Hindawi
Advances in Civil Engineering
Volume 2022, Article ID 4477178, 11 pages
https://doi.org/10.1155/2022/4477178

*Research Article*

# Benefit Evaluation of Preventive Maintenance of Highway Bridges Based on Fuzzy Neural Network

**Yiquan Zou, Jialin Fang, and Zedong Liu**

*School of Civil Engineering, Architecture and Environment, Hubei University of Technology, Wuhan 430068, China*

Correspondence should be addressed to Jialin Fang; 102000722@hbut.edu.cn

Received 24 March 2022; Revised 25 August 2022; Accepted 19 October 2022; Published 23 November 2022

Academic Editor: Nicola Baldo



Aiming at the deficiencies in the existing bridge preventive maintenance evaluation, this paper constructs a concrete bridge preventive maintenance benefit evaluation index system based on the common preventive maintenance methods of concrete bridges. The comprehensive evaluation vector is used as the training data of the neural network to construct a preventive maintenance benefit evaluation model of concrete bridges based on a fuzzy neural network, and use the model to evaluate the maintenance benefit of specific construction cases. The results show that the model has high accuracy and practicability for the evaluation of preventive maintenance benefits of concrete bridges.

## 1. Introduction

The preventive maintenance of highway bridges is an important part of the bridge engineering construction project. The maintenance engineering of highway bridges has two parts: preventive maintenance and corrective maintenance. Corrective maintenance refers to the maintenance and reinforcement after the maintenance object has problems. After completing the inspection of the bridge and discovering bridge diseases and problems, the maintenance is carried out, and various measures are taken to enhance the bearing capacity, passing capacity, and durability of the bridge, but relatively preventive maintenance is a relatively passive maintenance strategy, and it is not planned and global. The preventive maintenance rule is a more active, premaintenance based on the actual use of roads and bridges. That is to say, it is a relatively advanced maintenance method to carry out maintenance when road and bridge diseases have not yet appeared or may have symptoms of the disease. It is based on the current basic principle of "prevention first, combined with prevention and treatment" for road maintenance. Preventive maintenance measures from time to time can effectively improve the service life of bridges, and the construction is convenient and rapid, with little impact on traffic and society [1]. Compared with corrective maintenance, it has better maintenance benefits in most cases [2].

Some scholars at home and abroad have carried out research on the benefit evaluation of preventive maintenance of highways and bridges. In the 1980s, the United States first proposed the concept of preventive maintenance, which was defined by the American National Highway and Transportation Association (AASHTO, 1999). It is a systematic process of applying a series of preventive maintenance measures in the life cycle of the bridge, in order to ensure the good condition of the bridge, prolong the life of the bridge, and minimize the maintenance cost in the life cycle [3]. Actions taken in this process should not include corrective maintenance measures, such as additions to the completed road system and its ancillary facilities. Domestic research on preventive maintenance first started with reference to foreign preventive maintenance systems. Zhang et al. [4] established a preventive maintenance system for concrete bridges from multiple perspectives by drawing on foreign experience and combining domestic relevant technical status assessment methods. Sun et al. [5] established a set of fuzzy comprehensive evaluation system for preventive maintenance from the perspective of bridge reliability and economy. Wang et al. [6] established a comprehensive evaluation system after the preventive maintenance of bridges based on the grey system method. He [7] used the improved uncertainty analytic hierarchy process to study the comprehensive evaluation index system of bridge preventive maintenance. Yu et al. [8] established an evaluation system for the preventive maintenance of bridges in Tianjin.

Judging from the existing research, some preliminary results have been achieved on the analysis of the benefit factors of bridge preventive maintenance and related evaluation methods, but there are generally problems such as weak operability, strong subjectivity, and insufficient evaluation system. In view of this, in order to further improve the bridge preventive maintenance benefit evaluation system, improve the reliability and accuracy of bridge preventive maintenance evaluation. This paper proposes a fuzzy neural network method combining fuzzy evaluation and neural networks. A more complete bridge preventive maintenance benefit evaluation system should be established to improve my country's highway bridge evaluation theory system.

## 2. Evaluation Index System of Bridge Preventive Maintenance Benefit

*2.1. The Basis and Principles of the Construction of the Evaluation Index System.* To evaluate the benefits of bridge preventive maintenance, we must first build a scientific and reasonable evaluation index system. The comprehensive evaluation index system of bridge preventive maintenance benefits is the carrier of quantitative evaluation of maintenance benefits. Through the index system, the specific objects of maintenance benefit evaluation can be defined, so as to realize the conversion of qualitative indicators to quantitative evaluation data [9]. The comprehensive evaluation of the preventive maintenance benefits of bridges needs to be based on a scientific and reasonable comprehensive evaluation system. The influencing factors of bridge preventive maintenance benefits are complex and nonlinear, and it is difficult for different types of maintenance benefits to be classified into the same level, economy, transportation, and people's livelihood, so as to cover all aspects of bridge preventive maintenance benefit evaluation [10].

Take the technical benefit, economic benefit, traffic benefit, and people's livelihood benefit of the bridge as the first-level indicators of the indicator system, residents' travel convenience, surrounding environment improvement, cultural landscape preservation, passenger transportation cost reduction, freight cost reduction, enterprise transportation cost reduction, construction cost reduction, labor cost reduction as secondary indicators, and the final completion includes 4 primary indicators and 16 indicators The comprehensive evaluation index system including secondary indicators are shown in Table 1.

*2.2. The Weight of the Evaluation System Is Determined.* Usually in the process of building a multilevel comprehensive evaluation system, the importance of each evaluation index is different. Therefore, whether the weight of different indicators is scientifically determined or not affects the accuracy of the evaluation to a large extent. In this paper, the AHP method is used to determine the weight, through the above analysis of various factors, combined with expert discussion to construct a judgment matrix according to the 1–9 scale method [11]; first, a single-level ranking is performed, in which the first-level index layer constructs a matrix for the target layer, and the second-level index layer constructs a matrix for the target layer. The level indicator layer constructs 4 matrices. There are generally three methods for calculating weights using AHP: the arithmetic mean method to calculate the weight formula (1), the geometric mean method to calculate the weight formula (2), and the eigenvalue method to calculate the weight formula (3). In this paper, three methods are used to calculate and average to obtain the weight vector.

$$\omega_i = \frac{1}{n}\sum_{j=1}^{n}\frac{a_{ij}}{\sum_{k=1}^{n}a_{kj}}, \ (i = 1, 2, \ldots n), \tag{1}$$

$$\omega_i = \frac{\left(\prod_{j=1}^{n} a_{ij}\right)^{(1/n)}}{\sum_{k=1}^{n}\left(\prod_{j=1}^{n} a_{kj}\right)^{(1/n)}}, \ (i = 1, 2, \ldots n), \tag{2}$$

$$M\omega = \lambda_{\max}\omega. \tag{3}$$

In the formula, $\omega_i$ is the weight vector, $a_{ij}$, $a_{kj}$ for the matrix $i$ row $j$ column, $k$ row $j$ column element. $M$ is the judgment matrix; $\lambda_{\max}$ is the largest eigenvalue of the matrix $M$; $\omega$ is the normalized eigenvector corresponding to the largest eigenvalue.

In the AHP method, the single-level ordering needs to perform the single-level ordering test on the constructed matrix to calculate the consistency index $CI$, respectively. The formula is as follows:

$$CI = \frac{\lambda_{\max} - n}{n - 1}, \qquad CR = \frac{CI}{RI}. \tag{4}$$

In the formula, $n$ is the order of the judgment matrix, $CI$ is the consistency indicator, $CR$ is the consistency ratio, and $RI$ is the stochastic consistency indicator. The specific values are shown in Table 2.

After the single-level sorting is performed, the weight sorting of the relative importance of each index to the total target layer is calculated according to the results of the single-level sorting. This process is called total hierarchical sorting:

$$b_i = \sum_{j=1}^{m} b_{ij}\alpha_j, \tag{5}$$

where $\alpha_j$ is the sorting weight of the total target layer for the $m$ elements of this layer and $b_{ij}$ is for the $n$ elements of the next layer, the hierarchical single ordering weight of a factor in this layer.

Table 1: Evaluation system of preventive maintenance of highway bridges.

| Purpose | First-level indicator | Secondary indicators |
|---|---|---|
| The benefits of preventive maintenance of highway bridges | Technical benefits | Safety |
| | | Applicability |
| | | Durability |
| | Traffic benefits | Reduced vehicle travel time |
| | | Traffic growth |
| | | Traffic growth rate |
| | | Fewer casualties |
| | | Cargo damage is reduced |
| | People's livelihood benefits | Residents' travel convenience |
| | | Surrounding environment improvement |
| | | Cultural landscape preservation |
| | Economic benefits | Remaining life cycle cost |
| | | Construction cost |
| | | Environmental pollution cost |
| | | Direct economic benefits |
| | | Indirect economic benefits |

Table 2: Values of random consistency index RI.

| $n$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| $RI$ | 0 | 0 | 0.58 | 0.90 | 1.12 | 1.24 | 1.32 | 1.41 | 1.51 |

Hierarchical total ranking consistency test:

$$CR = \frac{\sum_{j=1}^{m} CI(j)\alpha_j}{\sum_{j=1}^{m} RI(j)\alpha_j}, \tag{6}$$

where $CI(j)$ is the single-rank consistency index obtained for this layer and $RI(j)$ is the average consistency index corresponding to $CI(j)$, and the values of $RI$ are shown in Table 2.

From formula (5), the total sorting weight vector of the target layer by the index layer can be obtained as $\omega = [0.08314, 0.08751, 0.08135, 0.023354, 0.114165, 0.15741, 0.062078, 0.036671, 0.053335, 0.029352, 0.016152, 0.022501, 0.035429, 0.09676, 0.044283, 0.058257]$. According to formula (6), the consistency ratio of the total ranking of the hierarchy can be obtained as follows: $\mathrm{CR} = 0.026004 < 0.1$, which meets the consistency requirements. Drawing of a histogram is shown in Figure 1.

## 3. Theoretical Analysis of the Fuzzy Neural Network

*3.1. The Basis and Principles of the Construction of the Evaluation Index System.* Fuzzy mathematics is a general term for a mathematical theory established by Professor L. A. Zadeh on the basis of fuzzy sets and logic, which can describe fuzzy objects with cognitive uncertainty. Using the fuzzy evaluation method designed by fuzzy mathematics theory, the uncertain fuzzy problem can be transformed into a relatively clear and definite quantitative problem through the corresponding comment set and membership function, so as to realize the description and analysis of the problem [12]. The artificial neural network is an artificial intelligence computing model that imitates the human brain neuron network and forms a network according to different connection methods. It has better self-learning function and associative memory function. With the help of computer, fast and accurate calculation can be conducted. It has strong advantages and ductility when dealing with multi-index evaluation problems of complex systems [13]. The limitation of fuzzy evaluation is that it is affected by the subjective factors of the implementer in the process of describing and analyzing the problem, and it is difficult to achieve high-precision calculation, while the neural network does not have the advantage in the process of data transformation of the initial research object. By combining fuzzy mathematics and neural network, the limitations of both can be effectively overcome, and the effective transformation of uncertain problems and scientific computing can be achieved.

*3.2. Applicability Analysis of the Model.* The benefit evaluation of preventive maintenance of highway bridges is an uncertain system process involving many types of uncertain factors. Usually, the description of benefit attributes is difficult to express with objective data with uniform dimensions and accurate numerical values, which requires the use of fuzzy mathematics to achieve qualitative problems. Transformation of vectorized descriptions. Combined with engineering practice, make full use of the experience and knowledge accumulation of on-site construction managers and experts and scholars in the field, determine the attributes and grades of specific bridge maintenance benefits, implement fuzzy evaluation, and input the evaluation results into the neural network model that has been trained to achieve operational accuracy. In the construction process, the evaluation operation is carried out with the help of the computer platform, and the risk evaluation of the construction process is effectively completed [14].


Figure 1: Indicator weights.

*3.3. Construction of Fuzzy Neural Network Evaluation Model.* Fuzzy theory is a method of quantifying fuzzy concepts, which uses the concept of membership. The determination of the fuzzy membership degree of an index usually requires a distinction between qualitative and quantitative indicators [15]. The calculation process of the membership degree of qualitative indicators is as follows. First, construct the membership comment set $U$. $U$ = [high benefit, , medium benefit, and low benefit]. After that, $n$ experts were invited to score the indicators, and the average $R_i$ of the scores of each indicator was calculated, which was used as the evaluation value of each indicator factor.

$$\overline{R}_i = \frac{\sum_{i=1}^{n} R_i}{n}. \tag{7}$$

In order to ensure the convenience and effectiveness of data processing, the scoring system adopts the percentage system. According to this, the membership degree of a single qualitative index to each comment can be calculated $\mu_{i,}$.

$$\mu_i = \frac{\overline{R}_i}{100}. \tag{8}$$

The commonly used methods for calculating the membership degree of quantitative indicators are the Gaussian function or fuzzy subjective ideal point method. This paper adopts the fuzzy subjective ideal point method. The basis for the implementation of the method is to first determine the optimal value $X_{\max}$ and the worst value $X_{\min}$ of the quantitative index. The determination of the relevant values is based on the completed project practice and acceptance and is given by the road and bridge preventive maintenance practitioners and relevant experts based on the experience set.

When the extreme value is determined, the lower benefit value, the middle benefit value, and the higher benefit value are determined in the process of data collection. The data collection results should all fall within the ($X_{\min}$, $X_{\max}$) interval. Membership is calculated separately for positive and negative indicators.

Membership of positive indicators:

$$\mu_i = \begin{cases} 0 & X_i \leq X_{\min} \\ \dfrac{X_i - X_{\min}}{X_{\max} - X_{\min}} & X_{\min} < X_i < X_{\max}. \\ 1 & X_i \geq X_{\max} \end{cases} \tag{9}$$

Membership of negative indicators:

$$\mu_i = \begin{cases} 1 & X_i \leq X_{\min} \\ \dfrac{X_i - X_{\min}}{X_{\max} - X_{\min}} & X_{\min} < X_i < X_{\max}. \\ 0 & X_i \geq X_{\max} \end{cases} \tag{10}$$

The index weight vector obtained by the AHP method and the membership degree matrix are multiplied step by step to obtain the comprehensive evaluation value of each secondary index and the preventive maintenance benefit of the bridge.

Combining the collected data and bridge maintenance specifications, this paper takes one second-level index under the four first-level indicators as an example to establish the reference value of the scoring standard, as shown in Table 3. The reference values of the remaining indicators will not be repeated. All reference values and equations (7)–(10) can be used to obtain the bridge preventive maintenance benefit grade, as shown in Table 4.

The benefit grade scale is the basis for the benefit evaluation of the preventive maintenance of highways and bridges, as well as the basic reference for bridge management. The reference to the benefit grade of the preventive maintenance of bridges will help bridge managers to assess the preventive maintenance of different bridges according to the constraints of funds and personnel. Maintenance plan decisions. Projects with five-level maintenance benefits are considered as high-efficiency bridge preventive maintenance

Table 3: Reference value of index system classification standard.

| Index | | Maintenance benefit level | | | | |
|---|---|---|---|---|---|---|
| | | One | Two | Three | Four | Five |
| Safety | Basic features | Excellent | Good | General | Poor | Very poor |
| | Reference | >95 | 95~85 | 85~80 | 80~75 | <75 |
| Traffic growth rate | Basic features | Excellent | Good | General | Poor | Very poor |
| | Reference | >100% | 100%~40% | 40%~10% | 10%~0% | <0% |
| Resident satisfaction | Basic features | Excellent | Good | General | Poor | Very poor |
| | Reference | >90 | 90~80 | 80~70 | 70~60 | <60 |
| Construction cost | Basic features | Excellent | Good | General | Poor | Very poor |
| | Reference | >90 | 90~80 | 80~70 | 70~60 | <60 |

Table 4: Benefit grades of preventive maintenance of highway bridges.

| Benefit class | Level 1 | Level 2 | Level 3 | Level 4 | Level 5 |
|---|---|---|---|---|---|
| Benefit evaluation value | >0.85 | 0.63~0.85 | 0.45~0.63 | 0.21~0.45 | <0.21 |

projects, and preventive maintenance should be carried out for such bridge projects first. Such projects should be given priority after the fifth-level projects; the third-level maintenance benefits are medium maintenance benefits, and preventive maintenance should be carried out after the fourth- and fifth-level projects are completed; the second-level maintenance benefits are relatively low, and preventive maintenance measures should be carefully evaluated to determine whether maintenance is required or not, the benefit of primary maintenance is low, and preventive maintenance is generally not performed on such bridges [16].

*3.4. BP Neural Network.* Artificial neural networks can be divided into different types according to the different network structures and learning algorithms. Among them, the feedforward neural network (backpropagation feedforward neural network, BPFNN/BPNN) of backward propagation learning is the most widely used. In BPNN, the learning algorithm of backward propagation is used to reflect the training process, which requires supervised learning; the feedforward network is a structure, which is reflected in the network structure of BPNN. The network connection weight $\omega_{ij}$ between two neurons will be initialized to a small random number (usually −1.0~1.0 or −0.5~0.5, determined by the designer according to the problem itself), in addition, each artificial neuron simulated by the computer will have a bias parameter $\theta_i$, also initialized to a random number. When this algorithm processes samples, input from the input layer and forward the structure to the first hidden layer, and then, the first hidden layer processes the received data as the output, which is used as the input of the second hidden layer, and so on, until the output of the output layer; backpropagation refers to getting the error by comparing the actual output of the output layer with the expected result, and then adjusting the network weight between the last hidden layer and the output layer through the error equation, and then performing error feedback from the last hidden layer to the penultimate hidden layer, adjusting the network weight between them, and so on, until the network weight between the input layer and the first hidden layer is adjusted. The network obtained after training can be used to stably evaluate the preventive maintenance benefits of highway bridges and obtain evaluation results [17].

The number of nodes in the input layer of the model is $n$, which is the number of indicators for the evaluation of preventive maintenance benefits of highway bridges [18]; related studies have shown that there is a neural network with a hidden layer; as long as there are enough hidden nodes, it can be approximated with arbitrary precision a nonlinear function. Therefore, this paper uses a three-layer input and a single-output BP neural network with a hidden layer to establish a prediction model; when designing the network, it is very important to determine the number of neurons in the hidden layer. If the number of neurons in the hidden layer is too large, it will increase the amount of network computation and easily lead to overfitting problems; if the number of neurons is too small, it will affect the network performance and fail to achieve the expected purpose. The number of neurons in the hidden layer in the network has a direct relationship with the complexity of the actual problem, the number of neurons in the input layer and output layer, and the corresponding expected error setting. At present, there is no clear formula for the determination of the number of neurons in the hidden layer at home and abroad, only some empirical formulas, or according to the designer's experience and a large number of experiments. In this paper, the following empirical formula is used to select the number of neurons in the hidden layer:

$$l = \sqrt{n + m} + a, \tag{11}$$

where $n$ is the number of neurons in the input layer, $m$ is the output layer neuron, and $a$ is the constant between 1 and 10.

The number of nodes in the output layer is set as 1, which is the benefit evaluation value of preventive maintenance of highway bridges; $\omega_{ij}, \omega_j$ are the weights of the BP neural network; the initial hidden layer and the output layer neuron bias is $\theta_i$ to act as the threshold and the learning rate and neuron activation function. Figure 2 shows that the BP neural network can be seen as a functional relationship mapping from $n$ to 1.

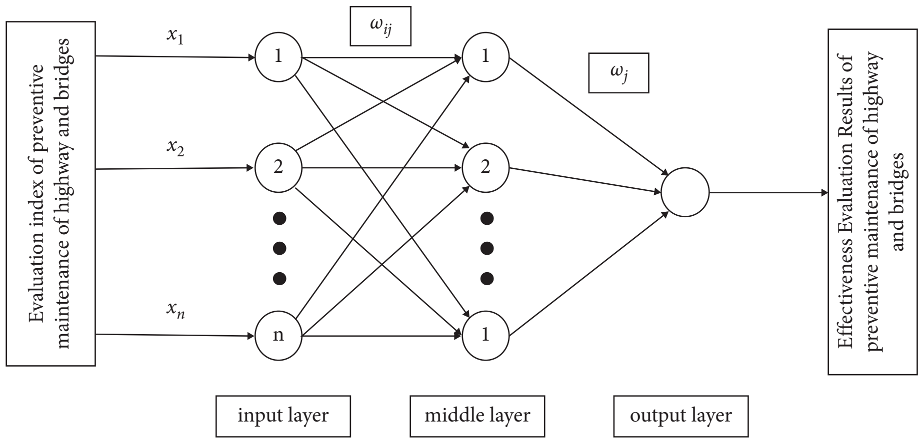


Figure 2: BP neural network architecture.

BPNN is divided into a training phase and a usage phase in practical applications. In the training stage, according to the given samples, the backpropagation learning algorithm is used to adjust the network parameters of the feedforward neural network structure, such as the number of layers of the network structure, the number of neurons in each layer, the connection weight, and the neuron bias, so that the trained network can have a good fitting effect on the samples. The network can have a good fitting effect on the samples [19]. The BP training process flow is as follows:

(1) Initialize the network weights: The network connection weight between every two neurons and the bias of each neuron are obtained from the random interval of 0 to 1 by the computer as a new starting point for the calculation.

(2) Forward propagating the input: First, the input layer of the network is provided according to the training sample $x$, and the output of each neuron is obtained by calculation. The calculation methods are the same, and they are all derived from the linear combination of their inputs. The specific formula is as follows:

$$O_j = \frac{1}{1+e^{-S_j}},\qquad S_j = \sum_i \omega_{ij} O_j + \theta_j. \tag{12}$$

Here, $\omega_{ij}$ is the network weight from unit $i$ to this unit $j$ in the previous layer, $O_j$ is the output of unit $i$ of the previous layer, $\theta_j$ is the offset of this unit, and $S_j$ is the total input.

(3) Backward error propagation: The error of each output unit $j$ is obtained by comparing with the expected output, as shown in the following formula:

$$E_j = O_j\left(1-O_j\right)\left(T_j - O_j\right). \tag{13}$$

Here, $E_j$ is the error of the output unit $j$ and $T_j$ is the expected output value of the output unit $j$.

The obtained error needs to be propagated from the back to the front. The error of the unit $j$ in the previous layer can be calculated by the error of all the units $k$ in the latter layer connected to it. The specific formula is as follows:

$$E_j = O_j\left(1-O_j\right)\sum_k \omega_{jk} E_k. \tag{14}$$

(4) Adjust the network weight and neuron bias: The method of adjusting the weight is to start with the connection weight of the input layer and the hidden layer and proceed backward in turn. Each connection weight $\omega_{ij}$ is adjusted according to the following formula.

$$\omega_{ij} = \omega_{ij} + \Delta\omega_{ij} = \omega_{ij} + (l) O_i E_j. \tag{15}$$

The adjustment method of neuron bias of each neuron $j$ is shown in the following formula.

$$\theta_j = \theta_j + \Delta\theta_j = \theta_j + (l) E_j. \tag{16}$$

In equations (15) and (16), $l$ is the learning rate, usually a constant between 0 and 1. This parameter will affect the training efficiency of the algorithm, too small a learning rate will lead to too slow learning, and too large the learning rate may cause the algorithm to vibrate between inappropriate solutions and fail to converge to the global optimal solution. The empirical rule is to set the learning rate to the reciprocal of the number of iterations $t$, that is, $l = 1/t$.

*3.5. Parameter Training and Validation.* On the basis of determining the fuzzy benefit level and the fuzzy comprehensive evaluation maintenance benefit value, a neural network evaluation model is constructed for scientific evaluation [20]. The evaluation indicators of different bridges are brought into the fuzzy analytic hierarchy process model to obtain the evaluation value of preventive maintenance benefits of these bridges [21]. The former part of the data and the benefit evaluation value are used as training

Table 5: Evaluation index data of preventive maintenance of highway bridges.

| Bridge | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| Evaluation metrics | 1 | 0.264 | 0.344 | 0.294 | 0.352 | 0.265 | 0.287 | 0.149 | 0.244 |
| | 2 | 0.327 | 0.328 | 0.352 | 0.329 | 0.297 | 0.310 | 0.323 | 0.338 |
| | 3 | 0.257 | 0.213 | 0.280 | 0.232 | 0.293 | 0.247 | 0.279 | 0.234 |
| | 4 | 0.185 | 0.151 | 0.159 | 0.173 | 0.182 | 0.163 | 0.167 | 0.170 |
| | 5 | 0.142 | 0.386 | 0.269 | 0.262 | 0.542 | 0.569 | 0.401 | 0.461 |
| | 6 | 0.456 | 0.120 | 0.208 | 0.857 | 0.271 | 0.856 | 0.735 | 0.008 |
| | 7 | 0.918 | 0.562 | 0.987 | 0.652 | 0.150 | 0.511 | 0.767 | 0.480 |
| | 8 | 0.644 | 0.255 | 0.367 | 0.103 | 0.194 | 0.495 | 0.203 | 0.670 |
| | 9 | 0.135 | 0.345 | 0.607 | 0.720 | 0.370 | 0.593 | 0.964 | 0.470 |
| | 10 | 0.289 | 0.147 | 0.190 | 0.126 | 0.108 | 0.309 | 0.109 | 0.123 |
| | 11 | 0.112 | 0.256 | 0.259 | 0.214 | 0.980 | 0.134 | 0.439 | 0.178 |
| | 12 | 0.964 | 0.530 | 0.117 | 0.671 | 0.536 | 0.395 | 0.047 | 0.180 |
| | 13 | 0.493 | 0.065 | 0.898 | 0.612 | 0.465 | 0.900 | 0.316 | 0.502 |
| | 14 | 0.918 | 0.892 | 0.770 | 0.035 | 0.106 | 0.201 | 0.791 | 0.294 |
| | 15 | 0.332 | 0.240 | 0.834 | 0.776 | 0.557 | 0.071 | 0.016 | 0.585 |
| | 16 | 0.634 | 0.915 | 0.525 | 0.561 | 0.079 | 0.911 | 0.447 | 0.505 |
| Assessed value | 17 | 0.5642 | 0.7356 | 0.4235 | 0.7235 | 0.4231 | 0.8213 | 0.5498 | 0.5124 |

samples, and the latter part of the data and the benefit evaluation value are used for validation.

## 4. Analysis

Based on the above theories, a program for evaluating the benefits of preventive maintenance of highway bridges based on the fuzzy neural network was developed using MATLAB 2020b.

*4.1. Background Information.* Wuxuan Expressway is located on the south bank of the Yangtze River in Anhui Province. The terrain rises from northwest to southeast. The engineering geological conditions are generally simple. The engineering geological conditions vary from north to south, but the south is stronger than the north. In the north, there is a problem of weak foundation, and in the south, although the bearing capacity of the foundation is higher, there is a problem of expansive soil. In addition, skating, landslides, mudslides, and earthquakes are not developed along the line.

Wuxuan Expressway starts from the south bank connection of Wuhu Yangtze River Bridge and ends at the interface of Xuancheng South Ring Expressway, with a total length of 56.683 km, passing through Guandou, Qingshui, Liulang, Zhaoqiao, Wanzhu, and Sanyuan. It is the Hefei-Hangzhou Expressway. Important part, the Wuxuan Expressway started on November 20, 1999, and was completed and opened to traffic on October 1, 2003. The Wuxuan Expressway has a total of 72 bridges (52 main bridges and 20 overpass bridges) with a total length of 8910.56 m: 1 extra-large bridge with a total length of 1125.22 m; 9 bridges with a total length of 5120.22 m; 26 middle bridges, the total length is 1817.84 m; there are 36 small bridges with a total length of 847.28 m.

According to the evaluation system of preventive maintenance of highway bridges established in Table 1, 122 bridges on Wuxuan Expressway were analyzed and evaluated, and each index data was converted into the fuzzy maintenance benefit grade value, and the weight value of each index was obtained by combining the analytic hierarchy process. For example, the results and maintenance benefit evaluation values of 8 bridges are shown in Table 5, and the rest 114 bridges are analogous.

Table 6: Implicit node selection calculation.

| Number of hidden layer nodes | Training set mean square error |
|---|---|
| 5 | 0.13068 |
| 6 | 0.1265 |
| 7 | 0.11622 |
| 8 | 0.11313 |
| 9 | 0.15737 |
| 10 | 0.18296 |
| 11 | 0.1892 |
| 12 | 0.20347 |
| 13 | 0.22368 |

*4.2. Computational Results and Analysis.* In order to test the performance and correctness of the neural network training model, two groups of test groups were set up, and the ratios of training samples and validation samples were 102 : 20 and 92 : 30, respectively, which was also to avoid the result error caused by different sampling ratios. First, take 102 bridge data as training samples and 20 bridge data as validation. The number of network input layers is $n = 16$, the number of output layer nodes is $m = 1$, the number of hidden layer nodes is calculated according to the formula (11) and the variance is compared, and the number of hidden layer nodes with the smallest mean square error is selected, and the number of hidden nodes is determined to be 8, the corresponding mean square error is 0.11313, and the calculation results of implicit node selection are shown in Table 6.

Set the network training error accuracy to 0.001; the learning efficiency $l = 0.01$; the neural network structure diagram is shown in Figure 3.

The evaluation value of the preventive maintenance benefit of highway bridges calculated by the neural network is compared with the real value of the fuzzy comprehensive

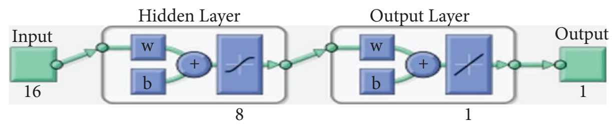


Figure 3: Network structure diagram.

Table 7: Comparison of analysis results.

| Bridge | Real | Output |
|---|---|---|
| 1 | 0.658 | 0.668 |
| 2 | 0.527 | 0.520 |
| 3 | 0.901 | 0.892 |
| 4 | 0.770 | 0.780 |
| 5 | 0.419 | 0.410 |
| 6 | 0.735 | 0.743 |
| 7 | 0.698 | 0.689 |
| 8 | 0.683 | 0.679 |
| 9 | 0.572 | 0.578 |
| 10 | 0.388 | 0.395 |
| 11 | 0.570 | 0.554 |
| 12 | 0.607 | 0.614 |
| 13 | 0.577 | 0.583 |
| 14 | 0.598 | 0.604 |
| 15 | 0.673 | 0.669 |
| 16 | 0.543 | 0.537 |
| 17 | 0.803 | 0.809 |
| 18 | 0.924 | 0.962 |
| 19 | 0.773 | 0.736 |
| 20 | 0.519 | 0.509 |

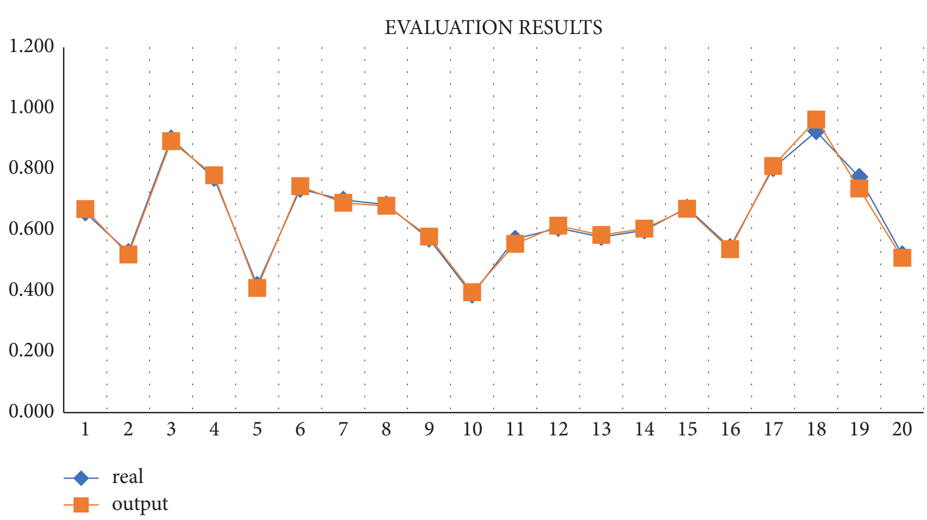


Figure 4: Evaluation results.

evaluation. The numerical comparison analysis results are shown in Table 7. The evaluation results are shown in Figure 4. The network performance graph is shown in Figure 5.

The other group sets 92 sets of data as training samples and 30 sets of data as verification samples and performs the same operations as the above. The number of hidden nodes is 8, and the corresponding mean square error is 0.12589. The evaluation results and network performance are shown in Figure 6 and Figure 7.

According to the neural network evaluation results of the above two groups, combined with Table 4, the maintenance benefits of each bridge can be obtained. It can be seen that the neural network output value and the fuzzy

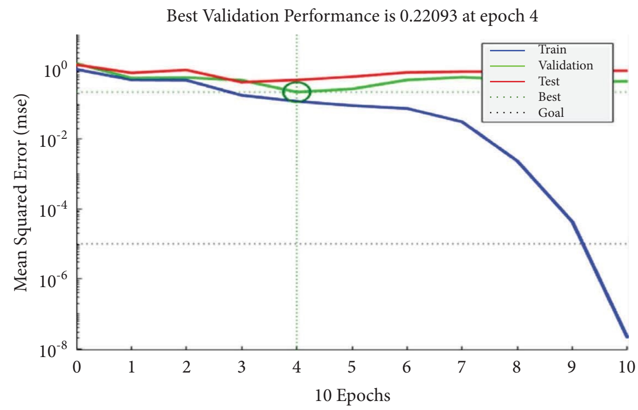


Figure 5: Network performance.

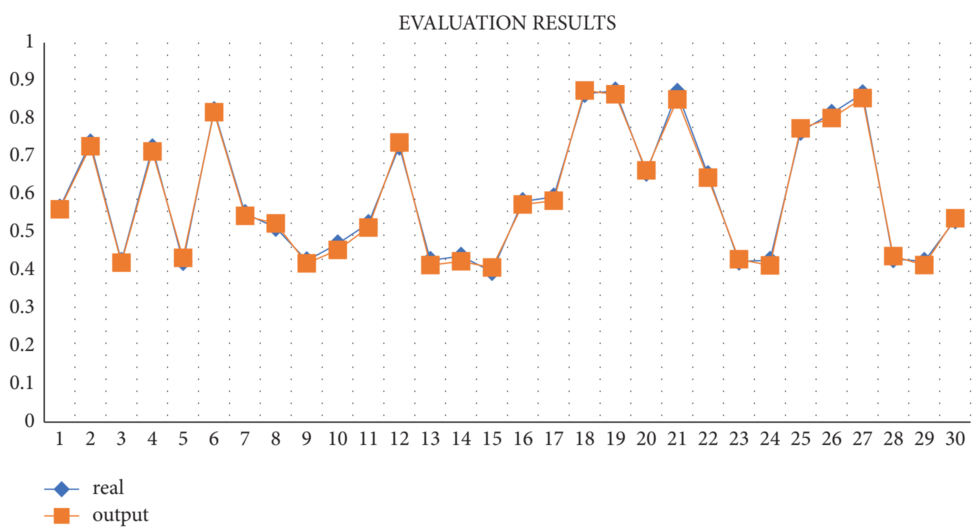


Figure 6: Evaluation results.

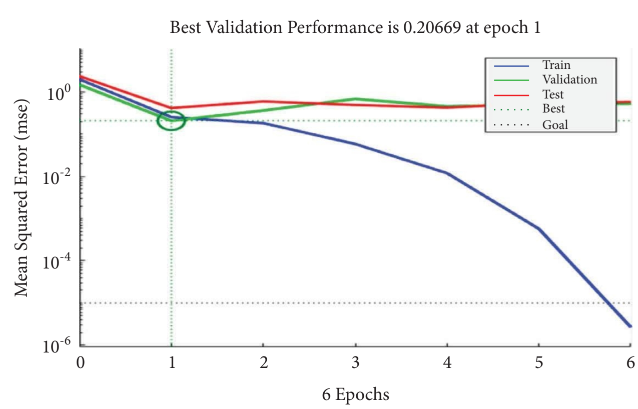


Figure 7: Network performance.

comprehensive evaluation results have a high degree of agreement, and the fuzzy evaluation results are basically consistent. It should be less than 0.01 to meet the accuracy requirements.

## 5. Conclusion

In this paper, a fuzzy neural network-based preventive maintenance benefit evaluation system for highway bridges is proposed, and a corresponding network architecture model is constructed. The model combines the advantages of fuzzy theory and the neural network model and can effectively evaluate the maintenance benefits of highway bridges more accurately. The results of this study show that the evaluation results of the model can provide a good reference for the preventive maintenance of highway bridges. The maintenance benefits of No. 1, No. 6, and No. 7 bridges should be given priority to take maintenance measures. The result size is sorted optimized. It can be seen that the model has strong practicability and accuracy, which is conducive to improving my country's bridge evaluation system and providing reference for bridge maintenance managers to make decisions.

## 6. Prospect

This paper studies and improves the preventive maintenance benefit evaluation system of highway bridges, which can be further optimized, and analyzes the impact of each impact target on the maintenance timing, so as to determine the best timing for preventive maintenance of highway bridges.

The highway bridge maintenance benefit evaluation model proposed in this paper cannot cover all situations. There are various types of highway bridges in actual engineering. Different types of evaluation indicators and weighting systems cannot be directly applied. Therefore, other types may need to reclassify indicators and model analysis.

The postevaluation of the preventive maintenance effect is an important part of the research of the bridge preventive maintenance system. In the future, a summary after evaluation of highway bridges can be carried out to find out the experience and lessons of the success or failure of project maintenance and put forward corresponding suggestions and improvement measures, so that preventive maintenance technology matures more quickly.

## Data Availability

No data available to support this article.

## Conflicts of Interest

The authors declare that there are no conflicts of interest.

## References

[1] W. Wang, C. Zhang, and J. Xing, "Integrated optimization of bridge preventive maintenance effect-cost-lifetime," *Journal of Chongqing Jianzhu University*, vol. 33, no. 4, pp. 24–28, 2014.

[2] X. Liu, *Theoretical Research on Concrete Bridge Preventive Maintenance Technology*, Southeast University, Dhaka 1213, Bangladesh, 2015.

[3] Y. Xu and T. Wu, "Horizontal comparative analysis of life cycle cost of bridge reinforcement engineering," *Journal of Chang'an University (Natural Science Edition)*, vol. 24, no. 3, pp. 30–34, 2004.

[4] C. Zhang, G. Qiao, and S. Ma, "Evaluation system of concrete bridge preventive maintenance," *Modern Traffic Technology*, vol. 7, no. 4, pp. 36–40, 2010.

[5] M. Sun, Q. Liu, and C. Xiang, "Research on the comprehensive evaluation index system of bridge preventive maintenance," *Journal of Chongqing Jianzhu University*, vol. 32, no. S1, pp. 899–902, 2013.

[6] W. Wang, C. Zhang, and G. Qiao, "Research on post-evaluation system of bridge preventive maintenance based on grey fuzzy comprehensive evaluation," *Highways*, vol. 59, no. 1, pp. 153–157, 2014.

[7] W. He, "Research on the comprehensive evaluation index system of bridge preventive maintenance based on improved uncertainty AHP," *Journal of Zhejiang Transportation Vocational and Technical College*, vol. 17, no. 3, pp. 6–10, 2016.

[8] H. Yu, Y. Wu, and X. Mei, "Research on the evaluation method of preventive maintenance of concrete bridges in Tianjin," *Highway Traffic Technology (Applied Technology Edition)*, vol. 15, no. 9, pp. 145–148, 2019.

[9] R. Song, *Technical Status Assessment and Preventive Maintenance of concrete Girder Bridges*, Henan University, He Nan Sheng, China, 2018.

[10] T. Wu and Y. Xu, "Economic evaluation of bridge reinforcement," *Highway Traffic Science and Technology*, vol. 23, no. S1, pp. 104–108, 2006.

[11] Ji You, F. Tao, and G. Fu, "Evaluation formula of bridge bearing capacity based on reliability theory," *Highways*, vol. 41, no. 3, pp. 13–16, 2013.

[12] P. Ziyao and Y. Li, "Risk assessment of new Austrian tunnel construction based on fuzzy neural network," *Road Construction Machinery and Construction Mechanization*, vol. 35, no. 3, pp. 124–128, 2018.

[13] Y. Zhang, J. Jiang, and W. Gang, "Research on intelligent algorithms in traffic structure disease monitoring [J]," *Modern Tunnel Technology*, vol. 57, no. S1, pp. 139–146, 2020.

[14] Q. Yan, W. Jinchang, and Shangguanping, "Analysis of maintenance optimization strategy for highway concrete girder bridge life cycle," *Highway Traffic Science and Technology*, vol. 36, no. 2, pp. 95–102, 2019.

[15] S. Fan, X. Wu, and J. Huo, "Performance prediction of PC bridge based on fuzzy neural network," *Highways*, vol. 67, no. 2, pp. 95–98, 2022.

[16] J. Zong, K. Zhang, B. Zhan, and R. Ma, "Fuzzy assessment of steel deck pavement for long suspension bridge of the fourth nanjing Yangtze River bridge," *Advances in Civil Engineering*, vol. 2021pp. 1–9, 9pages, Article ID 8857407, 2021.

[17] Z. Hossain, MdA. Hasan, and R. Ghabchi, "Neural network based estimation of service life of different metal culverts in Arkansas," *Advances in Civil Engineering*, vol. 2022, pp. 1–10, Article ID 6860287, 2022.

[18] S. Jolfaei and A. Lakirouhani, "Sensitivity analysis of effective parameters in borehole failure, using neural network," *Advances in Civil Engineering*, vol. 2022, pp. 1–16, Article ID 4958004, 2022.

[19] P. Miao, "Prediction-based maintenance of existing bridges using neural network and sensitivity analysis," *Advances in*

*Civil Engineering*, vol. 2021, pp. 1–17, Article ID 4598337, 2021.
[20] K. Hu and X. Wu, "Prediction of effective width of varying depth box-girder bridges using convolutional neural networks," *Advances in Civil Engineering*, vol. 2022, pp. 1–9, Article ID 4617392, 2022.
[21] X. Shi, B. Zhao, Y. Yao, and F. Wang, "Prediction methods for routine maintenance costs of a reinforced concrete beam bridge based on panel data," *Advances in Civil Engineering*, vol. 2019, pp. 1–12, Article ID 5409802, 2019.