Study on Prediction of Skid Resistance of Asphalt Pavement Based on Genetic Neural Network

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ABSTRACT

The prediction of skid resistance of asphalt pavement plays a pivotal role in formulating maintenance plans and determining maintenance schemes. At present, the typical intelligent algorithms such as the neural network and the genetic algorithm have seen extensive applications in the evaluation and prediction of pavement performance. The combination forecasting model can leverage the complementary advantages of the two, thereby enhancing the reliability of prediction. As a case study, this paper focuses on the prediction of pavement skid resistance for an expressway in Chongqing. The research establishes a pavement skid resistance forecasting model using a genetic neural network and compares it with the single neural network, genetic algorithm, and regression models. Through this comparative analysis, the study validates the applicability and reliability of the genetic neural network approach for predicting asphalt pavement skid resistance. The results demonstrate that the regression model exhibits a limited fitting degree for highly nonlinear problems, leading to noticeably lower prediction accuracy than the genetic algorithm or neural network algorithm. In contrast, the combination forecasting model significantly enhances prediction accuracy in comparison to a single neural network model or genetic algorithm. Notwithstanding, it is worth noting that the operational efficiency of the combination forecasting model is inferior to that of a single neural network model. Consequently, the genetic neural network combination forecasting model proves more suitable for pavement skid resistance prediction, and nevertheless, there is room for further improvement in the operational efficiency of the model.

Keywords: Asphalt pavement; Skid resistance; Genetic algorithm; Neural network; Combination forecasting model

1. INTRODUCTION

During the use of asphalt pavement, various factors come into play, including the inherent limitations of the material, the impact of traffic load, and the influence of environmental factors [1]. As a result, the microstructure of the pavement surface undergoes gradual polishing, while the macroscopic structure diminishes [2-4], leading to a continuous attenuation in pavement skid resistance. This deterioration significantly compromises road safety for drivers. To address this issue, timely and effective measures must be implemented to restore the anti-skid functionality of the pavement surface. As such, accurate prediction of pavement skid resistance becomes essential to plan and implement maintenance strategies efficiently. This prediction allows for the formulation of appropriate maintenance plans and schemes, ensuring the long-term usability of the pavement [5-6].

The skid resistance of asphalt pavement is contingent upon an abundance of uncertain factors. However, traditional methods like the general regression model and Markov model solely focus on the temporal variations of specific parameters in time series [7-8]. Their model structures are relatively simplistic, failing to account for the impact of intricate environmental factors on pavement skid resistance. Consequently, the prediction accuracy of these models remains curtailed. Indeed, artificial intelligence algorithms boast the capability to thoroughly explore the relationship between various factors and skid resistance. Among these algorithms, the back-propagation (BP) neural network model [7-8] stands out due to its robust self-learning abilities and effective handling of uncertain factors. It excels in establishing highly nonlinear relationships between complex factors and road skid resistance, making it well-suited for skid resistance prediction on the pavement. Simultaneously, the genetic algorithm [9-12] possesses notable characteristics such as global search capability, strong adaptability, and robustness. It effectively addresses the challenges in relation to local optima and the low learning efficiency of the neural network. The synergy between the genetic algorithm and neural network empowers the genetic neural network model to significantly enhance the prediction accuracy of pavement skid resistance.

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In this paper, we resort to a skid resistance prediction study for pavements I and II of an expressway in Chongqing. To achieve this, we have developed a pavement skid resistance forecasting model harnessing the genetic neural network approach. This model is compared with the single neural network, genetic algorithm, and regression models to calculate its prediction accuracy and operational efficiency. Through this comparison, we aim to validate the applicability and effectiveness of the genetic neural network model as a combination forecasting tool.

2. GENETIC NEURAL NETWORK MODEL

Back-Propagation (BP) neural network model is a multi-layer feedforward network model with forward propagation of information and the reverse transmission of errors [13]. Its algorithm principle involves continuously adjusting the connection weights and thresholds among the input layer, hidden layer, and output through the error function. The objective of this adjustment is to minimize the error between the predicted values and the actual values, thereby meeting the desired accuracy requirements. The model exhibits remarkable strengths, including high self-adaptability, strong self-study ability, and generalization ability, but the prominence of its weaknesses lies in the tendency to get trapped in local optima and relatively slow convergence speed.

The genetic algorithm operates as a parallel random search algorithm, driven by the concept of "survival of the fittest". It involves encoding samples in a specific manner, followed by the selection, crossover, and mutation processes applied to the population of each generation through a fitness function. In the aftermath, the genetic algorithm retains individuals with superior fitness while discarding those with lower fitness. This process creates a new population with improved fitness compared to the previous generation, and this cycle continues until the optimization criteria are met. The algorithm is capable of counterbalancing the shortcomings of the BP neural network model owing to the features of multi-point search, global search, and fast convergence speed.

The genetic neural network model coalesces the advantages of both the BP neural network and genetic algorithm and uses the genetic algorithm to optimize the solution space of the neural network. The main algorithm steps are as follows:

(1) Data normalization: To address the issue of varying dimensions and orders of magnitude in different sample data, the normalization technique is employed to ensure efficient training and improved prediction accuracy of the neural network. In MATLAB, the 'mapminmax' function is commonly used for this purpose.

(2) Individual coding: The coding mode is the key to the efficiency of the algorithm, and a quite lengthy general binary coding mode can affect the efficiency of the algorithm. Hence, we use MATLAB to write the 'code' function for real coding, and the coding length is:

$$n = i * h + h * o + h + o \tag{1}$$

where n denotes the code length, i indicates the number of input layers, h means the number of hidden layers, and o refers to the number of output layers.

(3) Fitness function: Each individual is trained N times after decoding, and the mean square error between the actual value and the predicted value is taken as the fitness function. MATLAB is used to write the 'fun' function to decode individual populations, train parallel networks, and calculate fitness. The formula is as follows:

$$f = k \sum abs(y_i - o_i)^2 \tag{2}$$

where f represents the fitness, y_i stands for the expected value of node i, o_i refers to the actual value of node i, and k denotes the coefficient.

(4) Selection operation: Genetic algorithm generally uses roulette to select individuals and utilizes MATLAB to write the 'select' function to select superior individuals and eliminate inferior individuals. The formula for individual selection probability is as follows:

$$p_i = k / f_i \tag{3}$$

$$q_i = f_i / \sum f_i \tag{4}$$

where f represents the fitness, y_i stands for the expected value of node i, o_i refers to the actual value of node i, and k denotes the coefficient.

(5) Cross operation: It resorts to MATLAB to write the 'cross' function to cross real numbers among individuals, in which the real number crossing mode of the k-th individual a_k and the i-th individual a_j in the i-th position is below:

$$a_{ki} = a_{kj}(1-b) + a_{ji}b \tag{5}$$

$$a_{ii} = a_{ji}(1-b) + a_{kj}b \tag{6}$$

where b is a random number between [0, 1].

(6) Mutation operation: MATLAB is employed to write the 'mutation' function to achieve individual mutation, in which the mutation method of the i-th individual in the j-th position is as follows:

$$a_{ij} = a_{ij} + (a_{ij} - a_{\max}) * f(g) \quad r > 0.5 \tag{7}$$

$$a_{ij} = a_{ij} + (a_{\min} - a_{ij}) * f(g) \quad r <= 0.5 \tag{8}$$

where $a_{\max}$ is the upper bound of a_{ij}, a_{min} is the lower bound of a_{ij}, and r is the random number between [0, 1].

(7) Network fine-tuning: It involves decoding the network weights after genetic optimization and using MATLAB neural network toolbox function to train the network on weights and thresholds, striving to achieve the set prediction accuracy.

3. ESTABLISHMENT OF A FORECASTING MODEL FOR PAVEMENT SKID RESISTANCE

The skid resistance of asphalt pavement is subject to substantial factors, both internal and external. The internal factors mainly include the types and properties of raw materials, gradation types of asphalt mixture, asphalt dosage, construction technology, quality control, etc. The external factors primarily encompass environmental effects such as temperature, rain, snow, light, traffic load, oil and gas pollution, etc. For high-speed under construction, it is more appropriate to choose internal cause as the input factor of skid resistance prediction. Conversely, for high-speed operation, it becomes challenging to detect and investigate the change law of internal cause with time, while external cause can be obtained by consulting relevant data or field investigation, which is relatively simple and direct. Moreover, the accumulation of external factors shows a strong correlation with the decline of pavement skid resistance, wherefore, choosing external factors for predicting the skid resistance of operating pavements is more appropriate in such cases. Thereby, this paper selects service life, traffic volume, temperature, rainfall, and illumination duration as the input parameters of the model, and SRI as the output parameters of the model. It culminates in establishing a forecasting model for pavement skid resistance based on the genetic neural network. The specific model parameters are set as follows:

(1)Network target accuracy: 0.00001;

(2) The maximum iteration of the network: 100;

(3) Network learning efficiency: 0.1;

(4) Population size: 50;

(5) Genetic algebra: 10.

4. VERIFICATION OF ENGINEERING EXAMPLES

In this paper, we focus on a high-speed operation in Chongqing and investigate the skid resistance index (SRI) of two pavement sections with varying service life and technical conditions. The research objectives encompass the collection and organization of data concerning the annual average traffic volume, annual average temperature, annual rainfall, and annual average illumination duration for Pavements I and II over multiple years. The detailed data can be found in Tables 1 and 2.

The established genetic neural network model is used to predict the skid resistance of Pavements I and II, in which the sample values of the previous five years are employed to train the network, while the data of the subsequent two years are utilized for testing the model. Tables 3 and 4 illustrate the prediction results.

Table 1 Statistic table of influencing factors of skid resistance in Pavement I

Factor	Unit	2011	2012	2013	2014	2015	2016	2017
Service life	Year	5	6	7	8	9	10	11
Annual average traffic volume	Volume/d	20914	23427	29095	32887	36997	39255	42119
Annual average temperature	℃	17.7	17.1	18.5	17.5	18.0	17.9	17.7
Annual rainfall	mm	992.8	1069.2	1071.5	1327.2	1220.4	1284.6	1260.6
Annual illumination duration	h	1326.8	947.4	1409.4	959.1	1090.3	1258.2	1121.3

Table 2 Statistical table of influencing factors of skid resistance in Pavement II

Factor	Unit	2008	2009	2010	2011	2012	2013	2014
Service life	Year	2	3	4	5	6	7	8
Average annual traffic volume	Volume/d	6137	6869	7836	8522	10558	11896	12931
Annual average temperature	℃	18.8	18.8	20.7	20.4	18.7	18.6	18.6
Annual rainfall	mm	814.8	1430.6	1125.4	1182.2	1188.6	1132.1	1134.4
Annual illumination duration	h	857.9	1170.5	888.0	1003.7	952.9	952.4	528.4

Table 3 Fitting and prediction results of skid resistance in Pavement I

Year	Actual value of SRI	Regression fitting		BP neural network		Genetic algorithm		Genetic neural network	
		Predicted value	Relative error (%)	Predicted value	Relative error (%)	Predicted value	Relative error (%)	Predicted value	Relative error (%)
2011	92.13	92.19	0.07	92.58	0.490	92.13	0.001	92.06	0.077
2012	90.82	90.42	0.44	90.82	0.000	90.80	0.024	90.82	0.000
2013	87.26	87.77	0.59	87.26	0.000	87.26	0.000	87.26	0.000
2014	85.52	85.11	0.47	85.62	0.120	85.52	0.002	85.50	0.027
2015	83.24	83.29	0.06	83.24	0.000	83.38	0.172	83.24	0.000
2016	81.12	83.16	2.51	80.35	0.946	82.12	1.233	81.18	0.073
2017	78.92	85.57	8.43	79.98	1.343	80.37	1.837	79.51	0.748

Note: The regression model is fitted by polynomials.

Table 4 Fitting and prediction results of skid resistance in Pavement II

Year	Actual value of SRI	Regression fitting		BP neural network		Genetic algorithm		Genetic neural network	
		Predicted value	Relative error (%)	Predicted value	Relative error (%)	Predicted value	Relative error (%)	Predicted value	Relative error (%)
2008	98.24	98.21	0.04	97.84	0.41	98.24	0.00	98.24	0.00
2009	94.36	94.57	0.22	94.38	0.02	94.15	0.22	94.13	0.24
2010	91.61	91.34	0.30	91.62	0.02	91.36	0.27	91.45	0.18
2011	87.65	87.86	0.24	87.64	0.01	87.65	0.00	87.65	0.00
2012	83.52	83.50	0.03	84.42	1.07	83.52	0.00	83.52	0.00
2013	81.77	77.59	5.12	83.08	1.60	79.24	3.10	80.75	1.24
2014	79.06	70.48	10.85	82.00	3.72	74.59	5.66	79.84	0.98

Note: The regression model is fitted by polynomials.

From the analysis of Tables 3 and 4, the following observations can be made: (1) The overall residual value analysis indicates that the skid resistance prediction accuracy for Pavement I is lower than that for Pavement II. This suggests that the accuracy of the skid resistance forecasting model is significantly contingent on the quality of the sample data; (2) Examining the entire trend of residual errors for the four forecasting models, it is observable that each model fits the sample data well. Notably, the fitting accuracy for the first five years of both Pavements I and II is underneath 1%; (3) From the perspective of skid resistance prediction accuracy of four forecasting models, the regression model performs the poorest, with the genetic algorithm and neural network following. Conversely, the combination forecasting model of the genetic neural network demonstrates the highest prediction accuracy. Building upon the specific analysis in Tables 3 and 4, the prediction accuracy of the intelligent algorithm remarkably surpasses that of the general regression model. In comparison with the regression model, the prediction accuracy of the genetic algorithm is enhanced by approximately 1 to 2 times on average, while the neural network shows an improvement of about 2 to 3 times on average. Strikingly, the combination forecasting model demonstrates the most substantial improvement, with an average enhancement of approximately 6 to 7 times. These findings sufficiently illustrate that intelligent algorithms offer distinct advantages when dealing with highly nonlinear fitting problems. Furthermore, the comparison between the individual genetic algorithm and neural network models with the combination forecasting model highlights a remarkable improvement in prediction accuracy for the latter. This finding serves as compelling evidence that the combination forecasting model of the genetic neural network represents an enhancement and optimization over the single forecasting models, making it more suitable for the prediction of pavement skid resistance.

At this juncture, to further substantiate the advantages and applicability of the genetic neural network model, we conduct a comparative analysis of the operation efficiency and iterative process of the three intelligent algorithms. Tables 5 and 6 detail the specific operation efficiency comparison.

Table 5 Comparison of operation efficiency of three forecasting models for Pavement I

Forecasting model	Neural network	Genetic algorithm	Genetic neural network
Operational efficiency/s	0.36	10.35	10.75
Number of iterations	2	10	3

Table 6 Comparison of operation efficiency of three forecasting models for Pavement II

Forecasting model	Neural network	Genetic algorithm	Genetic neural network
Operational efficiency/s	0.33	10.22	11.68
Number of iterations	2	7	3

The analysis of Tables 5 and 6 reveals the following insights: (1) The operation efficiency of the same forecasting model shows little disparity between Pavements I and II, indicating that the efficiency of the forecasting model is predominantly associated with the sample size; (2) Among the three forecasting models, the neural network model demonstrates the fastest solution speed when maintaining the same level of precision. In contrast, the genetic algorithm and the combination forecasting model exhibit comparable speeds. The reason for this discrepancy lies in the general genetic algorithm used in this study, which involves multiple iterations of random selection, crossover, and mutation operations, thereby affecting the evolution speed of samples.

Simply put, the genetic algorithm undergoes significant changes during its iterative process, leading to poor stability. While the iterative process of the neural network model and combination forecasting model is relatively stable. Therefore, from the point of view of algorithm stability, using the genetic algorithm to optimize the neural network represents a viable and feasible combination approach.

5. CONCLUSION

In this study, leveraging the distinctive traits of the genetic algorithm and neural network model, we employ the genetic algorithm to optimize the solution range and enhance the operation efficiency of the neural network. By harnessing the SRI detection data from a highway section in Chongqing, we establish a pavement skid resistance forecasting model based on the genetic neural network. Through comparison with the regression model, single neural network, and genetic model, we calculate and verify the prediction accuracy, operation efficiency, and stability of the combination model. The main conclusions and prospects are as follows:

(1) The quality of the sample data significantly impacts the prediction accuracy of the model, while the operational efficiency of the model is dependent on the sample size. It is essential to circumvent numbering and reference format confusion in the presentation of results.

(2) For complex and highly nonlinear fitting problems, the prediction accuracy of the intelligent algorithm is notably superior to that of traditional regression fitting;

(3) The genetic neural network model exhibits substantially improved prediction accuracy when compared to both the single neural network model and the genetic algorithm. This confirms that the combination model represents an enhancement and optimization of the single prediction models.

(4) The operation efficiency of the genetic neural network model is comparable to that of the genetic algorithm, but its running speed is notably slower than that of the single neural network model. This discrepancy is primarily due to the randomness inherent in the genetic algorithm.

(5) In an effort to emphasize the unique attributes of the genetic neural network model, this study has solely combined the general neural network model and genetic algorithm sequentially. However, the model itself, including the network structure, cost function, genetic crossover, mutation, and other algorithms, has not been optimized. The forthcoming step will resort to organically integrating the optimized neural network with the genetic algorithm to further enhance the prediction accuracy, operational efficiency, and adaptability of the combination forecasting model.

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