Hindawi
Scientific Programming
Volume 2022, Article ID 2420936, 10 pages
https://doi.org/10.1155/2022/2420936

Research Article

Risk Management of Prefabricated Building Construction Based on Fuzzy Neural Network

Maohua Yang

Chongqing Jianzhu College, Chongqing 400072, China

Correspondence should be addressed to Maohua Yang; ymh_870909@cqjzc.edu.cn

Received 16 March 2022; Revised 31 March 2022; Accepted 8 April 2022; Published 3 June 2022

Academic Editor: Jie Liu

With the rapid development of society, the risk management of personal health and assets has become an important content that cannot be ignored in all walks of life. With the in-depth advancement of risk management, most of the construction risks of prefabricated buildings adopt qualitative research based on experience and intuitive judgment and quantitative research on quantitative mathematical statistics, but there are few models for risk assessment of prefabricated buildings with dynamic characteristics to adapt to the rapid development of prefabricated buildings and the lack of prefabricated construction in various stages and complex environments, with risk prediction and effective response capabilities. Based on this, this paper attempts to propose a fuzzy neural network risk research method for prefabricated building construction, making full use of the fuzzy neural network's qualitative knowledge expression and quantitative numerical computing advantages, to establish a set of strong fault tolerance and better adaptive ability: fuzzy neural network evaluation model for extensive prefabricated building construction risk. Through the design of the fuzzy network model structure, the membership vector of the qualitative and quantitative indicators of the fuzzy comprehensive evaluation of the risk of prefabricated building construction is used as the input vector of the neural network, and the evaluation result is used as the output of the neural network. The samples were trained, programmed, and debugged, and it was found that the training results of the samples were in good agreement with the expected output results, which further verified the feasibility and applicability of the fuzzy neural network in the risk assessment process of prefabricated buildings. It is of good guiding significance to conduct continuous observation and formulate effective risk aversion and response plans.

1. Introduction

With the continuous advancement of construction industrialization, prefabricated buildings have achieved unprecedented development, injecting new kinetic energy into the advancement of global climate governance. With the continuous emergence of green construction appeals, the new construction method of prefabricated buildings will become more and more popular. Meanwhile, it is widely used in industry and residences because of its high production efficiency, high production accuracy, small environmental impact, and high degree of industrialization. Compared with traditional building forms, prefabricated buildings have different quality, technology, and construction period requirements in the detailed design stage, prefabrication transportation stage, and hoisting stage. In order to reduce and avoid risk losses, prefabricated buildings are effectively risked [1, 2].

Management is particularly important. In risk management, risk assessment is an important basis for risk management. It aimed to find, analyze, and predict the dangerous and harmful factors existing in the project and the system and the severity of the accident that may be caused, then propose reasonable and feasible safety countermeasures, and guide the source of danger [3, 4]. Monitoring and accident prevention are done to achieve the lowest accident rate, the least loss, and the best return on safety investment. Traditional risk assessment methods are divided into qualitative assessment and quantitative assessment. The qualitative method is mainly based on experience and intuitive judgment, while the quantitative method is based on a large number of experimental results and extensive statistical analysis of accident data. Both of these two methods have certain defects, which limit their application, and the method combining qualitative and quantitative can make up for the shortcomings of traditional methods [5].

Therefore, this paper adopts the fuzzy evaluation method based on neural network to study the risk management of prefabricated construction. Applications can also be a good way to overcome subjectivity in evaluation.

2. Related Work

In terms of risk management research on prefabricated building construction, the predecessors have conducted statistical modeling and analysis of various building risk factors such as cost, safety, and energy for analysis, evaluation, and decision-making for enterprises. For example, by combining factors such as the construction period of prefabricated buildings, energy consumption in the construction process, and seismic performance of prefabricated buildings, the dynamic case analysis research method is used to analyze the high probability risk of prefabricated buildings and the use of residential target comfort and prefabrication. The data monitoring of the prefabricated buildings explains the construction management risks of prefabricated buildings and the degree of influence of various risk factors on the public [6]. Lee et al., through literature review and detailed analysis of risk factors at the construction site, combined with the impact of the risk factors on the site of prefabricated building construction, used AHP to establish a weight system for risk indicators. According to the classification of risk factors in the construction management of conventional buildings, comprehensively use the statistical analysis method of accident cases and risk matrix to carry out risk assessment [7]. Hinze and others put forward suggestions on the safety management of prefabricated buildings and evaluate the construction risks of prefabricated buildings through the concept of leading indicators [8].

Through the construction of the F-QRAM model, Pinto evaluates inaccurate and vague risk variables, determines the key risk factors of prefabricated building construction, provides guidance for safety risk management during project construction, and guides decision makers in the process of risk assessment. It provides enterprises critical, scientific, and objective guidance for risk response [9]. Xiao et al., through the construction of a fuzzy-based prefabricated building risk assessment model, used the direct rights method to calculate the weights of various indicators, effectively reducing the deviation caused by subjective weighting [10]. Based on the existing research and analysis combined with rough set theory, Guo et al. discussed and analyzed DM (data mining) technology and redefined the risk factors affecting prefabricated buildings. Through the quantitative assessment of risk factors, redundant risk factors are reduced to form the final efficient and quick decision-making method [11].

Staub-French et al. use BIM applications and REPCON (Project Progress Management Program) to combine the Internet and prefabricated buildings to simulate and adjust the construction progress and the process of project implementation, so as to formulate effective control for the quality and safety in the construction management of prefabricated buildings measures [12]. Li et al. used SNA to identify various risk factors in precast concrete projects. Through BIM-centered strategic recommendations, the probability of risk occurrence can be reduced and the communication of target stakeholders can be promoted [13]. Sinha conducted in-depth research and analysis on the construction management of prefabricated frame systems based on the research foundation of predecessors, conducted research on various types of supporting structural components and evaluated construction management risks, and proposed the use of standardized supporting frame systems in construction, to ensure the quality of the structure and reduce the risk factors of construction management [14].

3. Related Theories

3.1. Fuzzy Theory. Fuzzy theory is developed on the basis of fuzzy mathematics. The theory is attached to the basic concept of fuzzy sets and the theory of continuous membership functions [15]. A large number of facts show that many things are put before the cart because of excessive pursuit of precision. If a suitable mathematical language is found to describe the ambiguity of things, proper fuzzy processing can achieve a more precise purpose.

3.1.1. Fuzzy Set. A fuzzy set has an indistinct boundary. For a fuzzy set, an element can both belong to the set and not belong to the set, and the boundary is blurred. In fuzzy logic based on fuzzy sets, the truth of any statement or proposition is only a certain degree of truth, that is, fuzziness. It reflects the uncertainty of events, which can be characterized by the degree to which an element belongs to a certain set, and a numerical value belonging to [0,1]—a membership function. In [16], fuzzy sets and membership functions are defined as follows: Given a universe of discourse X, any mapping from X to the closed region [0,1]:

$$\begin{aligned} \mu_A &: X \longrightarrow [0,1], \\ x &\longrightarrow \mu_A(x). \end{aligned} \tag{1}$$

μ_A is called the membership function of the fuzzy set A, and $\mu_A(x)$ is called x is the membership function of A. The degree of membership can also be denoted as $A(x)$.

3.1.2. Membership Function. Professor Zadeh first proposed the concept of membership function in 1965, which is used to describe the degree of membership of the element u to the fuzzy set U. Due to the uncertainty of this relationship, it is generally used from the interval [0,1]. The value taken replaces the two values of 0 and 1 to describe the "true degree" of an element belonging to a fuzzy set. Through membership

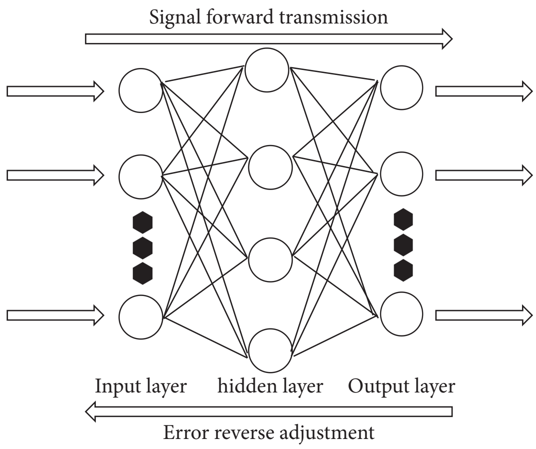

Figure 1: BP neural network structure.

function, a fuzzy concept can be expressed transitionally from "not belonging at all" to "belonging completely," and it is easier to quantitatively analyze and express all fuzzy concepts.

The qualitative description of objective things by membership function is relatively objective in nature, but different individuals have different cognitions to the same fuzzy concept, so there is subjectivity. The determination of the membership function is still based on experience and experiments, and there is no effective systematic method. At present, the common determination methods include fuzzy statistics method, assignment method, expert experience method, and so on. These methods improve the rough membership function through continuous "learning" and "practice," so as to achieve the unity of the subjective and the objective.

3.1.3. Fuzzy Logic System. Fuzzy logic system refers to a system including fuzzy concepts and fuzzy logic. When it exercises control function, it is called fuzzy logic controller.

Due to the randomness in fuzzy concept and fuzzy logic selection, fuzzy logic systems with various states can be constructed. For example, the combination of various fuzzy neurons constitutes a neural network logic system with fuzzy information processing functions.

3.2. BP Neural Network Algorithm

3.2.1. Principle of BP Neural Network. The BP neural network consists of three parts: input layer, hidden layer, and output layer. Each layer involves a large number of neurons, and these three layers are also organically combined by these neurons to form the integrity of the model [17–20].

In the BP neural network model, the feature vector is input from the input layer to carry out the model network. After the feature vector is recognized in the input layer, it is transmitted to the hidden layer by the neuron and performs certain data processing. Finally, it is also transmitted to the output layer by the neuron. The data is processed and compared according to the given expected value. When the output conditions are not met, the output layer starts to perform reverse transfer and weight adjustment, and this cycle is repeated until the output reaches the preset expected value. It can be seen that the BP neural network is an intelligent model that can continuously learn and self-adjust, and its structure is shown in Figure 1.

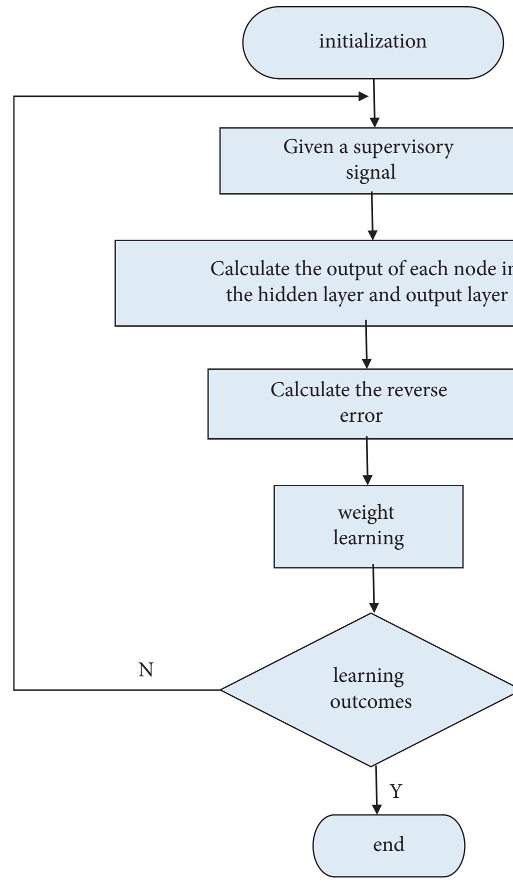

Figure 2: Flowchart of BP algorithm.

The learning of the BP neural network is mainly to adjust the connection weights between the neurons only through the learning algorithm, so that the output results are closer to the expected value. Guided learning with a tutor is divided into four processes: forward transmission of information, reverse adjustment of errors, model training, and "learning convergence."

3.2.2. Learning Algorithm of BP Neural Network. The flowchart of the BP neural network learning algorithm is shown in Figure 2; initialization is to select the initial weight of the network, generally a small random number around zero. When the specified number of learning times or the expected output error index is reached, or the change of the error index is less than a certain closed value, the learning ends; otherwise, the learning continues.

Combined with Figure 1, it is assumed that the input learning sample is p, the number of input neurons is n, the number of hidden layer neurons is m, the number of output neurons is r, and the conversion function adopts a sigmoid function, namely: $f(x) = 1/1 + e^{-x}$, the weight correction process is as follows:

(1) Forward propagation of information

① The output of the jth neuron in the hidden layer is

$$S_j = f\left(\mathrm{net}_j\right) = f\left(\sum_{t=1}^{n} \omega_{ij} x_{ti} + \theta_j\right), \quad j = 1, 2, \ldots, m; t = 1, 2, \ldots, p, \tag{2}$$

where x_{ti} is the input of the i-th neuron in the t-th sample, and ω_{ij} is the weight from the i-th neuron to the jth neuron.

② The output of the kth neuron in the output layer is

$$S_k = f\left(\mathrm{net}_k\right) = f\left(\sum_{j=1}^{m} \omega_{jk} s_j + \theta_k\right), \quad k = 1, 2, \ldots, r, \tag{3}$$

ω_{jk} is the connection weight from the jth neuron to the kth neuron.

③ Define the error function:

$$E = \frac{1}{2} \sum_{k=1}^{r} \left(S_k + s_k\right)^2 = \frac{1}{2} \sum_{k=1}^{r} \left(e_k\right)^2, \tag{4}$$

where S_k is the expected output of the kth neuron in the output layer.

(2) Weight change and backpropagation of error

① The weight change of the output layer

The weights from the jth input to the kth output are

$$\Delta\omega_{jk} = -\alpha \frac{\partial E}{\partial \omega_{jk}} = -\alpha \frac{\partial E}{\partial S_k} \cdot \frac{\partial S_k}{\partial \mathrm{net}_k} \cdot \frac{\partial \mathrm{net}_k}{\partial \omega_{jk}} = \alpha \left(S_k - s_k\right) \cdot f'\left(\mathrm{net}_k\right) \cdot S_j = \alpha \delta_{jk} S_j. \tag{5}$$

Among them, $\delta_{jk} = \left(S_k - s_k\right) \cdot f'\left(\mathrm{net}_k\right)$

Similarly:

$$\Delta\theta_k = -\alpha \frac{\partial E}{\partial \theta_{jk}} = -\alpha \frac{\partial E}{\partial S_k} \cdot \frac{\partial S_k}{\partial \mathrm{net}_k} \cdot \frac{\partial \mathrm{net}_k}{\partial \theta_{jk}} = \alpha \left(S_k - s_k\right) \cdot f'\left(\mathrm{net}_k\right) = \alpha \delta_{jk}. \tag{6}$$

② Changes in hidden layer weights

The weights from the jth input to the kth output are

$$\Delta\omega_{ij} = -\beta \frac{\partial E}{\partial \omega_{ij}} = -\beta \frac{\partial E}{\partial S_k} \cdot \frac{\partial S_k}{\partial S_j} \cdot \frac{\partial S_j}{\partial n\, et_j} \cdot \frac{\partial \mathrm{net}_j}{\partial \omega_{ij}}, = \beta \sum_{k=1}^{r} \left(S_k - s_k\right) \cdot f'\left(\mathrm{net}_k\right) \cdot \omega_{jk} \cdot f'\left(\mathrm{net}_j\right) \cdot x_{ti} = \beta \delta_{ij} x_{ti}. \tag{7}$$

Among them, $\delta_{ij} = e_j \cdot f'\left(\mathrm{net}_j\right)$, $e_j = \sum_{k=1}^{r} \delta_{jk} w_{jk}$

$$\Delta\theta_j = -\beta \frac{\partial E}{\partial \theta_j} = -\beta \frac{\partial E}{\partial S_k} \cdot \frac{\partial S_k}{\partial S_j} \cdot \frac{\partial S_j}{\partial \mathrm{net}_j} \cdot \frac{\partial \mathrm{net}_j}{\partial \theta_j}, = \beta \sum_{k=1}^{r} \left(S_k - s_k\right) \cdot f'\left(\mathrm{net}_k\right) \cdot \omega_{jk} \cdot f'\left(\mathrm{net}_j\right) = \beta \delta_{ij}. \tag{8}$$

Among them, α and β are called the step size of the gradient search algorithm, also called the convergence factor. The larger the value, the faster the weight adjustment. Generally, the values of α and β can be larger without causing oscillation.

(3) The error backpropagation process is actually by calculating the error e_k of the output layer and then multiplying it by the first derivative $f'\left(\mathrm{net}_k\right)$ of the activation function of the output layer to obtain δ_{jk}. Since the target vector is not directly given in the hidden layer, the δ_{jk} of the output layer is used to transfer the error backward to obtain the change $\Delta\omega_{jk}$ of the output layer weight and then calculate $= \sum_{k=1}^{r} \delta_{jk} \Delta\omega_{jk}$ and then multiply e_j by the first derivative of the activation function of the hidden layer $f'\left(\mathrm{net}_j\right)$ to obtain δ_{ij}, so as to obtain the variation of the weight of the previous layer $\Delta\omega_{ij}$.

(4) Weight correction

① Use δ_{jk} to correct the weights and thresholds between the output layer and the hidden layer

$$\begin{aligned} \omega_{jk}(t+1) &= \omega_{jk}(t) + \Delta\omega_{jk} = \omega_{jk}(t) + \alpha \delta_{jk} S_j, \\ \theta_k(t+1) &= \theta_k(t) + \Delta\theta_k = \theta_k(t) + \alpha \delta_{jk}. \end{aligned} \tag{9}$$

② Use δ_{ij} to correct the weights and thresholds between the input layer and the hidden layer

$$\begin{aligned} \omega_{ij}(t+1) &= \omega_{ij}(t) + \Delta\omega_{ij} = \omega_{ij}(t) + \beta \delta_{ij} S_j, \\ \theta_j(t+1) &= \theta_j(t) + \Delta\theta_j = \theta_j(t) + \beta \delta_{ij}. \end{aligned} \tag{10}$$

Calculate the function E after the corrected error again; if E is less than the specified upper limit of error, the algorithm ends; otherwise, the number of learning times $t = t + 1$ is updated, and the weights and thresholds are recorrected.

There are two ways to train the network with the BP network algorithm. One is to modify the weights every time a

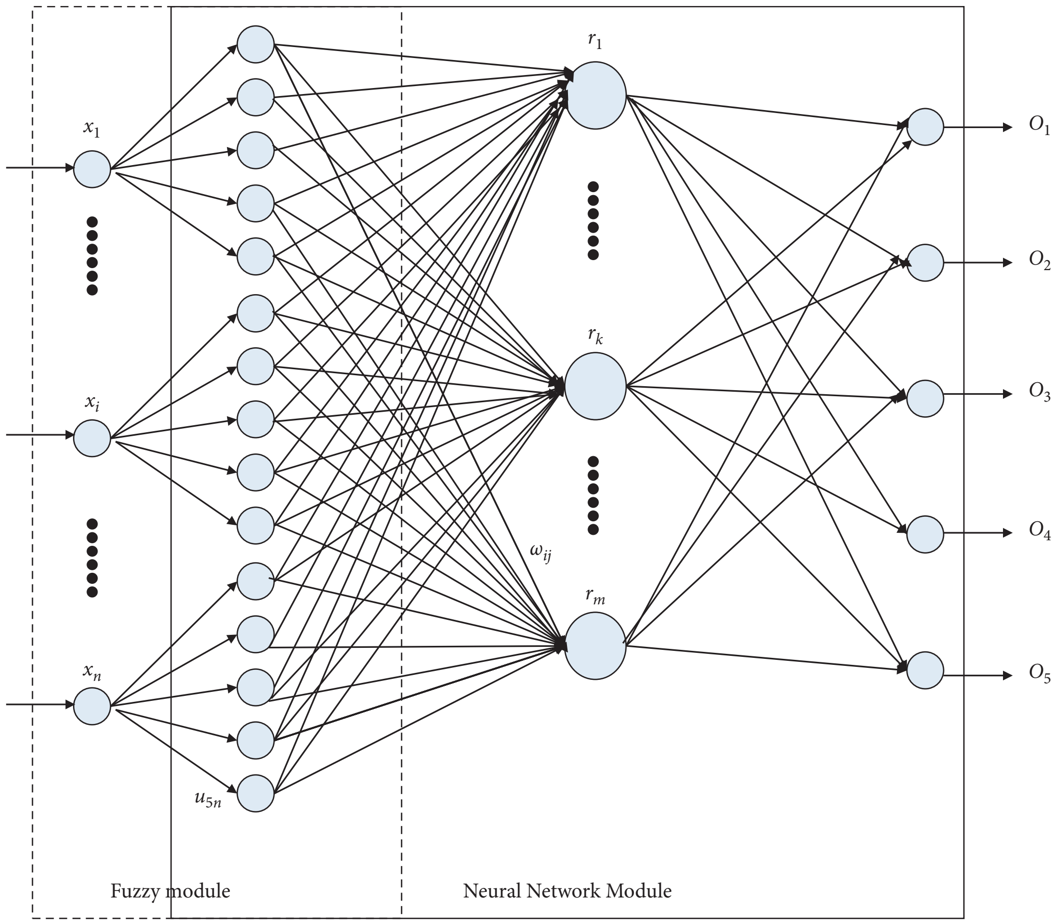

Figure 3: Fuzzy neural network topology diagram.

sample is input, which is the standard error propagation method; the other is the batch method, that is, all the samples that constitute a training cycle are computing the total average error after one input is a truly global gradient descent method. The number of corrections in the latter is significantly reduced, which can save learning time, but since the average of all mode errors is used, oscillations may occur in some cases.

4. Risk Assessment Model of Prefabricated Construction Based on Fuzzy Neural Network

4.1. Fuzzy Neural Network Model Construction. Fuzzy neural network can be divided into fuzzy neural network calculated according to fuzzy numbers and fuzzy neural network formed based on the logical reasoning process of fuzzy rules [21–24]. Based on the characteristics of knowledge management, this paper builds a 4-layer fuzzy neural network based on the first type of fuzzy neural network. The first and second layers are fuzzy modules, and the second, third, and fourth layers are neural network modules, as shown in Figure 3.

The first layer is the input layer, which is responsible for the input of the fuzzy neural network. Each node represents an input variable (risk index). According to the reliability and validity test in Chapter 2, the input layer has a total of 7 nodes.

The second layer is the fuzzification layer, whose role is to fuzzify the input variables and make them the input layer of the neural network module. This layer uses a Gaussian function as the membership function:

$$\mu x_i = \exp\left[-\frac{1}{2}\left(\frac{x_i - \mu_i}{\sigma_i}\right)^2\right]. \tag{11}$$

Among them, μ_i is the center of the membership function, σ_i determines the width of the membership function, and tthe mean value of all samples of the index x_i on the input layer is the μ_i value of the index at the corresponding level; the membership of the index on the fuzzification layer. The function width takes the following value:

$$\sigma_i = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(x_i - \mu_i\right)}. \tag{12}$$

The third layer of fuzzy reasoning layer is also the hidden layer of the fuzzy neural network. It mainly realizes the mapping from the fuzzy value of the input variable to the fuzzy value of the output variable and determines the number of nodes according to the above algorithm.

The fourth layer is the output layer, which outputs the result of fuzzy evaluation.

4.2. Learning Steps of Fuzzy Neural Network. The specific learning steps are as follows:

Step 1: Cluster the sample data using the K-means method, set the number of clusters to 5, and obtain the mean μ_i and variance $\sigma_i \in \{1, 2, 3, 4, 5\}$ of each category, respectively.

Step 2: Transform the input sample X_k $h \in (1, 2, \ldots, P) \cdots$ through the membership function to realize the fuzzification process, so that n nodes are mapped to $5n$ fuzzy layer nodes and used as the input of the fuzzy inference layer.

Step 3: Set the number of learning times $t = 0$, assign small random numbers to the network weights and thresholds, $\omega_{ij}(t) \in [-1, 1]$, $\omega_{jk}(t) \in [-1, 1]$ $\sigma_j(t) \in [-1, 1]$; $\sigma_k(t) \in [-1, 1]$.

Step 4: Input a sample (X_h, T_h); P is the number of samples, $X_h \in R^p, T_k \in R^r$.

Step 5: Calculate the actual output of the fuzzy inference layer and the output layer, respectively; $S_j = f(\text{net}_j), S_k = f(\text{net}_k)$, where $f(x)$ is a sigmoid function.

Step 6: Calculate the fuzzy inference layer error σ_{ij} and the error σ_{jk} of each node in the output layer.

Step 7: The t-th correction is made to the weights and the stop values, $\omega_{jk}(t+1) = \omega_{jk}(t) + \alpha\delta_{jk}S_j$, $\theta_k(t+1) = \theta(t) + \alpha\delta_{jk}$; $\omega_{ij}(t+1) = \omega_{ij}(t) + \beta\delta_{ij}S_j$, $\theta_j(t+1) = \theta(t) + \beta\delta_{ij}$;

Step 8: Calculate the error function E; if $E < \varepsilon$, the network training ends; otherwise, go to Step 5.

5. Risk Assessment and Analysis of Prefabricated Building Construction Based on Fuzzy Neural Network

In this section, on the basis of the relevant literature [25–33], the risk management evaluation index system and theoretical system of prefabricated building construction will be proposed, and the evaluation indicators will be integrated, and the empirical research on the risk evaluation of prefabricated building construction will be carried out by using the fuzzy neural network method, and the indicators will be verified. Verify the rationality and effectiveness of the index system and the operability of risk assessment work.

In the verification process, the computer is used as the realization tool, and the research methods combining BP neural network and SPSS statistical analysis are used, respectively. The generalization ability and training speed of the network can reduce the probability of the BP network falling into a local minimum point, and the BP neural network program is written by using the neural network toolbox in the MATLAB language program to provide decision support for the research on risk management of prefabricated buildings.

5.1. Prefabricated Building Construction Risk Data Acquisition

5.1.1. Acquisition of Input Layer Data. The acquisition of input layer data is mainly achieved through the factor score of each sample, that is, how the common factor is represented by a linear combination of statistical indicators, which refers to the estimated value F_j of the common factor $\widehat{F}_j\widehat{F}_j$:

$$\widehat{F}_j = b_{j1}X_1 + b_{j2}X_2 + \cdots + b_{jp}X_p, \quad j = 1, 2, \ldots, 7; p = 25. \tag{13}$$

Since this study uses correlation coefficient matrix for factor analysis, it is assumed that $x_1, x_2, \ldots, x_p$ are standardized variables of influencing factors; $b_{i1}, b_{i2}, \ldots, b_{ip}$ are factor score coefficients; $\widehat{F}_j$ is the estimated value of the jth factor, as shown in Table 1.

5.1.2. Fuzzy Layer into Data Acquisition. K-means clustering is performed on the 5 common factors of the sample, and the number of clusters is set to 5, which correspond to the high, high, medium, low, and low of the construction risk of prefabricated buildings; the clustering method of common factors adopts Iterate and Classify. The clustering method continuously iterates and replaces the center position on the basis of the starting class center and assigns the observations to the nearest class; after 10 iterations, the cluster center matrix is obtained, as shown in Table 2.

After the samples are classified, run the Analyze Compare Means command in SPSS 20.0 software to obtain the value of the membership function width δ_i of each factor at the corresponding level. The results are shown in Table 3.

According to the Gaussian function, the membership degree of each factor in each category in the sample can be obtained. As the output of the second layer of the fuzzy neural network, there are 25 in total.

5.2. Evaluation Results and Analysis of Construction Risks of Prefabricated Buildings

5.2.1. Determine the Number of Hidden Layer Nodes. Run MATLAB 2016a; use 160 sample data to train the neural network and 10 sample data to test the neural network to find the optimal number of hidden layer nodes. According to the relevant theory in Section 3.2.1, the optimal hidden layer of BP neural network should be between 7 and 16, and the number of nodes in the output layer is 5; (1,0,0,0,0), (0,1,0,0,0), (0,0,1,0, 0), (0,0,0,1,0), (0,0,0,0,1) represent the low, low, medium, high risk status of prefabricated building construction, respectively.

Run the following program in MATLAB, and adjust the number of hidden layer nodes between 7 and 16 in turn. After repeated training, the results are shown in Table 4.

```
p = []′; % training sample data
t = []′; % training sample target output
net = newff(minmax(p), [7, 5], ("logsig," "logsig," "traingd"); % Adjust the number of hidden layer nodes in turn
```

Table 1: Factor score matrix.

Variable	Component						
	1	2	3	4	5	6	7
Illegal wires	0.127	0.169	0.012	0.186	0.098	0.095	0.187
Not wearing protective equipment	0.215	0.109	0.096	0.128	0.118	0.011	0.232
Low sense of responsibility	0.145	0.119	0.239	0.125	0.058	0.132	0.077
Unskilled workers	0.244	0.040	0.095	0.065	0.296	0.015	0.219
Work fatigue or difficulty concentrating	0.153	0.025	0.017	0.630	0.149	0.139	0.029
Improper operation of staff	0.221	0.016	0.002	0.330	0.011	0.221	0.015
Unsafe factors of materials	0.159	0.079	0.017	0.320	0.100	0.112	0.111
The machine itself is faulty	0.069	0.018	0.094	0.180	0.224	0.126	0.125
Machine overload	0.129	0.050	0.930	0.134	0.055	0.214	0.236
Machine instability	0.085	0.189	0.080	0.097	0.437	0.053	0.043
Insufficient formwork or support strength	0.046	0.328	0.074	0.139	0.019	0.024	0.201
Safety electricity check is not in place	0.017	0.011	0.339	0.440	0.048	0.021	0.068
Inappropriate device selection	0.032	0.118	0.443	0.620	0.097	0.091	0.032
Scaffolding is not strong	0.037	0.018	0.276	0.220	0.008	0.321	0.013
Lack of safety rules and regulations	0.046	0.230	0.052	0.500	0.128	0.045	0.067
Working at heights in rain and snow	0.021	0.425	0.171	0.036	0.115	0.003	0.038
No protective equipment issued	0.021	0.114	0.036	0.220	0.246	0.025	0.068
Improper protective measures	0.047	0.084	0.134	0.300	0.368	0.053	0.054
The scheme design is unreasonable	0.022	0.158	0.025	0.620	0.231	0.044	0.550
Component positioning is not accurate	0.027	0.121	0.110	0.460	0.740	0.238	0.195
Component connection technology is immature	0.057	0.008	0.001	0.237	0.013	0.657	0.091
Installation detection technology is not in place	0.024	0.002	0.065	0.436	0.019	0.009	0.035
The venue is wet	0.045	0.142	0.247	0.410	0.063	0.083	0.372
Lightning strike	0.005	0.004	0.108	0.257	0.007	0.012	0.034
Unstable address conditions	0.028	0.026	0.580	0.003	0.139	0.069	0.569

Extraction method: principal component analysis. Rotation method: varimax with Kaiser normalization component scores.

Table 2: Final cluster center table.

Risk factor	Cluster				
	1	2	3	4	5
Construction man-made risk factors	0.30669	0.65002	0.37318	0.75269	0.99813
Construction object status risk factor	0.93776	0.60900	0.13977	0.96965	0.32387
Organizational management risk factors	0.01515	0.30078	0.43660	0.49873	0.49662
Technical risk factor	0.95545	1.10145	0.38124	0.19331	0.28419
Environmental risk factors	0.11760	0.6142	0.03631	0.17670	0.20122

Table 3: The number of observations in each cluster.

Cluster		Construction man-made risk factors	Construction object status risk factor	Organizational management risk factors	Technical risk factor	Environmental risk factors
1	Std.Deviation	0.77162	0.88396	0.85552	0.72690	1.04963
	N	30	30	30	30	30
2	Std.Deviation	0.81567	0.78319	0.78090	0.78561	0.98561
	N	33	33	33	33	33
3	Std.Deviation	0.50520	0.66778	0.83839	0.80372	1.10388
	N	35	35	35	35	35
4	Std.Deviation	0.85277	0.72303	1.12236	0.82401	0.80691
	N	31	31	31	31	31
5	Std.Deviation	0.70531	0.76015	0.98847	0.60445	1.02208
	N	41	41	41	41	41
Total	Std.Deviation	1.00000	1.00000	1.00000	1.00000	1.00000
	N	170	170	170	170	170

Table 4: The relationship between the number of hidden layer nodes and the training error and measurement error.

Number of hidden layer nodes	Error training	Test error
7	$9.9601e-006$	$1.5167e-005$
8	$9.9594e-006$	$1.3938e-005$
9	$9.9254e-006$	$1.4127e-005$
10	$9.9249e-006$	$1.5753e-005$
11	$9.9160e-006$	$1.1991e-005$
12	$9.9061e-006$	$1.0685e-005$
13	$9.8343e-006$	$1.5538e-005$
14	$9.8254e-006$	$1.6156e-005$
15	$9.7783e-006$	$1.4073e-005$
16	$9.4784e-006$	$2.9405e-005$

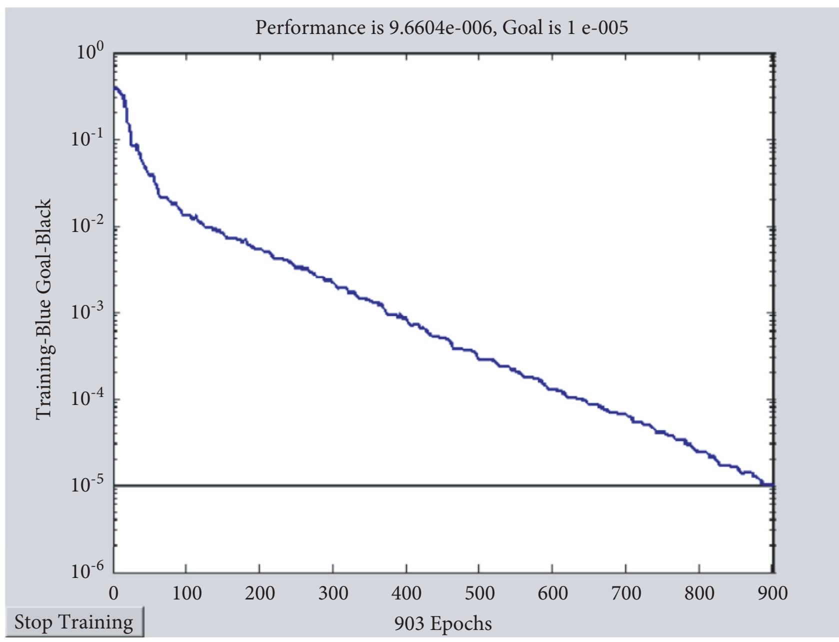

Figure 4: The training graph with the hidden layer node of 14.

```
net.trainParam.show = 100;
net.trainParam.goal = 1e – 5:
net.trainParam.epochs-8000;
net.trainParam.lr = 0.08;
net.trainParam.lr_inc = 1.4;
[net,tr] = train(net,p,t);
Y = sim(net,p);  e = t – y:
Q = mse(e)
% output training error
ptest = []′; % test sample data
ttest = []′; test sample target output
a4 = sim(net,ptest);
E = ttest-a4;
Perf = mse(E)
% output test error
```

(1) Save Netl Net. In Table 4, as the number of hidden layer nodes increases, the training error gradually decreases, but the test error slightly oscillates after more than 14. Therefore, the relationship between the number of hidden layer nodes, training error, and test error is comprehensively considered. And the number of nodes in the hidden layer is determined to be 14. It is not that the more the nodes in the hidden layer, the better the performance of the network. When testing samples, it was found that the training error first decreased and then gradually increased with the increase of the number of nodes in the hidden layer. Although the increase is not very large, it is enough to affect the performance of the neural network.

Figure 4 shows that, with the increase of training times, the network training error gradually decreases. When the training times reaches 903 times, the network reaches the set error; that is, the network completes the training.

5.2.2. Evaluation Results and Their Analysis. The actual output results and the expected output results of the 10

Table 5: Network output and expected output comparison table.

Sample	Network output	Expected output
1	(0.0000 0.0000 0.0000 1.0000 0.0000)	(0 0 0 1 0)
2	(0.0009 0.0012 0.9900 1.0000 0.0000)	(0 0 1 0 0)
3	(0.0000 0.0000 1.0000 1.0000 0.0066)	(0 0 1 0 0)
4	(0.0021 0.0007 0.0000 1.0000 0.9922)	(0 0 0 0 1)
5	(0.0000 0.0000 0.0000 0.0000 1.0000)	(0 0 0 0 1)
6	(0.0005 0.0000 0.0001 0.9876 0.0000)	(0 0 0 1 0)
7	(0.0000 0.0021 0.0000 0.9993 0.0022)	(0 0 0 1 0)
8	(0.4790 0.0000 0.0000 0.0000 0.9961)	(0 0 0 0 1)
9	(0.0000 0.0013 0.0000 0.9939 0.0000)	(0 0 0 1 0)
10	(0.0000 0.0000 0.7505 0.0000 1.0000)	(0 0 0 0 1)

sample data are shown in Table 5. It is found that the training results of the samples are in good agreement with the expected output. It can be seen that the trained fuzzy neural network can well obtain and store expert knowledge, experience, and judgment. It can be seen that the data-based serial fuzzy neural network has good scientificity, rationality, and practicability in the process of risk assessment of prefabricated buildings.

Through the above research, it can be seen that the neural network overcomes the inaccuracy of the fuzzy algorithm due to the insufficient discrimination of each component in the evaluation vector. And it can make the analysis results more realistic and convincing. The fuzzy evaluation of aspects and the principle of maximum membership ignore other evaluation information. Fuzzy BP neural network evaluation method not only has strong fault tolerance, but also has the characteristics of self-adaptation and self-correction, which will be more widely used in risk management in other fields.

6. Conclusion

As an emerging green construction method, prefabricated buildings have gradually accelerated with their development. In addition, the construction standards of ordinary construction teams are uneven, and the difficulty of risk management has also increased. Traditional risk assessment is mainly based on qualitative research and analysis. It is empirical and intuitive judgment. But quantitative research is based on a large number of experimental results and indicators or laws obtained by extensive statistical analysis of accident data to perform quantitative calculations. In different organizational management and project construction processes, the risks of prefabricated buildings have various forms and the size of the risks are also different. Therefore, the model for its evaluation should also have dynamic characteristics, so as to facilitate the reasonable prediction and control of risks. This paper attempts to apply the fuzzy neural network to the risk assessment and management of prefabricated buildings and does the following research:

(1) With the help of fuzzy theory to quantify risk factors and the advantages of BP neural network's effective intelligent behavior, learning ability, self-adaptive mechanism, and high flexibility, a prefabricated construction risk assessment model based on fuzzy neural network is established.

(2) In the design of fuzzy neural network, the number of hidden layer nodes usually needs to be determined by multiple experiments or experience. This paper proposes a method to select the optimal number of hidden layer nodes according to the formula and past experience. The method is concise, which can reduce the number of verifications, and it has good reference and use value.

(3) Through programming and debugging, the fuzzy neural network is trained, and it is found that the training results of the samples are in good agreement with the expected output results, which verifies the feasibility and applicability of the fuzzy neural network in the risk assessment process of prefabricated buildings. The dynamic characteristics of risks can be continuously observed, and effective risk aversion and response plans can be formulated with good guiding significance.

Data Availability

The dataset can be accessed upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] Y. Huang, "Research on the role of risk management and control in construction enterprise management," *Economic Management Digest*, vol. 18, no. 23, pp. 96-97, 2021.

[2] Z. Yu, *Research on Risk Management and Control in the Construction Phase of the Old City Renovation Project of Kunlun Real Estate Group T*, Yunnan Normal University, Kunming, China, 2021.

[3] G. Li, R. Xu, and Y. Li, "Safety risk management and control of prefabricated building construction," *China Building Decoration*, vol. 46, no. 11, pp. 168-169, 2021.

[4] J. Sun, "Research on financial risk management and control of construction enterprises under big data," *Small and Medium Enterprises in China*, vol. 37, no. 10, pp. 90-91, 2021.

[5] T. Jiang, *Research on Safety Risk Assessment and Control Countermeasures of Hoisting Operation of Prefabricated Buildings*, North China University of Technology, China, 2021.

[6] F. E. Boafo, J. Kim, and J. Kim, "Performance of modular prefabricated architecture: case study-based review and future pathways," *Sustainability*, vol. 8, no. 6, pp. 556–558, 2016.

[7] H.-S. Lee, H. Kim, M. Park, E. Ai Lin Teo, and K.-P. Lee, "Construction risk assessment using site influence factors," *Journal of Computing in Civil Engineering*, vol. 26, no. 3, pp. 319–330, 2012.

[8] J. Hinze, S. Thurman, and A. Wehle, "Leading indicators of construction safety performance," *Safety Science*, vol. 51, no. 1, pp. 23–28, 2013.

[9] A. Pinto, "QRAM a Qualitative Occupational Safety Risk Assessment Model for the construction industry that

incorporate uncertainties by the use of fuzzy sets," *Safety Science*, vol. 63, no. 3, pp. 57–76, 2014.

[10] W. Xiao, Z. Liu, and W. Zhong, "Multi-level fuzzy synthesis evaluation on construction supply chain risk," in *Proceedings of the Chinese control and decision conference*, pp. 266–269, Mianyang, China, May 2011.

[11] Z. L. Guo, W. B. Zhang, and L. H. Ma, "The prefabricated building risk decision research of DM technology on the basis of Rough Set," *IOP Conference Series: Earth and Environmental Science*, vol. 81, no. 1, pp. 12143–143, 2017.

[12] S. Staub-French, A. Russell, and N. Tran, "Linear sv," *Journal of Computing in Civil Engineering*, vol. 22, no. 3, pp. 192–205, 2008.

[13] C. Z. Li, J. Hong, F. Xue, and G. Q. X. M. K. Shen, "Schedule risks in prefabrication housing production in Hong Kong: a social network analysis," *Journal of Cleaner Production*, vol. 134, pp. 482–494, 2016.

[14] I. B. Sinha, "Prefabricated concrete skeleton system for residential buildings," *International Journal for Housing Science and its Applications*, vol. 25, pp. 163–174, 2011.

[15] P. Liu, Y. Han, X. Zhu, S. Wang, and Z. Li, "Research on information system risk Assessment Based on Improved AHP-Fuzzy theory," *Journal of Physics: Conference Series*, vol. 1693, no. 1, 2020.

[16] M. Oturakci, "A new fuzzy-based approach for environmental risk assessment," *Human and Ecological Risk Assessment: An International Journal*, vol. 25, no. 7, pp. 1718–1728, 2019.

[17] X. Wang, "Research on cost estimation of energy-saving buildings based on GA-BP algorithm," *China Engineering Consulting*, vol. 17, no. 5, pp. 29–32, 2017.

[18] H. Zheng, *Research on Construction Quality Evaluation System of Steel Structure Building Industrialization Based on BP Algorithm*, Shenyang Jianzhu University, Shenyang, China, 2015.

[19] Q. Meng, "Application of improved BP algorithm in construction cost estimation," *Industrial Control Computer*, vol. 26, no. 10, pp. 115-116+118, 2013.

[20] W. Su, *Research on the Cost Review Method of Residential Building Design Stage Based on BP Neural Network*, Guangdong University of Technology, Guangzhou, China, 2013.

[21] Xu Moli, Xiong Deping, and Yang Mengyuan, "Risk recognition and risk classification diagnosis of bank outlets based on information entropy and BP neural network," *Journal of Intelligent and Fuzzy Systems*, vol. 38, no. 2, 2020.

[22] X. Wang and Y. Wang, "The research on bridge engineering risk management and assessment model based on BP neural network," *IOP Conference Series: Earth and Environmental Science*, vol. 455, 2020.

[23] Li Xiaochen, "Construction of abalone sensory texture evaluation system based on BP neural network," *Journal of Korea Multimedia Society*, vol. 22, no. 7, 2019.

[24] J. Zhang, L. Hu, Y. Sun, X. Wang, and H. Sun, "Research on green construction evaluation based on OWA operator and BP neural network," *Journal of Qingdao University of Technology*, vol. 42, no. 6, pp. 29–34, 2021.

[25] K. Yang, H. Wu, and X. Yang, "Research on safety risk assessment of tunnel construction based on fuzzy neural network method," *Highways*, vol. 59, pp. 157–160, 2014.

[26] Y. Li, "Risk assessment of international petroleum contracts based on fuzzy neural networks," *Statistics and Decision Making*, vol. 32, no. 23, pp. 55–58, 2014.

[27] 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.

[28] Y. Huang, Z. Gong, X. Deng, L. Peng, and R. Wang, "Risk assessment of highway tunnel entrance section construction stage based on fuzzy neural network," *Journal of Engineering Management*, vol. 32, no. 3, pp. 119–123, 2018.

[29] C. Zhang, H. Guo, M. Xiao, Y. Wang, and Y. Liu, "Risk assessment of prefabricated building construction," *Engineering Economics*, vol. 28, no. 10, pp. 31–34, 2018.

[30] C. Chang and R. Yan, "Safety risk assessment and management measures of prefabricated building construction," *Journal of Shenyang Jianzhu University (Social Science Edition)*, vol. 19, no. 4, pp. 399–403, 2017.

[31] Z. Liu, G. Sun, and X. Yang, "Research on construction risk assessment of prefabricated concrete buildings," *Journal of Liaoning University of Technology (Social Science Edition)*, vol. 22, no. 1, pp. 39–42, 2020.

[32] Y. Liu, "Research on risk management and control of prefabricated building construction," *Engineering Economics*, vol. 31, no. 9, pp. 50–54, 2021.

[33] Y. Duan, S. Zhou, Y. Guo, and X. Wang, "Safety risks and strategies of prefabricated building construction based on SEM," *Journal of Civil Engineering and Management*, vol. 37, no. 2, pp. 70–75+121, 2020.