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Prediction for asphalt pavement water film thickness based on artificial neural network

Ma Yaolu[1] Geng Yanfen[1] Chen Xianhua[1] Lu Yankun[2]

([1]School of Transportation, Southeast University, Nanjing 210096, China)

([2]Liaoning Provincial Transportation Planning and Design Institute Co., Ltd., Shenyang 110000, China)

Abstract: In order to study the variation of the asphalt pavement water film thickness influenced by multi-factors, a new method for predicting water film thickness was developed by the combination of the artificial neural network (ANN) and two-dimensional shallow water equations based on hydrodynamic theory. Multi-factors included the rainfall intensity, pavement width, cross slope, longitudinal slope and pavement roughness coefficient. The two-dimensional hydrodynamic method was validated by a natural rainfall event. Based on the design scheme of Shen-Shan expressway engineering project, the limited training data obtained by the two-dimensional hydrodynamic simulation model was used to predict water film thickness. Furthermore, the distribution of the water film thickness influenced by multi-factors on the pavement was analyzed. The accuracy of the ANN model was verified by the 18 sets of data with a precision of 0.991. The simulation results indicate that the water film thickness increases from the median strip to the edge of the pavement. The water film thickness variation is obviously influenced by rainfall intensity. Under the condition that the pavement width is 20 m and the rainfall intensity is 30 mm/h, the water film thickness is below 10 mm in the fast lane and 20 mm in the lateral lane. Although there is fluctuation due to the amount of training data, compared with the calculation on the basis of the existing criterion and theory, the ANN model exhibits a better performance for depicting the macroscopic distribution of the asphalt pavement water film.

Key words: pavement engineering; water film thickness; artificial neural network; hydrodynamic method; prediction analysis

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An excess of water on the pavement leads to a lower bearing capacity of the pavement structure and reduces pavement life. The existence of water on the pavement may cause hydroplaning because of splash and spray. Little is known clearly so far if there is a well-defined quantitative relationship between the factors and water film variation. The reason is perhaps that the water film variation is difficult to obtain with a high precise based on the limit samples[1]. Most of the previous studies focused on the introduction of the theories or empirical equations, and lacked consideration of pavement width. Most of them simply studied the single hydrodynamic parameter, and the influence of multi-factors such as width, slope, and rainfall intensity is still unclear[2]. Furthermore, traditional theoretical calculation cannot provide a well depiction on pavement water film variation. Therefore, a suitable prediction method for water film on the asphalt pavement is essential.

Efficient numeric modeling is a beneficial tool for water film simulation[3]. Compared with one-dimensional models, for pavement surface flow, two-dimensional shallow water equations have the advantage on solving the numerical instability and the backwater phenomenon caused by irregular bottom and curbs[4-5]. It is acceptable to mathematically simulate a variety of free surface flows. However, numerous simulation cases are required to analyze the water film variation. For this reason, the artificial neural network (ANN) is a forecasting tool that can handle the complicated issue efficiently. It does not rely on the subjective factors from multivariate regression analysis[6]. The ANN model has been extensively applied for solving highly nonlinear function approximations in the fields of asphalt pavement, rigid pavement and composite pavement[7-9]. Fast and accurate prediction results can be achieved by the ANN model based on limited data[10-11].

However, most previous studies focused on the pavement water film calculation by empirical equations, and limited work has described the prediction approach for water film distribution on the pavement. In this paper, a prediction model based on the ANN is proposed. The training data obtained by the hydrodynamic method is used to predict the water film thickness. Cases of the pavement with different widths and rainfall intensities are taken as examples to analyze the spatial variation of water film thickness. Pavement submerge risk identification is further explored. This approach is beneficial for predicting pavement water film rapidly once the amount of

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Biographies: Ma Yaolu (1989—), male, graduate; Geng Yanfen (corresponding author), female, doctor, associate professor, yfgeng@seu.edu.cn.

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training data is obtained, which is important for the pavement driving safety.

1 Artificial Neural Network Model

Artificial neural network (ANN) functions as a multilayer feed forward network depending on the error back-propagation algorithm by training data. Unlike a model which addresses the mapping interaction by a mathematical equation, the ANN model is a supervised learning procedure that minimizes the sum of error between the desired and predicted outputs by back-propagation. Mathematically, the ANN model can be treated as a universal approximation. The net structure, activation function, net parameters (weights, thresholds, learning speed and momentum coefficient) and learning error are essential for an ANN model. The network consists of three layers: input layer, hidden layer and output layer[12]. The data is put into the input layer and the hidden layer, and then the information is transmitted to the output layer on the basis of activation function[13]. The structure of the ANN model is shown in Fig. 1.

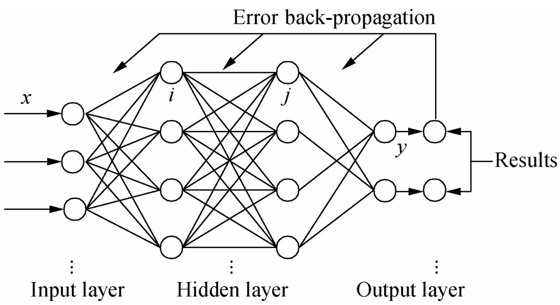

Fig. 1 ANN model structure

Fig. 1 illustrates the structure of an ANN model, in which x and y refer to the input and output; i and j represent the number of neurons in each hidden layer. Mathematically, the ANN basically carries out the training process by combining the input samples as[14]

$$y = f\left(\sum (X_1 w_1 + X_2 w_2 + \ldots) + e\right) \tag{1}$$

where y is the output result; X_1, X_2, ... represent the input variables; w_1, w_2, ... represent the weighting value of each input variable; and e is the bias.

The sigmoid function is widely used by a majority of ANN models[15], and it can be represented as

$$f(x) = \frac{1}{1 + e^{-|x|}} \tag{2}$$

In order to eliminate the error caused by the order of magnitude, the input and output data should be normalized before the training process in the ANN model according to Ref. [16].

The normalized equation is

$$Y_i = \frac{(Y_{\max} - Y_{\min})(X_i - X_{\min})}{(X_{\max} - X_{\min})} + Y_{\min} \tag{3}$$

where Y_i is the output data after normalization and training; $Y_{\min}$ and $Y_{\max}$ are the minimum and maximum values of the training data after being normalized; $X_{\min}$ and $X_{\max}$ are the minimum and maximum values of the training data before being normalized; X_i is the input data before being normalized.

2 Acquisition of Training Data for ANN

To calibrate the simulation model for obtaining the training data, pavement flow depth is monitored through a remote road surface state sensor with infrared light detection based on the practical project of the Shen-Shan expressway (The pavement cross slope is 2% and longitudinal slope is 0.464%). An on-site monitoring program was launched in the year of 2013 and lasted for more than one year (see Fig. 2).

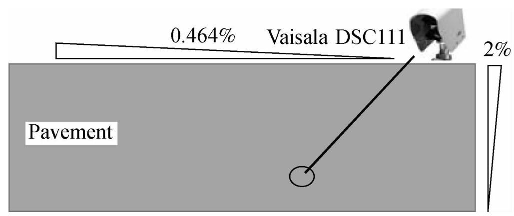

Fig. 2 Monitoring device layout

To analyze the effects of multi-factors on pavement water film thickness, a three-dimensional model is established with the length of 100 m in the X direction, and the width varying from 11 to 25 m (see Fig. 3). The influence of pavement aggregate is not considered based on two-dimensional shallow water equations. Simulation is implemented by the following equations:

$$\frac{\partial h}{\partial t} + \frac{\partial(uh)}{\partial x} + \frac{\partial(vh)}{\partial y} = Q_{(t)} \tag{4}$$

$$S_0 = \begin{bmatrix} \dfrac{\partial z_b}{\partial x} \\ \dfrac{\partial z_b}{\partial y} \end{bmatrix} \tag{5}$$

$$S_f g h = \tau_b \tag{6}$$

where

$$\tau_{b,x} = \zeta u \sqrt{u^2 + v^2}, \quad \tau_{b,y} = \zeta v \sqrt{u^2 + v^2}$$

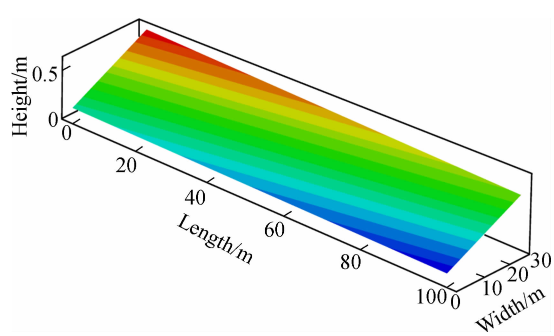

Fig. 3 Three-dimensional model of pavement

$$S_{f,x}=n^2\frac{u\sqrt{u^2+v^2}}{h^{4/3}},\quad S_{f,y}=n^2\frac{v\sqrt{u^2+v^2}}{h^{4/3}} \tag{7}$$

$$\frac{\partial}{\partial t}\begin{bmatrix}h\\uh\\vh\end{bmatrix}+\frac{\partial}{\partial x}\begin{bmatrix}uh\\u^2h+\frac{1}{2}gh^2\\uvh\end{bmatrix}+\frac{\partial}{\partial y}\begin{bmatrix}vh\\uvh\\v^2h+\frac{1}{2}gh^2\end{bmatrix}=\begin{bmatrix}Q\\ghS_{0,x}-ghS_{f,x}\\ghS_{0,y}-ghS_{f,y}\end{bmatrix} \tag{8}$$

where h is the water depth on the pavement surface, m; t is the time, s; u and v are the horizontal velocity components in X and Y directions, m/s; Q is the rainfall intensity, mm/h; z_b is the bottom elevation, m; g is the acceleration of gravity, m/s^2; n is the roughness coefficient of the pavement; S_0 is the bottom slope; ζ is the experience coefficient; τ_b is the bottom shear stress, (kg · m)/s^2; S_f is the bottom friction gradient.

Fig. 4 shows that the simulated value is in agreement with the measured value under a natural rainfall event, and the two curves are identical for the peak value. This means that the two-dimensional shallow water equations are accepted for simulating flow characteristics of the pavement water film. However, many more cases need to be done when the multi-factors are considered. For this reason, the ANN model is proposed for predicting the water film thickness rapidly and effectively once an amount of training data is collected. This capability makes it very powerful for precisely predicting the variation of the water film on the pavement surface.

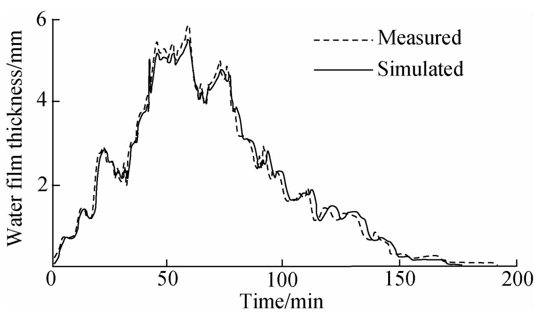

Fig. 4 Simulated and measured curves of water film thickness at the monitoring point

3 Water Film Prediction Model by ANN

Although the ANN model shows good performance in many situations, Ji[11] showed that the ANN model cannot precisely predict the water film thickness which exceeds the range of training data. Therefore, obtaining representative typical training data as much as possible can improve the prediction accuracy of the ANN model. In this paper, the number of training data is 414 which is sufficiently reliable for expressing the distribution characteristics of the water film thickness. The water film prediction model by the ANN includes one input layer of five neurons, one hidden layer of fifteen neurons and one output layer of one neuron. The input variables are the distance from the median strip, rainfall intensity, cross slope, longitudinal slope, and roughness coefficient. The output variable is the water film thickness (see Tab. 1). The sigmoid function is selected as the activation function. Refs. [16 − 17] illustrated that the number of neurons was from 6 to 15 based on the empirical formula. After the comparison, the suitable neurons' number in the hidden layer is 15 with the error of 0.003 58 (see Fig. 5) and the scatter plot accuracy of 0.991 (see Fig. 6). Then, 18 sets of data are randomly selected to verify the application of the ANN model. The relative error of the predicted values are all below 10% (see Tab. 2), which demonstrates that the predictive results have a good correlation with the simulation data.

Tab. 1 Training data

Factors	Range
Distance from median strip/m	3.7 to 29.1
Rainfall intensity/(mm · h^{-1})	25 to 187.68
Cross slope/%	2 to 3
Longitudinal slope/%	0.3 to 2
Pavement roughness coefficient	0.013 to 0.015

Tab. 2 The relative error of calibration data

Number	Relative error/%	Number	Relative error/%
1	2.67	10	0.64
2	5.87	11	7.42
3	0.42	12	7.08
4	0.88	13	5.35
5	0.92	14	1.13
6	4.40	15	1.82
7	1.03	16	0.72
8	1.40	17	8.98
9	9.71	18	2.36

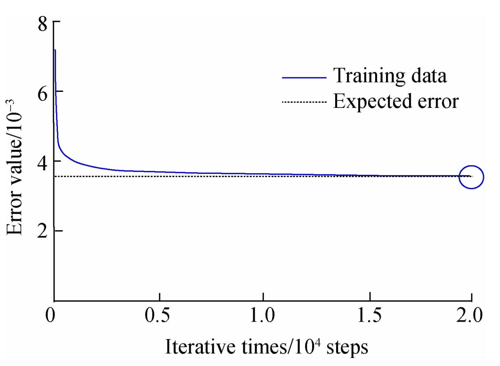

Fig. 5 Error statistics of training data

4 Application of ANN Model

4.1 Water film simulation

The goal of this application is to predict the water film thickness from the influence of multi-factors which are the distance from median strip, rainfall intensity, cross slope, longitudinal slope, and roughness coefficient[18].

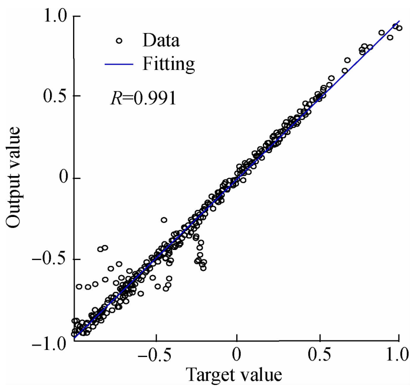

Fig. 6 Water film thickness comparison between simulation and prediction

When the selected variable changes between its minimum and its maximum value of initial data, other variables are invariable. It is necessary to add a parameter to the fixed variables' in order to analyze the variables' variation in an accepted range[18]. The variation of input variables are determined by

$$P_i = P \pm a \tag{9}$$

where P_i is the input data; P is the average value of input data; and a is the accepted range.

For the pavement with a width of 20 m, according to the specifications for drainage design of highway (JTGT D33—2012)[19], the calculated value of water film thickness is 11.21 mm under the conditions as shown in Tab. 3. From Fig. 7, it is found that the trend of variations of the prediction value on the pavement are different from the calculation value. The thickness of the water film increases clearly as the distance from the median strip increases. The maximum value exceeds 20 mm. It can be concluded that the two-dimensional characteristics on the pavement surface cannot be explained clearly by the calculation value. As schematically shown in Fig. 8, it can be concluded that the area of lateral lanes (Y = 14 to 17 m) has a larger water film thickness, which has a significant impact on the driving vehicles.

Tab. 3 Calculated value by the specifications for the drainage design of highway

Factors	Value
Rainfall intensity/(mm · h^{-1})	30
Cross slope/%	2
Longitudinal slope/%	1
Roughness coefficient	0.015

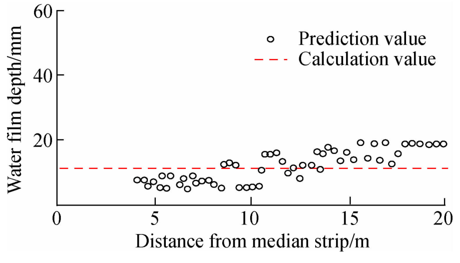

Fig. 7 Water film distribution on cross-section

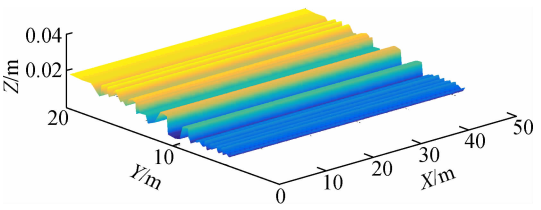

Fig. 8 Water film distribution on pavement surface

4.2 Effect of rainfall intensity

Rainfall is a crucial factor for water film variation. As is shown in Tab. 4, compared to the minimum value of water film thickness, the maximum value of water film thickness of the pavement is obviously influenced by rainfall intensity due to the flow confluence on the pavement. In particular, Fig. 9 shows that when the rainfall intensity is 100 mm/h, the water film thickness is greater than 50 mm in the location of 14 to 20 m away from the median strip. So, the lateral lane may suffer a worse situation in a strong rain intensity. On the other hand, the prediction value curve shows a fluctuation under the condition of various rainfall intensities. The fluctuation becomes more obvious as the rainfall intensity becomes stronger. It can be seen from Fig. 9 that the pavement water film thickness has an abnormal fluctuation on the location of 8 to 10 m from the median strip because the small thickness is influenced by multi-factors more easily, and this also illustrates that the ANN model has not achieved enough accuracy for small local water depths.

Tab. 4 Water film thickness value influenced by rainfall intensity

Rainfall intensity/(mm · h^{-1})	Water film thickness/mm
30	4.03 to 21.66
60	7.51 to 25.69
80	4.64 to 41.99
100	4.64 to 52.93

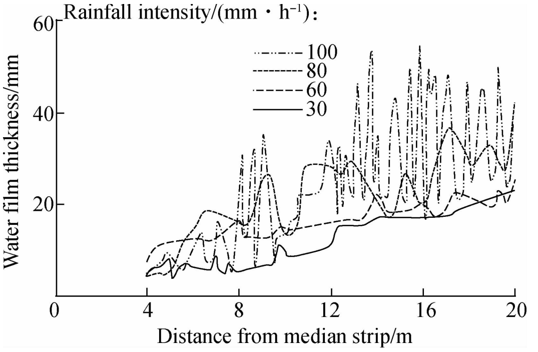

Fig. 9 Water film thickness distribution influenced by rainfall intensity

4.3 Risk identification

Having investigated the impact of water film thickness distribution by the ANN model, we subsequently studied the risk of hydroplaning depending on water film thickness, and this is beneficial to driving safety under bad weather conditions. The pavement area can be classified into a high risk area, medium risk area and low risk area. Fig. 10 shows the pavement risk identification by a variation width from 11 to 25 m. Low risk means that the pavement water film thickness is 30% lower than that of the maximum value; high risk means that a pavement water film thickness is 70% higher than that of the maximum value; and others are medium risk. The high risk area exceeds half of the pavement surface when the width of the pavement increases to 25 m. It can definitely be seen that high risk area gradually expands with the increase in the width. This is because more discharge is accumulated easily by a wider pavement. As a result, a wider pavement requires efficient drainage facilities to eliminate the adverse influence caused by the water film.

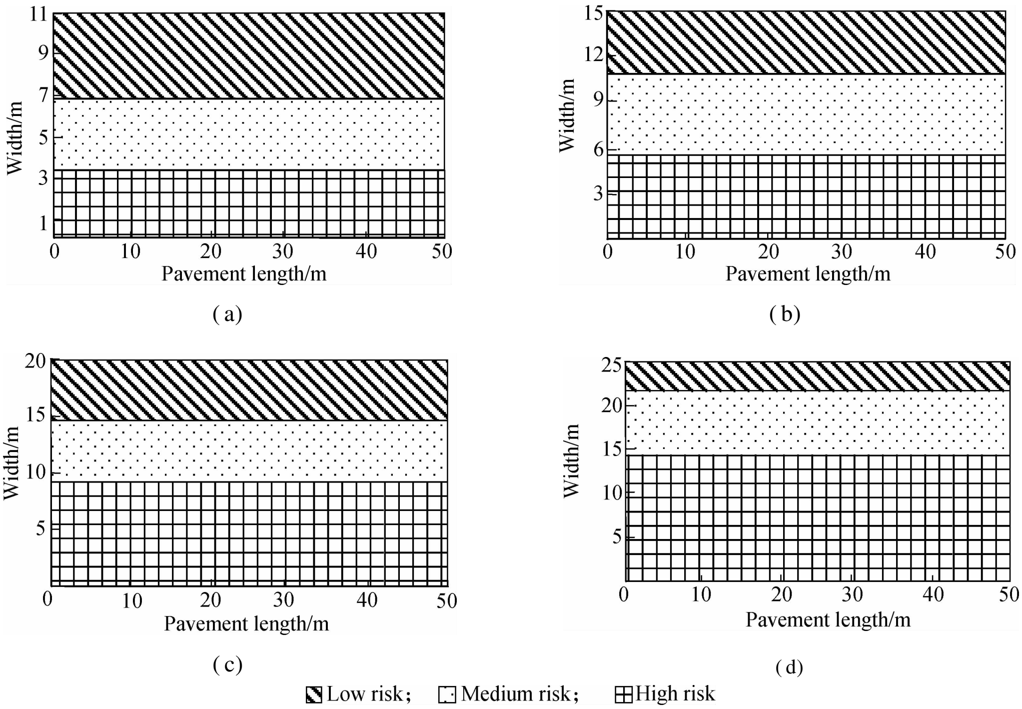

Fig. 10 Risk identification under different pavement widths. (a) 11 m; (b) 15 m; (c) 20 m; (d) 25 m

5 Conclusion

In this study, the distribution of the asphalt pavement water film is systematically predicted by an ANN model. The artificial neural network is an alternative approach for revealing the influence of multi-factors for pavement water film thickness. The approach is capable of predicting the water film distribution on asphalt pavement by using limited data. It is valuable for the design of expressway geometry and drainage. Based on this method, an operational forecasting circumstance can be achieved when using a trained ANN network, which means that the ANN model can depict the distribution of water film thickness on the asphalt pavement. Future work will focus on developing and increasing the capability of this methodology by comprising the geometric line type design of the pavement. Expanding the model to a superelevation transition section and transition curve will allow it to be applied more widely in pavement engineering.

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基于人工神经网络的沥青路面水膜厚度预测

马耀鲁[1]　耿艳芬[1]　陈先华[1]　卢艳坤[2]

([1] 东南大学交通学院,南京 210096)
([2] 辽宁省交通规划设计院有限责任公司,沈阳 110000)

摘要:为了研究多因素影响下沥青路面水膜厚度的变化,结合基于水动力学理论的二维浅水方程,提出一种利用人工神经网络(ANN)预测沥青路面水膜厚度的方法.多因素包括降雨强度、路面宽度、路面横坡、路面纵坡和路面粗糙系数.二维水动力仿真模型经过实测数据验证并根据沈山高速公路工程设计方案仿真得到有限数量的训练数据用于沥青路面水膜厚度的预测,进而分析了多因素对水膜厚度在路面分布的影响.经过18组数据的验证,人工神经网络模型预测精度可达0.991.预测结果表明:水膜厚度从中央分隔带向道路边缘逐渐增加,降雨强度对水膜厚度的变化有明显影响.在路面宽度20 m,降雨强度30 mm/h的条件下,路面内侧车道内的水膜厚度低于10 mm,外侧车道的水膜厚度为20 mm.受训练样本数量的影响,预测结果存在一定的波动,但与现行规范和理论计算值相比,人工神经网络模型能够更好地描述沥青路面水膜的宏观分布特性.

关键词:路面工程;水膜厚度;人工神经网络;水动力学方法;预测分析
中图分类号:U416.2