. Eighteen sections and nearly 90 data points are selected as a prediction set to validate the predictive ability of the model. Training set is different from those prediction set and training set are greater than prediction set. Faulting distribution is shown in Fig. 2.

Faulting Prediction Modeling and Analysis

Faulting Prediction Model with 10 Factors

Faulting Prediction Modeling

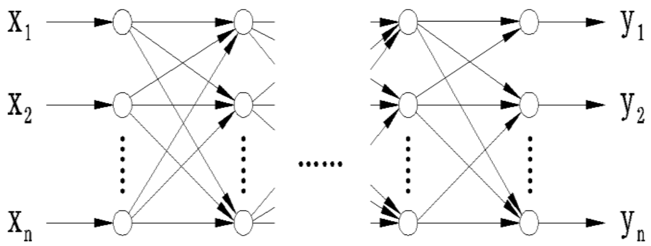

Fig. 1. The Structure of BPN.

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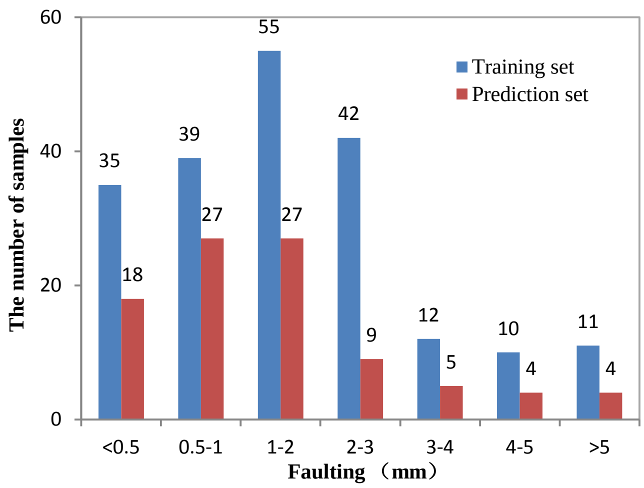

Fig. 2. Faulting Distribution of Training Set and Prediction Set.

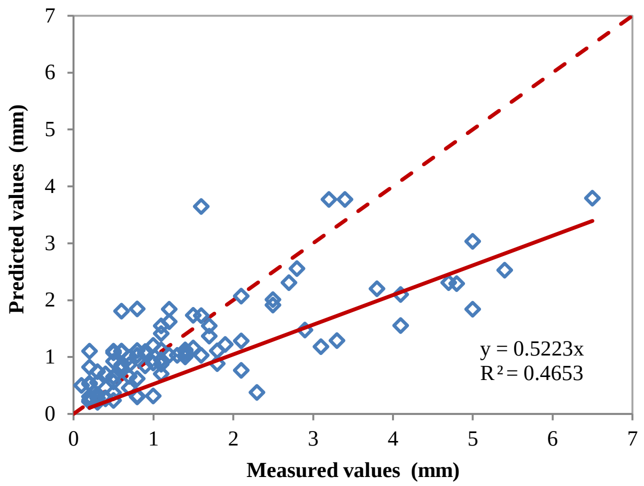

Fig. 3. The Relationship Between Measured and Predicted Values of a 10-factor Model.

The number of the input and output layers of BPN is determined by the number of dimensions of the input and output vectors. The dimension of the input vector is the number of factors. Previous study shows that road age, cumulative axle load, dowel, base type, pavement thickness, joint spacing, drainage system, shoulder type, the average annual rainfall and freeze-thaw cycles are important factors for faulting [11]. So this paper selects six design features: dowel, base type, pavement thickness, joint spacing, drainage system, shoulder type. The average annual rainfall and freeze-thaw cycles are selected as two important environmental factors. Road age and cumulative axle load are important factors affecting faulting and even sections of the performance, should be considered. By considering the various factors affecting roadways, the prediction model is established that considers 10 factors: road age, cumulative axle load, dowel, base type, pavement thickness, drainage system, joint spacing, shoulder type, freeze-thaw cycles, and average annual rainfall. There are 10 neurons in the input layer.

Because the data are normalized, the data are between [0, 1]. So, the Tansig, which is S-type tangent function, can be used in transfer function of the neurons in the output layer and the hidden layer. The function Traindx is the gradient descent method, and its rate is adaptive because it has good adaptability. So, the Traindx is selected as the training function. When the number of the hidden layer of network design is based on the data set is 13 and combined with the empirical formula of the calculation of the number of hidden layer neurons, the predictive ability of the network achieves the best results. In summary, the BPN of cement concrete pavement faulting prediction is a network structure containing 10 inputs, 1 output, and 13 neurons in the hidden layer.

Analysis of Results

The mean standard error of estimate between the predicted and measured values is 0.97 for the prediction model, which considers 10 factors. As shown in Fig. 3, there are two situations. One is the points distribute around the bisector and another is the points deviate from the bisector. The deviation points are fitted with linear function, as presented in the solid red line and these data points have a value of greater than 3 mm. That is to say, when the faulting value is greater than 3 mm, the predicted value, the predicted value is only about 52% of the measured value, and the prediction is poor. When the faulting value is less than 3 mm, the prediction of the model is good, and the distribution of the corresponding point of predicted and measured values are located near the bisector.

In order to analyze the effect of the model predictions, the relationship between the measured values and the predictive value with CESAL is analyzed by considering the dowel or no-dowel section. As shown in Fig. 4, the pavement faulting prediction for dowel sections is relatively good, even CESAL is 30,000,000, the predicted and measured values are more consistent. But the prediction of no-dowel sections is relatively poor. The predicted values of sections are smaller than the measured values.

Especially when faulting value is larger than 3mm, the predicted value is much smaller than the measured value. This is due to the number of samples greater than 3mm, which is relatively small in the training data as shown in Fig. 2. The number of these samples is only 15.4% of the total sample, and only 33 samples are used for training. So, the distribution of different samples may affect the predictive ability of the BPN model.

Faulting Prediction Model with 8 Factors

Faulting Prediction Modeling

The paper selects 4 design features factors which have a strong influence: dowel, base type, pavement thickness, and drainage. Also, the average annual rainfall and freeze-thaw cycles are selected as two important environmental factors. Road age and cumulative axle load, which are important factors affecting faulting, should be considered. By considering the various factors affecting road, the prediction model is established using 8 factors related to road age, cumulative axle load, dowel, base course type, pavement thickness, drainage system, freeze-thaw cycles, and the average annual rainfall. There are 8 neurons in the input layer.

Combined with the empirical formula of the calculation of the number of hidden layer neurons, when the number of hidden layer of network design based on the data set is 8, the predictive ability of the network has the best results. In summary, the BPN of cement

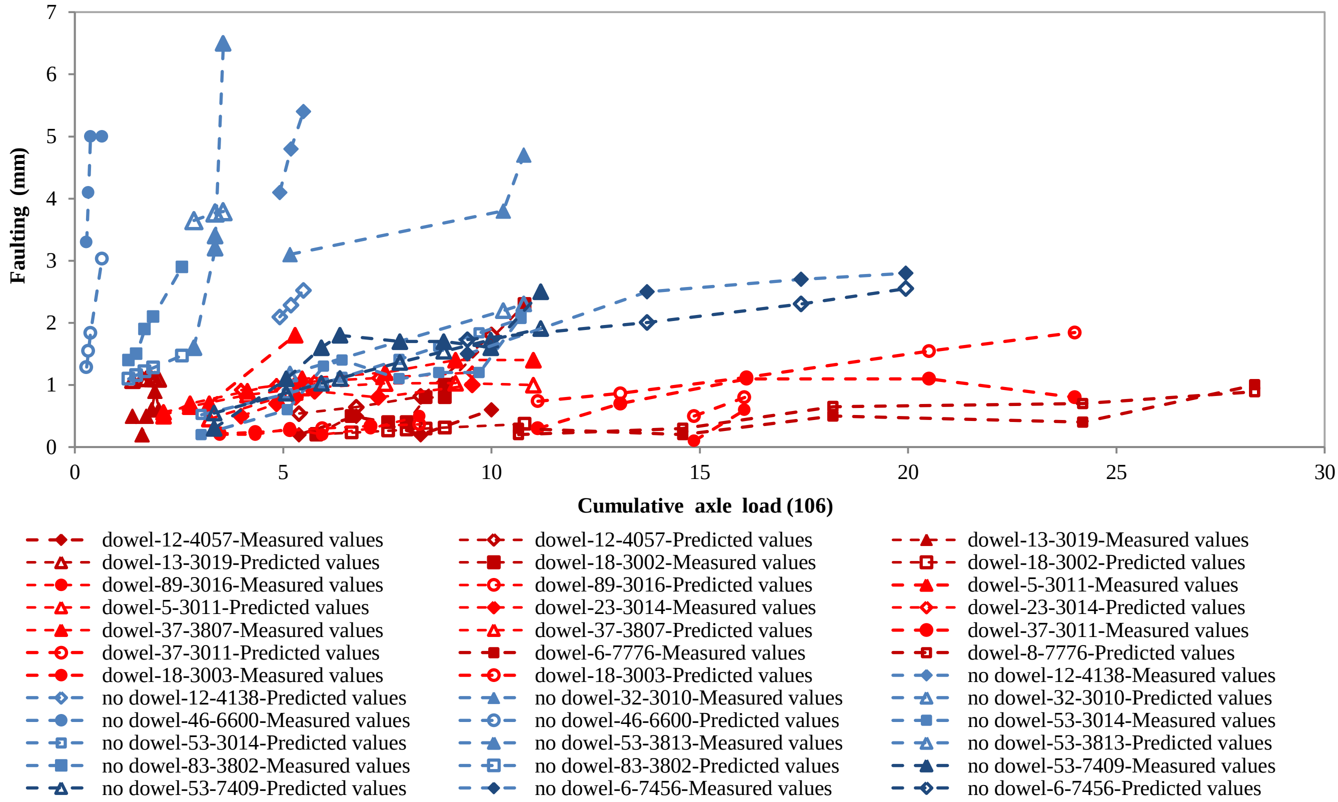

Fig. 4. The Relationship of the Measured and Predicted Values with the Cumulative Axle Load in a 10-factor Model.

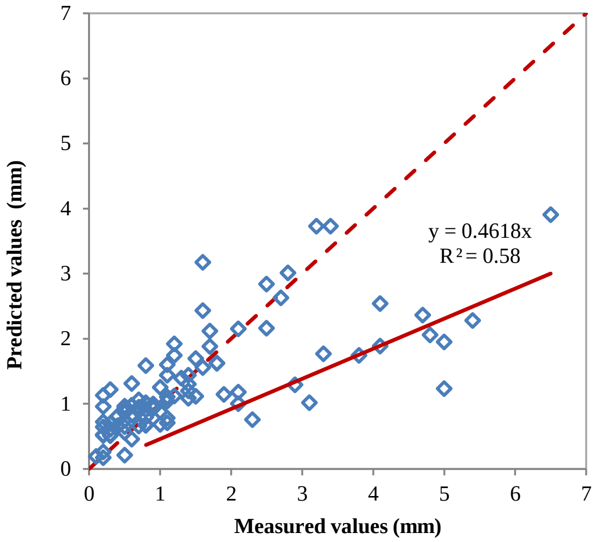

Fig. 5. The Relationship Between the Measured and Predicted Values of a Model with 8 Factors

concrete pavement faulting prediction is a network structure containing 8 inputs, 1 output, and 14 neurons in the hidden layer.

Analysis of Results

The mean standard error of estimate between the predicted and measured values is 0.99 for the prediction model considering 8 factors. Fig. 5 shows similar law as Fig. 3. The deviation points are fitted with linear function. It is shown that the predicted value is only about 46% of the measured value. The deviation distribution with 8-factors model is a little greater than 10-factors model. As shown in Fig. 6, the pavement faulting prediction for dowel sections is good, and the predicted and measured values for dowel sections are more consistent. The prediction for no-dowel sections is relatively poor. Especially, the faulting value is larger than 3mm; the predicted value is much smaller than the measured value. The law of predicted results of model with 10 and 8 factors is substantially the same, and the predictive ability of the model with 10 factors is a little better than the model with 8 factors.

Faulting Prediction Model with 6 Factors

Faulting Prediction Modeling

A prediction model considering 6 factors (road age, cumulative axle load, dowel, base type, pavement thickness, and the average annual rainfall) is established. So there are 6 neurons in the input layer.

When the number of the hidden layers of network design is based on the data set of 12, the predictive ability of the network achieves the best results. In summary, the BPN of cement concrete pavement faulting prediction is a network structure containing 6 inputs, 1 output, and 12 neurons in the hidden layer.

Analysis of Results

The mean standard error of estimate between the predicted and measured values is 1.16 in the prediction model with 6 factors. As shown in Fig. 7, when the faulting value is smaller than 1mm, the

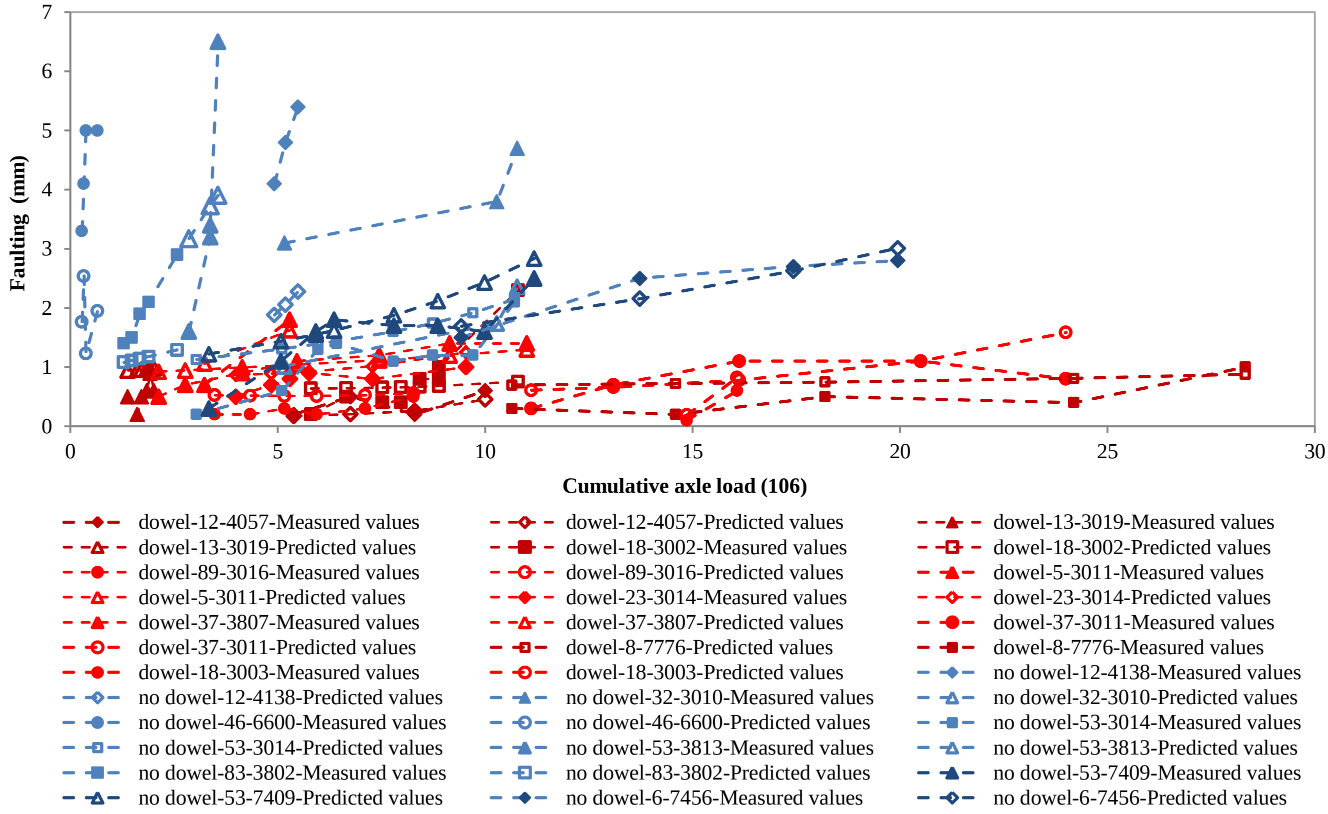

Fig. 6. The Relationship of the Measured Values, the Predicted Values, and the Cumulative Axle Load of a Model with 8 Factors.

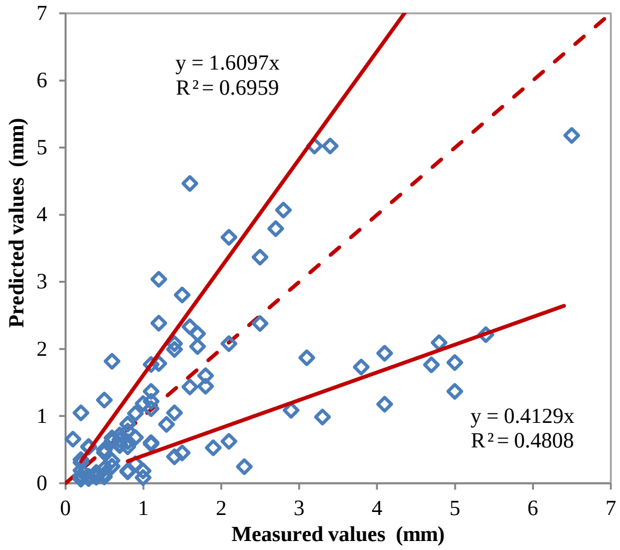

Fig. 7. The Relationship Between the Measured and Predicted Values of a Model with 6 Factors.

prediction ability is good. However, the distributions of the corresponding points of others are not located near the bisector. There are two kinds of points deviated from the bisector. These two kinds of deviation points are then fitted with a linear function. One shows that the predicted value is only about 0.41 of the measured value. The other shows that the predicted value is about 161% of the measured value. Only a few points distribute around the bisector. To analyze the effect of the model predictions, the relationship between the measured and predictive values with the cumulative axle load is analyzed considering the dowel and no-dowel sections. As shown in Fig. 8, the pavement faulting prediction for no-dowel sections is poor: the predicted and measured values are not consistent. The prediction values for most sections are much smaller. And for dowel sections, when CESAL is more than 10,000,000, this model cannot predict correctly. It is shown that the choosing factors affect the prediction capability.

Faulting Prediction Model with 4 Factors

Faulting Prediction Modeling

A prediction model considering 4 factors (cumulative axle load, dowel, base type, and pavement thickness) is established. There are 4 neurons in the input layer.

When the number of hidden layer of network design based on the data set is 6, the predictive ability of the network achieves the best results. In summary, the BPN of cement concrete pavement faulting prediction is a network structure containing 4 inputs, 1 output, and 6 neurons in the hidden layer.

Analysis of Results

The mean standard error of estimate between the predicted and measured values is 1.31 in a prediction model with 4 factors. As shown in Fig. 9, the distribution of the corresponding points of all predicted and measured values are not located near the bisector, and the distribution is discrete. As shown in Fig. 10, the pavement faulting prediction for dowel and no dowel sections are both poor.

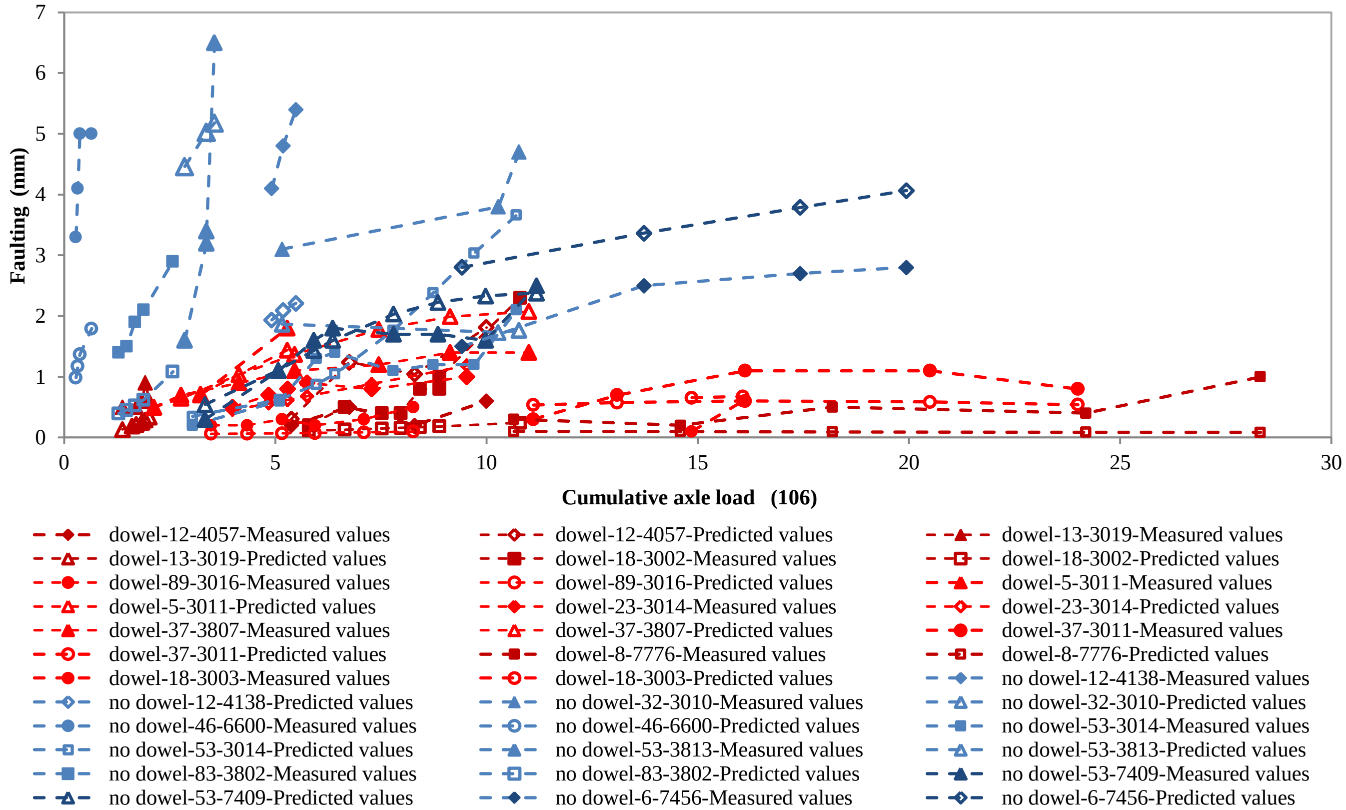

Fig. 8. The Relationship of the Measured Values, the Predicted Values, and the Cumulative Axle Load of a Model with 6 Factors.

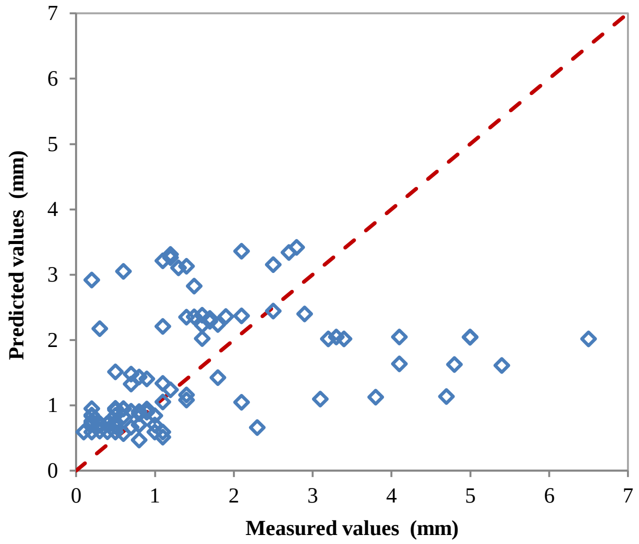

Fig. 9. The Relationship Between the Measured and Predicted Values of a Model with 4 Factors.

The development of prediction values with an increasing cumulative axle load is not obvious. It shows that the predictive ability of the modeling with fewer factors is poorer. It is concluded that the number of factors has a greater impact on faulting prediction modeling.

Discussion

In order to study the impact of the different factors for modeling, the mean standard error of estimate of the predicted and measured values of the 4 prediction models are compared. As shown in Fig. 11, the predictive ability of 10-factor model is a little better than the 8-factor model; the mean standard error of estimate of the predicted and measured values is 0.97 and 0.99, respectively. The accuracy does not improve obviously. In Table 1, it is found that joint spacing and shoulder type are not included in the 8-factor model. That is to say, if the data is limited, these two design features may not be included. It is also found that joint spacing and shoulder type, are not important as other factors.

The predictive ability of the 6-factor model is not as good as the 10-factor model and the 8-factor model. In Table 1, it is found that drainage type and freeze-thaw cycle times are considered in the 8-factor model but not in the 6-factor model. It is concluded that drainage type and freeze-thaw cycle times are important for the faulting. It also shows that reducing the number of factors in the model will affect the prediction accuracy.

As shown in Fig. 11, the predictive ability of the 4-factor model is worse than the 6-factor model. Table 1 shows age and average annual rainfall are not considered in the 4-factor model but are considered in the 6-factor model. As mentioned, the prediction model based on 4 factors has difficulty predicting the faulting development with CESAL. It may be because the 4-factor model does not consider age or any environmental factors.

Conclusions

This paper presents a successful use of the back-propagation neural networks to model the complex relationship between pavement age

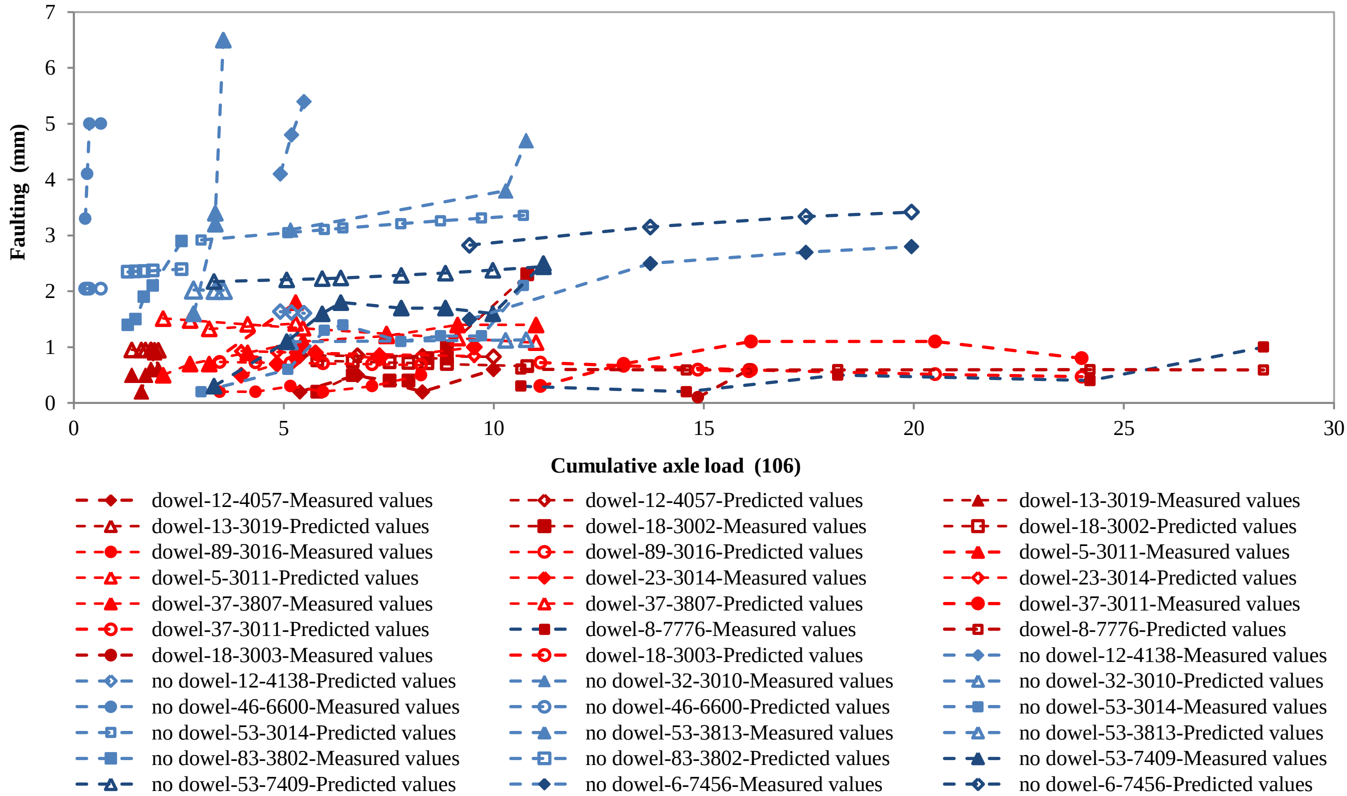

Fig. 10. The Relationship of the Measured Values, the Predicted Values, and the Cumulative Axle Load of a Model with 4 Factors.

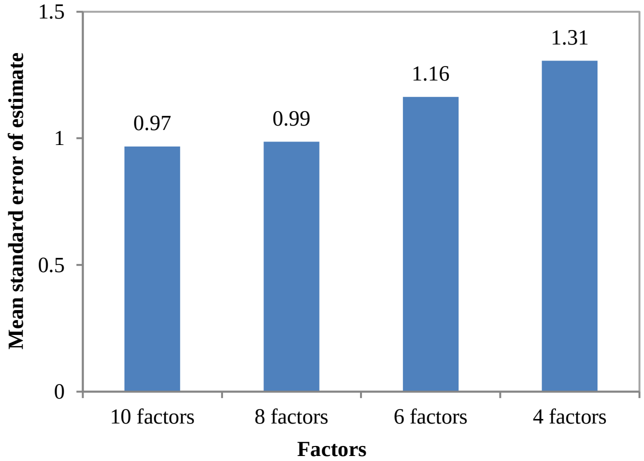

Fig. 11. Comparison of the Different Models.

Table 1. Factors Considered in Different Neural Network Models.

Factors	CESAL	Age	Dowel	Base Type	Thickness	Drainage	Joint Spacing	Shoulder Type	Average Annual Rainfall	Freeze-thaw Eycle times
10	√	√	√	√	√	√	√	√	√	√
8	√	√	√	√	√	√			√	√
6	√	√	√	√	√				√	
4	√		√	√	√					

and parameters related to base layer conditions and joint faulting in cement concrete pavements. In the back-propagation neural network modeling, four types of models, including 10-factor model, 8-factor model, 6-factor model and 4-factor model, are proposed in this paper which shows the predictive ability of 10-factor model is the best, but just a little better than 8-factor model. Since the 8-factor model save more computer time and needs fewer inputs, it is concluded that 8-factor model is the most effective and these factors are CESAL, age, dowel, base type, thickness, drainage, average annual rainfall, freeze-thaw cycle times. But all these models do not perform well for no-dowel section, further study is suggested to develop model with dowel sections and no-dowel sections, respectively.

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