Applied Mathematics, Modeling and Computer Simulation
C.-H. Chen et al. (Eds.)

doi:10.3233/ATDE221138

Research on the Prediction of Traffic Accident Severity Based on BP Neural Network

Xuelian WANG[a], Ziwen ZHANG[b,1], Hui LI[b], Xing WEI[b], Junhao CHEN[a], Maozhen DING[a], Qianwen MU[b]

[a]*Guangzhou Maritime University, Guangzhou, 510700, China*
[b]*Liaoning Chemical Geological Survey Institute Co., Ltd. Jinzhou, 121007, China*

Abstract. A traffic accident severity prediction study is an estimation of the expected future traffic accidents in combination with available data. One of the core objectives of this study is to predict the number and severity of possible traffic accidents so that optimal solutions can be taken in case of accidents. In this study, we propose a research method for traffic accident severity prediction based on BP neural network. Firstly, we perform principal component analysis on accident causative factors to determine the input and output factors of BP neural network; then we analyze the principle of neural network based on the composition structure, operation mechanism and learning method of BP neural network model. In the experimental part, a traffic accident dataset of Guangzhou city from 2009 to 2016 is used as an example sample for validation and the prediction results are analyzed. The results show that the prediction value of the model is accurate between 87%-91% compared with the true value, and the prediction accuracy is high, which can effectively predict the severity of traffic accidents and has certain theoretical guidance and practical significance for the prediction of the severity of future road traffic accidents.

Keywords. Traffic Accident Prediction; BP Neural Network Model; Accident Severity; Principal Component Analysis

1. Research Background

Road traffic accident severity prediction is of great practical significance for road traffic safety evaluation, planning as well as decision making. Road traffic system is a complex system influenced by many factors, with few samples, poor information, no specific law, and showing nonlinear characteristics. The traditional linear prediction methods have great limitations in solving the nonlinear problems, and thus the prediction accuracy of traffic accident severity is not high. Considering the advantages of neural network model for solving the problem of "small amount of samples with little information" and the advantages of neural network model to approximate any nonlinear function, this study uses BP neural network as a prediction method to establish the traffic accident severity prediction model. The principal component

[1] Corresponding Author, Liaoning Chemical Geological Survey Institute Co., Ltd. Jinzhou, 121007, China; E-mail: zhzw2018@163.com

analysis of the cause of the accident is conducted by SPSS software to determine the input and output factors of the neural network, and then the principle of the neural network applied to the example is analyzed according to the composition structure, operation mechanism and learning method of the BP neural network model. The technical route is shown in figure 1[1-11].

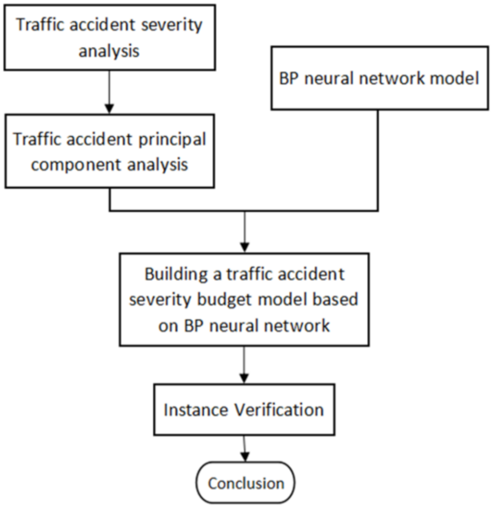


Figure 1. Technology Roadmap

2. Design Principles and Key Technologies

2.1.China's Traffic Accident Severity Classification

The Measures for Handling Road Traffic Accidents issued by the Ministry of Public Security stipulates that traffic accidents are classified as minor accidents, general accidents, major accidents, and mega accidents based on the degree and amount of personal injury or property damage, as shown in table 1. To provide some theoretical basis for the type selection of output variables of this study.

Table 1. Traffic accident severity classification

Projects	Minor	General	Major	Extra large
Deaths (people)			1-2	>3
Serious injuries (people)		1-2	3-10	>11
Minor injuries (people)	1-2	>3		
Property damage (yuan)	<1000(Motor Vehicles) <200(Non-motorized vehicles)	<30000	30000-60000	>60000

2.2. Traffic Accident Principal Component Analysis

There is a complex non-linear relationship between road traffic accidents and their causes. There are many causes of accidents, such as pedestrians, drivers, vehicles, visibility, road class, and dryness of the road surface.

The original data of the traffic accident set included 15 attributes such as weather conditions at the time of the accident, and the useless attributes in the original data were deleted, and 7 attributes related to the accident such as the number of vehicles were selected, and the primed attributes were datamined. Then principal component analysis is performed to screen out several factors that trigger the most obvious principal component loading values of serious accidents, i.e., influence indicators, and after analyzing the influence indicators, bivariate correlation analysis is performed using SPSS software to correlate the screened influence indicators with the severity or the number of accident casualties to determine the input and output factors of the neural network and lay the foundation for the subsequent establishment of road traffic safety models.

3. BP Neural Network Model

BP neural network model consists of neurons arranged distribution composition layer, according to the functional characteristics are divided into input layer, implicit layer and output layer, the neurons between the layers by the weights are fully connected to each other, the standard BP neural network structure diagram is shown in figure 2.

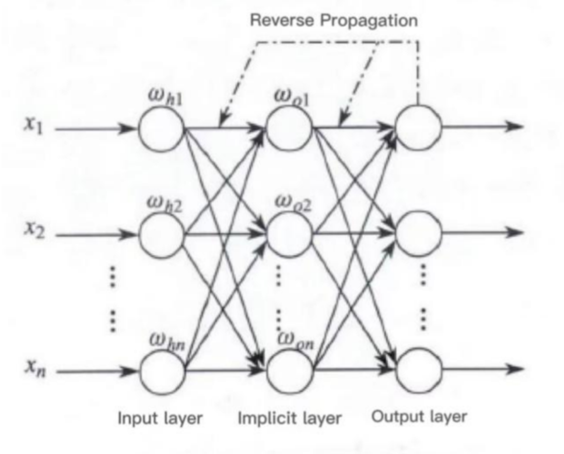


Figure 2. BP neural network structure diagram

After the topology of the BP neural network is constructed, the neural network still needs to be trained and learned in order to make the BP neural network have intelligent characteristics. The learning process of the network consists of forward propagation and backward propagation, and in the forward propagation process, the input layer passes the relationship to the hidden layer as follows.

$$Y_{hk} = F\left(\sum_{i=1}^{n} w_{hi} \cdot x_i - \theta_{hk}\right) \tag{1}$$

The formula w_{hi} is the weight from the input layer to the hidden layer, θis the threshold from the input layer to the hidden layer, X_i is the input factor of the input layer, Y_{hk} is the output factor transmitted from the input layer to the hidden layer, and also as the input factor transmitted from the hidden layer to the output layer, and the function F is the transfer function. After the samples are computationally integrated by the transfer function of the neurons in the implicit layer, they are transmitted to the output layer with the following transfer relation.

$$Y_{ok} = F\left(\sum_{i=1}^{M} w_{oi} \cdot x_i - \theta_{ok}\right) \tag{2}$$

The formula w_{oi} is the weight from the hidden layer to the output layer, θis the threshold from the hidden layer to the output layer, X_i is the input factor passed from the hidden layer to the output layer, Y_{ok} is the outward output factor, and the function F is the transfer function.

The actual output is calculated in the output layer, and if the actual output error value is too large, it is transferred to back propagation. The rule of back propagation is to modify the weights according to the change of the current error value, and decide whether to continue the iteration according to the number of required iterations and the mean squared error of the current network, and the mean squared error is calculated as follows.

$$E = \frac{1}{S}\sum_{i=1}^{S}(Y_i - y_i)^2 \tag{3}$$

Among them, Y_i denotes the desired output value and y_i denotes the network output value.

The direction of the weight modification of the BP neural network is derived by selecting the direction of the gradient of the current error reduction by the following equation.

$$w' = w + \Delta w = w - \eta \frac{\partial E}{\partial w} \tag{4}$$

Among them, w' is the new weight, η is the learning rate, and $\frac{\partial E}{\partial w}$ is the gradient direction of the error.

At this point, the error signal is back-propagated from the output layer to the input layer, and the weights of each layer are corrected and adjusted along the way, so that the error is continuously reduced until the accuracy requirement is reached. the BP neural network training process is shown in figure 3.

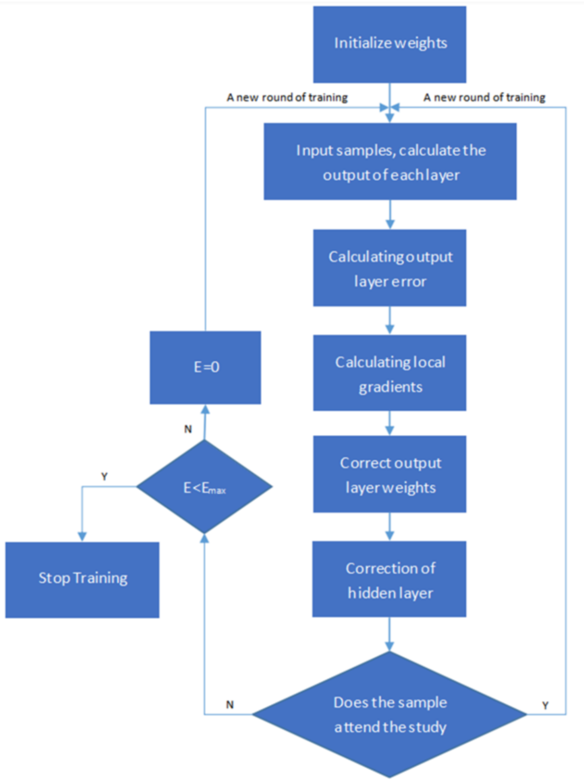


Figure 3. BP neural network training process

The principle of BP neural networks to correct the approximation function by reversing the weights is to stop the training of the network by training a large number of samples several times, using the fastest gradient descent method, so that the weights change in the direction of the negative gradient of the error function and converge to the minimum point. Reaching the maximum number of iterations or reaching the required minimum error value will also cause the network to stop training.

4. Instance Verification

The public road accident dataset of a city was used, and 4182 road traffic accident severity and accident influencing factors from 2009 to 2016 were used as the training data samples of BP neural network using the neural network to analyze the nonlinear association between accident severity and its influencing factors, and then 776 road traffic accident severity in 2017 were predicted based on the accident influencing factors in 2017, and the predicted values were derived and compared with the true values.

The first layer is the input layer, where the predictor variables (i.e., input factors) are the dryness of the road surface, light conditions, road class, vehicle type and number of vehicles obtained from the previous screening, the middle layer is the implicit layer, where the neuron connection weights are adjusted through the training set so that the network approximates the nonlinear relationship between the input and output data sets in the training set, and the last layer is the output layer, which is used to output the accident severity The final layer is the output layer, which is used to output the accident severity. The network output is processed accordingly to obtain the predicted values.

The premise of using neural network is to filter out the input and output factors of the network, and select the factors that have a greater impact on the severity of road accidents as the input of the network and the severity of accidents as the output of the network.

4.1. Data Pre-Processing

Prior to neural network modeling, the learning samples are datamined, normalized and classified.

(1)Sample datatization: Since there are a large number of textual narratives in the accident set that cannot be recognized by the software, the model is built by first datatizing the samples by road dryness, light conditions, road class, vehicle weight, and accident severity.

(2)Sample normalization: For the accuracy of the experimental results and to eliminate the influence of the magnitude of the data, the input and output data of the network need to be kept in a small range. In this study, the normalization function (mapminmax) is used to process the data into the interval [-1,1]. The formula is:

$$y = \frac{(y_{max} - y_{min}) * (x - x_{min})}{x_{max} - x_{min}} + y_{min} \tag{5}$$

y_{max} and y_{min} are the interval ranges to be normalized to, respectively, 1 and -1; x_{max} is the maximum value of the input data; x_{min} is the minimum value of the input data; x is the input data; y is the normalized data.

The normalized data can be reduced to the original data by using the following formula for inverse normalization. The predicted value after prediction by BP neural network model is also the number in the interval [-1,1], which can be reduced using the inverse normalization formula to get the predicted value.

$$x = \frac{(y - y_{min}) * (x_{max} - x_{min})}{(y_{max} - y_{min})} + x_{min} \tag{6}$$

(3)Sample classification. Before actually using the BP neural network model for accident prediction, the model is trained using learning samples. The learning sample data is divided into training data, validation data and test data. The training data generally accounts for 70% of the total learning samples, which is used for network training and model construction; the validation data generally accounts for 15% of the total learning samples, which is used to test the training of the network and can be used several times; the test data accounts for 15% of the learning samples, which is only used to test the generalization ability of the completed training model and cannot be used several times, otherwise it will lead to overfitting of the model with the learning samples and reduce the prediction ability of the model.

4.2. Determine the Number of Hidden Layer Neurons

The hidden layer of the BP neural network is determined by the empirical equation $a=\sqrt{b+c}+\alpha$, where a denotes the number of neurons in the hidden layer; b denotes the number of input factors; c denotes the number of output factors; α is a constant from 1 to 10; the number of input factors in this study is 5 and the number of output factors is 1; therefore, the number of hidden layer neurons should be from 2 to 13.

According to the principle of determining the number of hidden layer neurons, the number of hidden neurons should be between the size of the input layer and the size of the output layer; the number of hidden neurons should be the sum of 2/3 of the size of the input layer and 2/3 of the size of the output layer; twice the size of the input layer should be larger than the number of hidden neurons; after calculation, the optimal number of hidden layer neurons is initially determined to be 4, and the number of hidden layer neurons is selected as the control group when the number of hidden layer neurons is 2, 3 and 5.

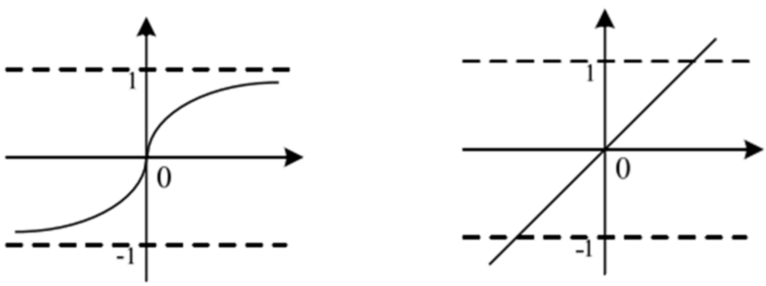
4.3. Selection of Transfer Function

The sigmoid function is often used as the transfer function for the hidden layer of BP neural networks, and the formula is as follows:

$$F(x)=\frac{1}{1+e^{-x}} \tag{7}$$

The commonly used sigmoid conversion functions are tansig and logsig, both of which can make nonlinear adjustments to the amplification coefficients, i.e., smaller amplification coefficients for larger signals and larger amplification coefficients for smaller signals, which are conducive to approximating nonlinear variables and improving the stability and accuracy of prediction models, and therefore, sigmoid functions are often used to deal with nonlinear problems.

The prediction results of the neural network show that the accuracy of the model is higher when the tansig function is used as the transfer function of the model compared to the logsig function, therefore, the tansig function is used as the transfer function of the model in this study. In order that the output of the network can take arbitrary values, the purelin function is used as the transfer function of the output layer of the model. Figure 4 shows the transfer function image.



logsig or tansig function image purelin function image

Figure 4. Transfer function image

4.4. Selection of Training Function

Section selected the accident set from 2009-2016 as the training set of the model to predict the severity of accidents in 2017. After several training sessions to compare the error values and determine the network parameters, the training function was selected to train the display interval 25, the momentum factor 0.9, the minimum mean square error (learning rate) was set to 0.01, the training target was set to 1e-7, and the maximum number of training sessions was set to 10000. The model is trained with the Traingdm training function, i.e., the model is trained using the momentum gradient descent algorithm, and it is obtained from table 2 that when the hidden nodes are 4 and the transformation function is tansig, the medium error value is the smallest and the best prediction is achieved.

Table 2. Prediction error statistics of traingdm training function

Number of hidden layer nodes	N=2		N=3		N=4		N=5	
Convert Functions	tansig	logsig	tansig	logsig	tansig	logsig	tansig	logsig
Medium error value	61.9573	87.2533	8.3247	8.2887	5.5174	8.3247	8.7178	41.9404

From the plot of gradient versus learning times for the validation data in figure 5, it can be obtained that the training step is longer than the gradient change and the model training is better. From figure 6, it can be obtained that the mean square error has been reduced to the specified value before the end of training, and the model training effect is better.

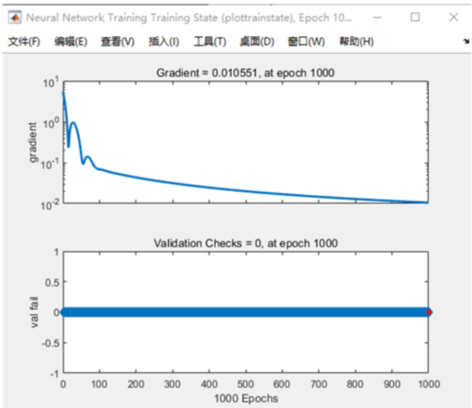


Figure 5. The gradient of the validation data versus

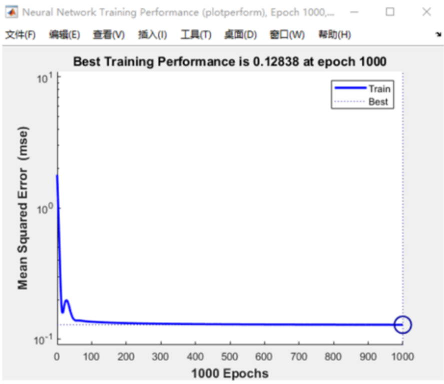


Figure 6. Plot of training data gradient the number of learning versus mean square error

When the model is trained with traingdm training function, the hidden layer nodes are 4, and the transformation function is tansig, the medium error value is the smallest, the model training effect is better, the prediction is the most accurate, and the convergence speed is fast, therefore, this study intends to use the above design to compose the BP neural network model structure. the BP neural network structure design diagram is shown in figure 7.

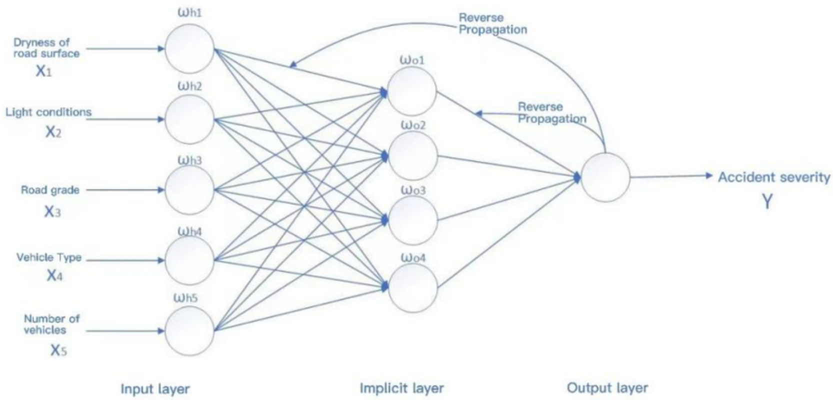


Figure 7. BP neural network structure design diagram

4.5. Comparison of Model Prediction Results

The prediction results of 776 road traffic accident severity BP neural network prediction models in 2017 were compared with the true values as shown in table 3 below.

Table 3. Comparison of predicted and true values of BP neural network

Traffic accident severity	True Value	BP neural network predicted value	Accuracy
Minor	95	83	87%
General	128	114	89%
Major	185	168	91%
Extra large	368	331	90%

As seen from table 3, the predicted values of the BP neural network model are in the range of 87%-91% accuracy compared with the true values, which is a practical and effective method for predicting the severity of traffic accidents.

5. Summary of Innovation Points and Application Prospects

This study focuses on the road traffic accident severity prediction based on the analysis of road traffic safety influencing factors, and establishes a BP neural network model for road traffic accident severity prediction. Due to the superiority of neural network in the problem of nonlinear and not easy to build mathematical models, the model can converge well to a certain value and can predict the accident severity well, which can reveal the relationship between road traffic accident severity and its influencing factors within a small error range, and can be used in the prediction of future national road traffic safety.

Acknowledgments

This research content of this paper is supported by Guangdong Science and Technology Innovation Strategy Special Funds(pdjh2022b0392, pdjh2022b0394)and College Students' innovation and Entrepreneurship Projects(C2106001310, 202211106008).

References

[1] Yu Bo-Xiang, Yang Jin-Yun. Analysis and prediction of traffic accident influencing factors under big data[J]. Electronic Components and Information Technology, 2021,5(05):61-63.
[2] WANG Lei, QIU Feng, XIA Yongxu, HAN Xingbo. Traffic accident prediction in road tunnels based on road environment factors[J]. Tunnel Construction(in English and Chinese),2019,39(08):1301-1307.
[3] Li YJ. Research on the analysis of factors influencing road traffic accidents and severity prediction in China[D]. Jilin University, 2020. DOI:10.27162/d.cnki.gjlin.2020.006108.
[4] Yang X.G., Li D.S., Ren G.Y.. Analysis of road traffic accident prediction in Beijing based on residual modified gray prediction model[J]. Practice and understanding of mathematics,2018,48(03):159-166.
[5] Wang Yanhao. Research on traffic accident prediction method based on graph neural network[D]. North China Electric Power University (Beijing), 2021. DOI:10.27140/d.cnki.ghbbu.2021.001327.
[6] ZHANG Zhihao, YANG Wenzhong, YUAN Tingting,LI Donghao, WANG Xueying. Traffic accident prediction based on LSTM neural network model[J]. Computer Engineering and Applications,2019,55(14):249-253+259.
[7] Wang S.F.,Zhu Y.Q.. Road traffic accident prediction based on gray BP neural network model[J]. Journal of Baicheng Normal College,2019,33(06):36-40+51.
[8] Liu Y, Yang L, Peng Z R, Huang K Y. Establishment and effect evaluation of BP artificial neural network prediction model for road traffic accidents in Guangxi[J]. Guangxi Medicine,2013,35(03):257-259.
[9] Sun Keda. Research on BP neural network road traffic accident prediction model based on GA [D]. Zhejiang University of Technology, 2008.
[10] Yu, Haisheng. Research on road traffic accident prediction system based on GM-BP combined model[D]. Chongqing Jiaotong University, 2020. DOI:10.27671/d.cnki.gcjtc.2020.000814.
[11] Ministry of Transportation. Interim Regulations on Traffic Accident Statistics [Z]. 2004-05-20:,2004.