Research on structural modulus inversion method of asphalt pavement based on BP neural network

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Abstract. The current inversion methods based on pattern recognition method, database search method, genetic algorithm and other inversion methods are difficult to solve the absolute convergence problem of structural modulus inversion for asphalt pavements with more than three layers, while the deep learning models and methods widely used in the scenarios of image recognition, speech recognition, etc. as well as the ways to implement them have been increasingly improved, and they can be applied to solve the problem of structural modulus inversion for asphalt pavements. This study aims to solve the modulus inversion problem of multi-layer asphalt pavement structures, obtaining enough theoretical bending basin data of asphalt pavement structures as training samples through mechanical theory and programming calculations, and using the BP neural network model to train the prediction model of structural layer modulus inversion. The test results show that the BP neural network inverse asphalt pavement structural modulus model established in this paper can not only get the prediction results quickly and effectively, but also the prediction results have high accuracy, which provides an effective way for solving the modulus inversion problem of asphalt pavement structure with more than three layers by using the BP neural network to solve the pain point and bottleneck problems in the industry.

Keywords: asphalt pavement; Modulus inversion; BP neural network; pavement structural assessment.

1. Introduction

Pavement structural assessment, whether conducted using destructive or non-destructive methods, provides road agencies with valuable information on pavement structural strength, load carrying capacity, remaining service life, pavement layer condition, and selection of appropriate maintenance and rehabilitation (M&R) strategies.[1] And the back-calculated pavement layer modulus based on deflection measurements is one of the important bases for pavement structural condition assessment. Pavement deflection measurements that back-calculate the modulus of the pavement layer from deflection measurements have traditionally used non-destructive methods such as falling weight deflectometer (FWD), geophones inserted into the pavement, and rolling wheel deflectometer (RWD).[2,3] Among them, applying a load (generally 0.7MPa) through FWD, using displacement sensors to detect the multi-point vertical displacement value of the road surface under the action of the load, and obtaining the structural modulus parameter information of the asphalt pavement through the backcalculation of the information of the bending sink basin is a practical way at present.

Pavement modulus inversion is a very complex and difficult problem, whether linear or nonlinear or considering static or dynamic loads and other mechanical analysis models to calculate the bending settlement of the pavement structure, the modulus inversion can ultimately be reduced to a nonlinear optimization problem, i.e., how to use effective optimization algorithms and data processing methods to find the optimal combination of mechanical parameters of the structural layers of the pavement, so as to achieve an optimal fit between the measured bending basin of the FWD and the theoretical bending basin of the mechanical calculations. theoretical bending basin to achieve the best fit between the FWD measured bending basin and the mechanically calculated bending basin. However, the initial value and local convergence of the nonlinear optimization problem and the uniqueness of the solution, as well as the reasonableness of the inversion result itself, have always been the problems that the research on modal inversion has been devoted to solving. The current pavement modulus backcalculation methods mainly include regression formula method, iterative method, pattern recognition method, database search method, genetic algorithm, etc. However, these methods have the problems of poor generalization of backcalculation and poor backcalculation accuracy, which make it difficult to solve the problem of absolute convergence of the modulus backcalculation of asphalt pavements with more than three layers of structure.

After nearly a decade of development, the deep learning models and methods, as well as the implementation pathways, which are widely used in scenarios such as image recognition and speech recognition, have become increasingly sophisticated. Artificial neural networks, especially deep learning networks, are one of the fastest growing AI technologies and are leading the development of many industries.[4] In the 1990s, artificial neural network methods were used to solve the problem of pavement inversion, and in 1994, the U.S. Army Engineer Airway Laboratory was the first to use BP networks for modal inversion. 2019 FF Aubdulnibe, KA Jassim [5] discussed that the difference between the dynamic nature of FWD tests and the static assumptions produces significant errors on the module, which means that their application in conventional backcalculation procedures is impractical, paving the way for the application of artificial neural network techniques.Aubdulnibe, Jassim applied artificial neural network application to flexible pavement modulus backcalculation confirms the development of artificial neural networks as a tool for backcalculating flexible pavement modulus from precursor-driven data, promising results such as speed and efficiency. In the future, the use of artificial neural networks as a means to back-calculate FWD-generated data will contribute to the cost-effectiveness of commuting and traffic control-related expenses. In 2020 Vidhi Vyas [6] et al. demonstrated the appropriateness of using neural network models for numerical prediction of structural performance parameters of asphalt pavements by using artificial neural networks and FWD bending basin parameters to predict asphalt pavement conditions. In 2021 Gamal M. Mabrouk, Omar S. Elbagalati, Samer Dessouky [7], et al. used artificial neural network modeling to create a synthetic traffic speed deflection database using a pre-developed finite element modeling approach when investigating a new method of backcalculating the pavement layer modulus as a function of traffic speed deflection. The generated library was then used to train, test and validate a neural network model for modulus inversion, and it was shown that the developed neural network model exhibited acceptable accuracy regardless of the simulation, demonstrating the accuracy of artificial neural networks for inverting the modulus of pavement structural layers as compared to conventional methods. Zhang et al. used an artificial neural network (ANN)-based back calculation procedure with a genetic algorithm (GA) optimization algorithm to back calculate the modulus of a three-layer flexible pavement layer with root mean square error (RMSE) of 0.51%-1.99%. Li et al. combined an ANN-based inversion calculation procedure with a GA optimization algorithm to calculate the modulus of the three flexible pavement layers by inversion of the FWD test. The results of the validation process were compared with the original inputs in the synthetic database for the sigma curve parameter (21° C), the WLF functional coefficient of the asphalt layer, and the nonlinear material parameters of the base layer and the roadbed. The results show that the calculated results are in good agreement with the synthesized parameters. The regression coefficients were as high as 0.96 or more, although some outliers were found near the reference fit line. [8]

Among the previous researches, ANN shows significant advantages in real-time analysis, speed and efficiency, appropriateness, and accuracy, but most of the researches focus on the three-layer structural modulus inversion problem, and the convergence problem for multi-layer structures still needs to be solved urgently. This paper utilizes BP neural network to further expand the modulus inversion of asphalt pavement structural layer to four-layer or even five-layer structure, in order to break through the bottleneck of the current modulus inversion of asphalt pavement structural layer, and to provide a more effective analytical method and analytical tool for the quality assessment of asphalt pavements, the evaluation of old roads, and the health analysis.

2. Research Methodology

The accuracy and range of applications of BP neural networks are limited by the synthetic database and the range of parameters considered in the training process. Therefore, a broad-based, data-rich synthetic database is needed to optimize accuracy and reliability. In this paper, sufficient theoretical bending basin data for asphalt pavement structures can be obtained through mechanical theory and programming calculations as training samples and validation datasets. Tables 1-Table 4 summarize the input variable data for the BP neural network.

Table 1 Theoretical Pavement Static Bending Basin Data Pavement Calculation Scheme （Five-layer asphalt base pavement program = 8.339760*10^6）

Material type	Thickness (cm)			Bituminous base layer (MPa)		
	realm		interval (math.)	Modulus range		interval (math.)
top layer	4	22	4	3000	15000	6
grass-roots unit	8	12	3	2000	12000	11
substrate	18	54	5	3000	20000	18
functional	15	20	3	100	400	3
soil foundation		-		30	150	13

Table 2 Theoretical Pavement Static Bending Basin Data Pavement Calculation Scheme （Five-layer granular base pavement program = 9.907920*10^6）

Material type	Thickness (cm)			Bituminous base layer (MPa)		
	realm		interval (math.)	Modulus range		interval (math.)
top layer	4	22	4	3000	15000	6
grass-roots unit	16	20	3	200	1000	9
substrate	18	54	5	3000	20000	18
functional	15	20	3	100	400	4
soil foundation		-		30	150	13

Table 3 Theoretical Pavement Static Bending Basin Data Pavement Calculation Scheme （Four-layer semi-rigid base pavement program = 1.825200*10^6）

Material type	Thickness (cm)			Bituminous base layer (MPa)		
	realm		interval (math.)	Modulus range		interval (math.)
top layer	4	22	10	3000	15000	13
-	0	0	1	0	0	1
substrate	18	54	5	3000	20000	18
functional	15	20	3	100	400	4
soil foundation		-		30	150	13

Table 4 Theoretical Pavement Static Bending Basin Data Pavement Calculation Scheme （Four-layer granular base pavement program = 1.135680*10^6）

Material type	Thickness (cm)			Bituminous base layer (MPa)		
	realm		interval (math.)	Modulus range		interval (math.)
top layer	4	22	10	3000	15000	13
grass-roots unit	15	30	6	200	800	7
-	0	0	1	0	0	1
functional	15	30	4	100	400	4
soil foundation		-		30	150	13

The total number of cases in the range of material parameters considered in this study is 2.12664*107. BP neural networks are capable of searching for the most approximate solution of a nonlinear problem for any input and output variables, and are therefore naturally used to gather information and generate computational models similar to human minds. A typical multilayer neural network structure consists of an input layer, a hidden layer, and an output layer, as shown in Figure 1.

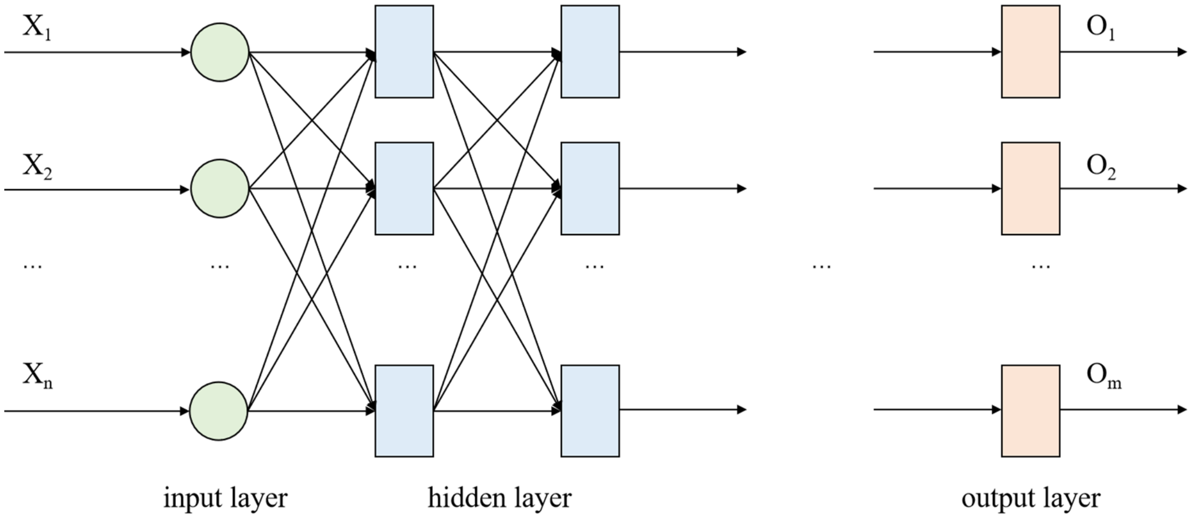

Fig. 1 BP neural network model

Neurons are indispensable units in the layers. The layers primarily use individual neurons to perform transfer functions. The transfer function is based on weights and biases and implicitly connects information from the input to the output in a feed-forward process. At the same time, the error back propagation mechanism comes into play.

The neural network can update the weights and biases from the output to the input through performance functions such as root mean square error (RMSE) and gradient descent.

BP neural networks require a training process that uses a synthetic database to train the weights and biases of the constructed BP neural network. The training process has three steps to complete the fitting procedure. The first step is to determine the number of working layers. The neural network contains at least three layers: an input layer, a hidden layer, and an output layer. The number of hidden layers can be varied to adjust and enhance the learning ability of the neural network. After adjustment, the selection of two hidden layers can achieve better results.

The next step is to set the number of neurons in each layer. In this study, the number of neurons in the input and output layers are consistent with the number of input variables in the input layer in Table 5-Table 8, respectively, and the hidden layers of 128 and 32 neurons were chosen in this study based on the experimental procedure.

Table 5 Neural network inverse asphalt pavement structural modulus model (five-layer asphalt base) architecture

Input layer input variables	hidden layer		Output Layer Output Variables	R^2
	Number of hidden layers	Number of neurons		
$D_0,D_{20},D_{30},D_{45},D_{60},D_{90},D_{150},D_{180},D_{210}, \mu_1,h_1, \mu_2,h_2, \mu_3,h_3, \mu_4,h_4, \mu_5,h_5$	2	128	E_1	0.9905
			E_2	0.9868
			E_3	0.9952
$D_0,D_{20},D_{30},D_{45},D_{60},D_{90},D_{150},D_{180},D_{210}, \mu_1,h_1,E_1, \mu_2,h_2,E_2, \mu_3,h_3,E_3, \mu_4,h_4, \mu_5,h_5,E_5$		32	E_4	0.9805
$D_0,D_{20},D_{30},D_{45},D_{60},D_{90},D_{150},D_{180},D_{210}, \mu_1,h_1, \mu_2,h_2, \mu_3,h_3, \mu_4,h_4, \mu_5,h_5$			E_5	0.9999

Table 6 Neural network inverse asphalt pavement structural modulus model (five-layer granular base) architecture

Input layer input variables	hidden layer		Output Layer Output Variables	R^2
	Number of hidden layers	Number of neurons		
$D_0,D_{20},D_{30},D_{45},D_{60},D_{90},D_{150},D_{180},D_{210}$, $\mu_1,h_1,\mu_2,h_2,\mu_3,h_3,\mu_4,h_4,\mu_5,h_5$	2	128	E_1	0.9967
			E_2	0.9868
			E_3	0.9836
$D_0,D_{20},D_{30},D_{45},D_{60},D_{90},D_{150},D_{180},D_{210}$, $\mu_1,h_1,E_1,\mu_2,h_2,E_2,\mu_3,h_3,E_3,\mu_4,h_4$, μ_5,h_5,E_5		32	E_4	1.0000
$D_0,D_{20},D_{30},D_{45},D_{60},D_{90},D_{150},D_{180},D_{210}$, $\mu_1,h_1,\mu_2,h_2,\mu_3,h_3,\mu_4,h_4,\mu_5,h_5$			E_5	0.9999

Table 7 Neural network inverse asphalt pavement structural modulus model (four-layer semi-rigid base) architecture

Input layer input variables	hidden layer		Output Layer Output Variables	R^2
	Number of hidden layers	Number of neurons		
$D_0,D_{20},D_{30},D_{45},D_{60},D_{90},D_{150},D_{180},D_{210}$, $\mu_1,h_1,\mu_2,h_2,\mu_3,h_3,\mu_4,h_4,\mu_5,h_5$	2	128	E_1	0.9668
$D_0,D_{20},D_{30},D_{45},D_{60},D_{90},D_{150},D_{180},D_{210}$, $\mu_1,h_1,\mu_2,h_2,\mu_3,h_3,\mu_4,h_4,\mu_5,h_5$			E_3	0.9936
$D_0,D_{20},D_{30},D_{45},D_{60},D_{90},D_{150},D_{180},D_{210}$, $\mu_1,h_1,E_1,\mu_2,h_2,E_2,\mu_3,h_3,E_3,\mu_4,h_4$, μ_5,h_5,E_5		32	E_4	0.9854
$D_0,D_{20},D_{30},D_{45},D_{60},D_{90},D_{150},D_{180},D_{210}$, $\mu_1,h_1,\mu_2,h_2,\mu_3,h_3,\mu_4,h_4,\mu_5,h_5$			E_5	0.9995

Table 8 Neural network inverse asphalt pavement structural modulus model (four-layer granular base) architecture

Input layer input variables	hidden layer		Output Layer Output Variables	R^2
	Number of hidden layers	Number of neurons		
$D_0,D_{20},D_{30},D_{45},D_{60},D_{90},D_{150},D_{180},D_{210}$, $\mu_1,h_1,\mu_2,h_2,\mu_3,h_3,\mu_4,h_4,\mu_5,h_5$	2	128	E_1	0.9998
			E_3	0.9960
		32	E_4	0.9778
			E_5	0.9751

The third step consists of selecting the function and configuring the running parameters in the BP neural network. In this section, Softplus activation function and MSELoss loss function were finally decided to be used. batch was set to 128, learning rate was 0.003, epoch was 1000, and a pre-stop mechanism was set up, i.e., the model exited the training early if the effect of the model did not improve for 20 consecutive times to prevent overfitting.

During BP neural network training, a separate validation set is generated for model validation. During the training process, the initial training set is very important to build the BP neural network to form the original weights and biases, and the validation set is used to verify the reasonableness of the established BP neural network. Therefore, separate validation sets are generated with the purpose of independent checking.

3. BP neural network model fitting effect analysis

The above results show that the BP neural network modulus inversion R2 is as high as 0.96, which indicates that the training of the BP neural network is successful, and the established network model can be used to predict the structural modulus of asphalt pavement, and the accuracy fully meets the engineering requirements. Taking a pavement scheme with five layers of asphalt base layer as an example, the material parameters and prediction results are shown in Table 9 and Table 10, and the absolute values of relative errors are controlled within 5%, which meet the accuracy requirements.

Table 9 Theoretical pavement structures and corresponding material parameters

road structure	Thickness h/cm	Modulus of elasticity E/MPa	Poisson's ratio μ
top layer	4	3000	0.25
grass-roots unit	8	2000	0.25
substrate	18	3000	0.25
functional	15	100	0.35
soil foundation	∞	30	0.40

Table 10 Comparison of predicted and theoretical values of BP network

structural layer	Modulus of elasticity of structural layer/MPa		Relative error absolute value/%
	BP Neural Network Predictive Value	theoretical value	
top layer	3119.9685	3000.0	4.00%
grass-roots unit	2013.1354	2000.0	0.66%
substrate	9655.6787	9235.0	4.56%
functional	400.12146	400.0	0.03%
soil foundation	103.76512	104.0	0.23%

4. Summary

In this study, 2.12664*107 sets of total pavement structure samples with 1.66266*105 sets of pavement structure validation datasets can be generated according to the mechanical theory and programming calculations to generate an assembled synthetic database.The BP neural network model takes into account the different subgrade properties, thicknesses, Poisson's ratio and so on, and training and validation have been carried out using the synthetic database. The test results show that the BP neural network inverse asphalt pavement structural modulus model established in this paper can not only obtain the prediction results quickly and effectively, but also has high accuracy in the prediction results, which provides an effective way for solving the modulus inversion problem of asphalt pavement structures with more than three layers by using deep learning models and methods to solve the industry pain points and bottlenecks.

The input variables of the BP neural network can be obtained from the FWD test. Compared with the traditional back-calculation procedure, the BP neural network model established in this study expands the modulus inversion from three-layer structure to multi-layer structure, which fills the research gap.

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