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Damage Identification and Comprehensive Safety Evaluation of Artificial Neural Network for High-rise Buildings

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Abstract: With the rapid development of high-rise buildings, structural health testing has become a research hotpot in the field of civil engineering. Effective and rapid identification of the location and extent of possible damage to high-rise building structures has become particularly important. The purpose of this paper is to study the damage identification and safety evaluation of artificial neural networks in high-rise buildings. Based on the theory of artificial neural networks and structural damage recognition, this paper proposes a method of damage recognition based on artificial neural networks. In the experimental part, the modal strain energy difference (first-order mode) was used as the input of the BP neural network.A total of 9 networks were trained and tested. Through statistical analysis of the test results, it was shown that a single damage index was used as the BP neural network. The input of the network is a single hidden layer network. With enough training samples, the trained network can make accurate damage prediction for a new set of data. Experimental results show that this method can identify the location and degree of damage at the same time, and the accuracy rate is greatly improved. In this paper, through the training and testing of single injury, when the dimension is 121, the accuracy of positioning is 100%, and the accuracy of identifying injury is 92%.

1. Introduction

With the rapid development of the national economy, China’s construction industry has also made great progress. At the same time, as the rapid development of buildings, due to design and construction reasons, there are many bean curd projects in China. Therefore, there is a need for a fast and effective nondestructive testing and identification technology to detect damage early and take appropriate remedial measures. In recent decades, with the development of fracture mechanics, signal analysis, testing technology, and computer science, nondestructive estimation has become a common technology of modern human production and has penetrated into machine manufacturing, aviation, aerospace, nuclear industry, metallurgy, shipbuilding, civil engineering Chinese people regard the application and development of non-destructive testing technology as an indicator to measure the quality of products and the level of industry. The damage of an engineering structure can be defined as the decrease of the structural bearing capacity during the service period. The decline of the structural bearing capacity is generally caused by the damage of the structural members and their connections. For all load-bearing structures, such as building bridges and offshore platforms, the damage is gradually formed during the service period.Some damages that are not detected will accumulate and aggravate, and eventually cause structural damage. Causing major economic losses and even casualties. In foreign countries, there have been many accidents such as house collapses and bridge breaks that have brought miserable lessons to people, so that people have paid increasingly attention to the safety monitoring and damage detection of various engineering structures. In addition, the annual maintenance costs due to the aging infrastructure are getting higher and higher. People are anxious to find the damage as soon as possible so that they can be repaired in time to save costs.

With the development of modern science and technology, such as the rapid development of computer technology in terms of memory and speed, the development of contactless remote sensors, the gradual improvement of finite element methods, the development of modal testing technology, and the identification of linear and nonlinear systems. All have promoted the development of damage detection, location, and assessment technology in aviation, aerospace, nuclear industry, metallurgy, shipbuilding, and civil engineering. In the past two decades, people have developed many damage identification methods based on vibration analysis. These methods can be used to identify structural damage through changes in the dynamic characteristics of structural systems and have been widely used. Artificial neural network (ANN) is a research area that has been booming in recent decades. It has a new and different way of message expression and processing that has traditionally made artificial intelligence research attractive. At present, the application of neural network theory has penetrated into various fields, and it has played a large role in structural damage recognition. However, the research on the effects of neural networks applied to different structures is not very deep.Therefore, to make neural networks better used in structural damage identification, this paper attempts to combine vibration analysis methods with artificial neural networks, which do some research in this area.

Cukrowski and his team comprehensively examined the improvement of artificial neural networks (ANN) and various experimental designs (ED) to improve the experiments obtained in polarographic metal-ligand equilibrium studies of polar metal (unstable) metal complex data. Artificial neural networks were tested on uniformly and randomly distributed experiments with no errors and corrupted data. It is found that the experimental data of random distribution will not affect the prediction ability of artificial neural network. They found that ANN with appropriate ED can provide accurate predictions of stable constants with absolute errors in the range of ± 0.05 log units or less. Artificial neural networks were found to be extremely powerful. Even if a pH error of up to ± 0.1 pH units is introduced, random experimental errors will not have much effect on the estimation of the stability constant. A special procedure has been developed to further minimize the impact of erroneously corrupted data. No significant difference was observed between the results obtained with error-free and error-damaged data. The program can also obtain the standard deviation of the calculated stability constants, which is usually a difficult task when using ANN. The results obtained from the ANN are compared with those obtained from a hard model-based nonlinear regression technique. No significant difference was found in the evaluation data of the two soft and hard model-based methods. The ANN for polarographic data described here has general properties and can in principle be applied to other analytical techniques commonly used in metal-ligand equilibrium studies [1]. Lee E T and his team believe that in the absence of baseline information before damage, damage should only be detected by measuring data. Most non-baseline damage detection methods may be sensitive to external noise, and it is difficult to detect damage when the sensor is not close. The purpose of this study was to propose a nonbaseline damage detection method that uses only a small number of measurements and is less sensitive to noise. A set of false reference data established at the instant of the measurement is compared with another set of measurement data on the structure, causing additional damage at known locations. Damage was found at this location to represent a sudden change in the difference between the two response data sets. Compared with the global deviation method, this method has the advantages of reducing the influence of noise and being able to detect damage by several sensors. The experimental work also investigated the sensitivity of accelerometers and strain gages in detecting damage. The validity of the method is verified in numerical applications and experiments [2]. Xiong F and his team designed a comparative model of two soil structure systems to reveal the mechanism of dynamic crossover effects and changes in structural behavior caused by adjacent buildings. Under the same site soil conditions, one model contains one superstructure and the other model contains five. Two shaking table tests were performed to obtain responses from key parts of the structure under ground vibration excitation. They found that there was a significant interaction between the internal structures of high-rise buildings under the action of the earthquake. The settlements and inclination of collective buildings have increased to individual buildings. Due to the presence of adjacent buildings, the frequency of the structure is reduced. Adjacent buildings increase or decrease the acceleration response and the top displacement of the structure, depending on the input seismic wave. The acceleration and displacement response of the intermediate building is stronger than the surrounding buildings [3].

Based on the theory of artificial neural network and structural damage recognition, this paper proposes a method of damage recognition based on artificial neural network. In the experimental part, the modal strain energy difference (first-order mode) was used as the input of the BP neural network.A total of 9 networks were trained and tested. Through statistical analysis of the test results, it was shown that a single damage index was used as the BP neural network. The input of the network is a single hidden layer network. With enough training samples, the trained network can make accurate damage prediction for a new set of data.

2. Proposed Method

2.1 Artificial Neural Network

Artificial neural network (Artificial Neural Network, ANN) is called Neural Network (NN) for short, which is a field that has grown up with the development of neurobiology [4]. The artificial neural network started as a simple artificial neural structure, and later formed an artificial neural network by mimicking the central nervous system of the human brain.It works very efficiently, is not subject to the constraints of modeling, and can adapt to the given sample data by adapting sample case self-learning to obtain useful data and is a powerful data classifier and an important data identifier [5-6].

(1) Artificial neuron model

Artificial neuron is a multi-input, single-output information processing unit [7]. The output of artificial neurons is affected by two factors, one is the input vector, and the other is the number of hidden layers. In artificial neurons, there is another input signal called threshold. The artificial neuron model is shown in Figure 1.

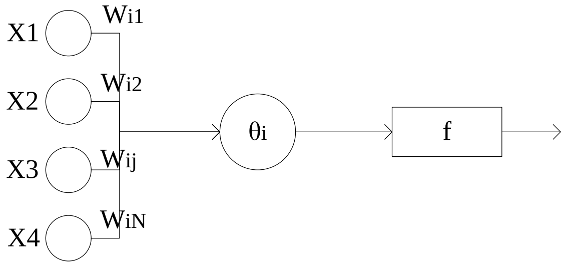

Figure 1: Artificial neuron model

Among them, $x_j(j=1,2,...,N)$ is the input signal of neuron i, and w_{ij} is the connection weight. u_i is the output after the input signal, and θ_i is the net input of neuron i. b_i is the deviation of the neuron, v_i is the adjusted value of the deviation, f is the excitation function, and y_i is the output of the neuron i.

$$u_i = \sum_{j=0}^{n} w_{ij} v_j \tag{1}$$

$$v_i = u_i + b_i \tag{2}$$

$$y_i = f(\sum_{i=0}^{n} \omega_i x_i + b_i) \tag{3}$$

As can be seen from equation (3), when ω_i, b_i is a fixed value, it is easy to calculate the output value for a given x_i. The idea of this paper is that for a given input value, the calculated value obtained as much as possible matches the actual value. The main work of artificial neural network is to determine the value of ω_i, b_i and build a suitable model. What is used later in this paper is the use of forward and feedback artificial neural networks (BP neural networks).

(2) The working mechanism of artificial neural network

Artificial neural networks are mathematical systems that are organically linked by many useful processing units.These processing units are similar to a single neuron in the human brain.They perform various complex tasks in parallel, although each processing unit looks at it’s very simple, but the function of a single neuron is holistic.Since a neural network is a complex system, a large number of nodes connected to each other by these single neurons are used to adjust the internal relationships of the system to complete the processing of the required information, The purpose also saves us a lot of time and frees us from complicated calculations [8-9]. The artificial neural network can rely on its own environment to adapt to the environment, then learn by itself, summarize its laws through its strong nonlinear mapping ability, and finally complete the calculation, analysis, and identification process.

The artificial neural network has a training process before the test, and the network judges the correctness by continuously learning a large number of sample data through the network, and then adjusting and recording the gate value [10-11]. After the network learning is completed, when it encounters the relevant sample data again, it can make a correct judgment based on its own learning and memory.

2.2 BP Neural Network

Back-Propagation Neural Network, or BP neural network for short, uses an error back-propagation algorithm, and its essential purpose is to find the optimal network connection weight [12-13]. It can contain multiple hidden layers to realize the learning problem of multilayer networks, and it can handle linear inseparable problems.

The BP network learning algorithm is as follows:

Problem description: For a given BP neural network with a total number of layers L and a given learning sample set $(X_t, D_t), t = 1,2,..., S$, the purpose of network learning is to find the weight function $w_{ij}^{(k)}, k = 1,2,..., L$ of each layer, so that equation (4) reaches a minimum.

$$E = \sum_{t=1}^{S} \left\| D_t - Y_t \right\|^2 = \sum_{i=1}^{S} \sum_{j=1}^{M} (d_{jt} - y_{jt})^2 \tag{4}$$

Among them, E is the training error function, which is the sum of the squared output errors generated by all samples in the entire training set, S is the number of training samples, M is the number of neurons in the output layer; $X_t = (x_{1t}, x_{2t},..., x_{Nt})$ is the input of the t-th training sample; N is number of neurons in the input layer; $Y_t = (y_{1t}, y_{2t},..., y_{Nt})$ is the actual output of the input network corresponding to the f-th training sample; X_t is the ideal output of the input $D_t = (d_{1t}, d_{2t},..., d_{Nt})$ network corresponding to the f-th training sample. To make the training error function E gradually decrease to the minimum according to the gradient of the network weight, the training of the network uses the error back propagation algorithm (BP algorithm) based on the gradient descent principle.

(1) Select the initial value of the network weight;

(2) Iterate according to the following formula until the training error function E decreases to a minimum, and the network training is completed.

$$\Delta W(p) = -\eta \frac{\partial E}{\partial W(p)} \tag{5}$$

Write the component number formula as

$$\Delta w_{ij}^{(k)}(p) = w_{ij}^{(k)}(p+1) - w_{ij}^{(k)}(p) = -\eta \frac{\partial E}{\partial w_{ij}^{(k)}(p)} \tag{6}$$

Among them, $\Delta W(p)$ is the weight correction amount of step p, and $\Delta W(p) = W(p+1) - W(p)$ and η are the learning rate constants. For the input X_t of the t-th training sample, the input-output relationship between the k-th layer and the i-th neuron is

$$\begin{aligned} I_i^{(k)} &= \sum_{j=0}^{N_{k-1}} w_{ij}^{(k)} y_j^{(k-1)} \\ y_i^{(k)} &= f(I_i^{(k)}) \end{aligned} \tag{7}$$

Among them, $w_{ij}^{(k)}$ is the connection strength (weight) of the j-th unit in the k-1th layer and the i-th unit in the k-th layer; N_{k-1} is the number of neurons in the k-1th layer.

2.3 Modal Analysis of Structural Damage

(1) Identification method based on frequency response function

The method based on the frequency response function can now locate and quantify single damage and multiple damages. Its main advantage is simplicity. It does not require modal analysis of modal shapes or frequencies. The study of system dynamic characteristics requires a comprehensive the input signal and output signal change function with time, and the frequency response function combines these two aspects. The frequency response function curve uses frequency as the horizontal axis and reflects the frequency range.The displacement, velocity, or acceleration response of the measurement point is used as the vertical axis.The displacement frequency response function, speed frequency response function, and acceleration frequency response function are collectively referred to as the frequency response function. The response function describes the inherent characteristics of the system in the frequency domain [14-15]. Under simple harmonic excitation, the frequency response function of the system displacement is defined as the ratio of the steady-state displacement response to the excitation amplitude, which is expressed by $H(\omega)$ as:

$$H(\omega) = \frac{X}{F} = \frac{1}{k - m\omega^2 + j\omega c} \tag{8}$$

Similarly, the speed frequency response function and acceleration frequency response function are expressed as:

$$H_V(\omega) = \frac{V}{F} = \frac{j\omega}{k - m\omega^2 + j\omega c} \tag{9}$$

$$H_A(\omega) = \frac{A}{F} = \frac{\omega^2}{k - m\omega^2 + j\omega c} \tag{10}$$

X, *A*, *V* are the response signals of displacement, velocity, and acceleration; *F* is the amplitude of the excitation; k, m, and c are the stiffness, mass, and viscous damping coefficients; ω is the frequency.

(2) Identification method based on natural frequency

The natural frequency of a structure is a function of its mass and stiffness. Damage will cause the stiffness of the structure to decrease, which in turn will cause the natural frequency to decrease. This is the principle of applying the frequency method to damage identification. The system tends to absorb more energy from the surrounding environment and reach a large amplitude at the resonance frequency, so a structure may collapse when it resonates, so it is of great significance for the study of natural frequencies [16-17] .

The frequency-based indicators are as follows:

1) Frequency change ratio index

The basic theory based on the frequency change ratio index is to determine the frequency of the structure before and after damage, assuming that the mass does not change before and after damage, only the stiffness and damping have changed, and the ratio of the value of any two-order frequency change before and after damage to the structure is the location of the damage Function [18-19].

$$\frac{\Delta\omega_i}{\Delta\omega_j} = \frac{g_i(r)}{g_j(r)} = h(r) \tag{11}$$

In the formula, $\Delta\omega_i, \Delta\omega_j$ represents the change of frequency before and after the i-th and j-th damage; r represents the position vector; and $g_i(r), g_j(r)$ represents the i-th and j-th position functions.

2) Frequency change

Index of square ratio When it is difficult to identify the small damage in the structure, an effective method is to amplify the small changes and apply a suitable amplification factor, such as the square ratio of the frequency change [20-21]. Assuming that the mass of the structure has not changed before and after the damage, for the same damage unit, the squares of the i-th and j-th frequency changes contain the same information indicating the damage. The ratio of the square of any two-order frequency changes before and after the damage to the structural damage location is functional relationship, then:

$$\frac{\Delta\omega_i^2}{\Delta\omega_j^2} = \left(\frac{\phi_i^T K_k \phi_i}{\phi_i^T M \phi_i}\right) / \left(\frac{\phi_j^T K_k \phi_j}{\phi_j^T M \phi_j}\right) \tag{12}$$

In the formula, ϕ_i, ϕ_j represents the i-th and j-th mode shapes, respectively; ϕ_i^T, ϕ_j^T is the transpose of the corresponding mode; the damage unit is denoted by M, and K_K represents the stiffness of the damage unit.

(3) Identification method based on modal shapes

1) Modal curvature

The damage of the structure will change its mode shape, but this change is small and not obvious.The curvature of the second derivative of the displacement, which reflects the rate of change of the displacement, plays an amplification role, so it is better than using the mode, it is more sensitive to damage identification [22-23].

The beam is deformed and its curvature is calculated as follows:

$$\rho(x) = \frac{M(x)}{E(x)I(x)} \tag{13}$$

In the formula, $\rho(x)$ is the curvature; M (x) is the bending moment; $E(x)I(x)$ is the bending stiffness. Structural damage occurs as a decrease in stiffness. As can be seen from the above formula, when the bending moment is constant, the stiffness decreases and the curvature increases. The abrupt point of the curvature curve is the location where the damage occurred. In addition, the curvature is obtained through the quadratic difference of the displacement, which can also be obtained using the following formula:

$$y_i'' = \frac{2\Delta l_1 (y_{i+1} - y_i) - 2\Delta l_1 (y_i - y_{i-1})}{\Delta l_1 \Delta l_2 (\Delta l_1 + \Delta l_2)} \tag{14}$$

The displacements corresponding to three adjacent points i + 1, i, i-1 are y_{i-1}, y_i, y_{i+1}, the distance between point i-1 and point i is Δl_1, and the distance between point i and point i + 1 is Δl_2.

2) modal confidence

Modal confidence is actually detecting the correlation between two different states of the same thing.The correlation between the modals of the same order before and after the damage is used to identify the damage.Modal Assurance Criteria (Modal Assurance Criteria, MAC) to indicate [24-25]. The expression is as follows:

$$MAC = \frac{(\phi_{uj}^T \phi_{dj})^2}{(\phi_{uj}^T \phi_{uj})(\phi_{dj}^T \phi_{dj})} \tag{15}$$

ϕ_{uj}, ϕ_{dj} represents the j-th mode modes before and after damage, respectively. When the MAC value is greater than 0.9, the two are considered related and the structure is not damaged. When the MAC value is less than 0.05, the two are unrelated modals, which proves that the structure is most likely to be damaged.

3) Strain mode

Structural damage will cause stress redistribution in the damaged area, so the strain will also change. The strain field of a vibration system can be seen as the superposition of several characteristic strain fields, and the first derivative of the displacement is used to obtain the strain.

The strain modal method is also limited in practical applications. The method can identify the damage of simple structures, and for large and complex structures, and the damage is more complicated, the application of this method needs to be perfected. During the test, the frequency response function should be measured, which requires more work than the direct measurement of displacement. The strain method requires higher accuracy of the data. In practical engineering applications, due to environmental interference, when using this method, instruments with higher measurement accuracy are used.

2.4 Artificial Neural Network for Structural Damage Identification

The core technology of damage recognition and detection is pattern recognition, and pattern recognition is to match the damage pattern feature library obtained from theoretical analysis with the measured pattern. Generally, a pattern library is established by analyzing various damage sequences or damage modes, and then observing the change of the measured vibration signal, and comparing it with a database of possible damage patterns to select the most similar pattern. The traditional pattern recognition technology is difficult to solve the problems of multiple damage combination, explosions, and mode distortion caused by noise. The neural network itself has the ability of pattern matching and memory, and the recognition effect is better for patterns with certain noise. Using pattern recognition for damage detection and neural network for damage detection are two different diagnostic methods, but the two are closely related, and neural networks can be used to implement pattern recognition for damage detection. In the following, the traditional pattern recognition diagnostic method Bayesian theory is used to explain how the neural network implements structural damage detection and recognition.

Assuming the conditional probability density function of the pattern samples to be identified is a normal distribution, expressed as

$$f(\frac{X}{w_i}) = \frac{1}{2^{\frac{n}{2}} |C_i|^{\frac{1}{2}}} \exp[-\frac{1}{2}(X - m_i)^T C_i^{-1}(X - m_i)](i = 1,2,..., c) \tag{16}$$

In the formula, $X = [x_1, x_2,..., x_n]^T$ is the input pattern sample; w_i is the i-th pattern set in the w-th pattern class; m_i is the mean vector of the i-th pattern class; and C_i is the covariance matrix of f pattern classes.

Generally, the pattern distribution is irregular, which requires that the damage diagnosis method can form various nonlinear segmentation planes in the pattern space. Although the K-nearest clustering method can achieve arbitrarily complex decision planes, it is similar to using neural networks to implement compared to this task, there is still a certain gap. The neural network-based structural damage detection method can not only form various decision planes in the pattern space, but also the neural network has the ability of self-adaptation and self-learning. It can adaptively adjust the weight of the network to achieve the purpose of learning. The layer itself is equivalent to the extraction of feature parameters, and it is not sensitive to the incomplete or defective input parameters.The measurement noise and errors in damage detection are inevitable. Therefore, the neural network method is the same as the traditional damage identification and compared with the diagnostic method, its recognition effect is better and it shows better generalization performance.

3. Experiments

3.1 Data Collection

The space steel frame is ten-span, with 121 members and 40 nodes. Each member is set as a unit. The damage is still simulated by the reduction of the elastic modulus. The model is modeled with ABAQUS software. In the frequency analysis step, the modal strain energy of 121 members is extracted in the postprocessing. The parametric analysis of ABAQUS can conveniently obtain the training data and calculate the modal strain energy difference. The BP network uses a single hidden layer and uses an optimized LM algorithm. The modal strain energy from the first to the 121st member under each damage condition is extracted as a 121-dimensional column vector, which is the difference in modal strain energy, that is, the modal strain energy in the intact condition minus the damage condition. The modal strain energy is used as the input of the BP neural network. The output is a 121-dimensional column vector that corresponds to the corresponding damage conditions. Assuming the damage condition is 40% damage on the 30th member, the output is 0.4 in the 30th bit of the 121-dimensional column vector. Fill with 0. For the damage conditions of two or more members, similar to the multiple damage conditions, the damage degree is recorded at the corresponding damage position, and the rest is filled with 0.

3.2 Experimental Environment

The MATLAB neural network toolbox has many function interfaces, which is the basis for the programming of the program and can be used for user-defined neural networks. The neural network graphical interface provided by MATLAB makes it easier for users to operate, such as neural network tools, classification and clustering tools, and fitting tools. It consists of the preprocessing of data, initialization of the network, training of the network, testing of new data, and postprocessing of the output data. Like a typical fitting tool, the mapping relationship between one data set and another data set can be used to build and train the network.

3.3 Judging Criteria

There are two points in the network's actual output with the correct criteria. One is to determine the location of the damage, and the other is to determine the extent of the damage. When the position of the largest positive number in the output vector corresponds to the position of the damage, the recognition position is considered correct. Single damage is based on the position of the largest positive number, double damage is the position of the first two largest positive numbers, and three damages is the first three positions. The position of the largest positive number. In the case where the recognition position is correct, the degree of damage is further recognized.When Equation (16) is satisfied, it can be judged that the recognition degree is correct.

$$0.8y \le \bar{y} \le 1.2y \tag{17}$$

Where y is the target output and $\bar{y}$ is the actual output.

4. Discussion

4.1 Statistical Analysis of Training and Testing of Single Injury and Two Injuries by the Network

(1) Statistical analysis of network training and testing for single injury

The single damage training data includes all members.This structure has a total of 121 members.The single damage design is based on the first member being damaged, and the other members are intact. %, 40%, 50%, 60%, 70%, 80% of the six injury levels, and so on, to simulate the second and third roots up to the 121st, the amount of training data for a single injury is 121 × 6 = 726 groups. The test data of single damage was 121 rods with 45%, 55%, 65% damage in turn, and the amount of single damage test data was 121 × 3 = 363 groups. To discuss the impact of different input dimensions on the test results, 121, 90, and 60 input dimensions were taken, respectively, and the unit modal strain energy difference of 121, 90, and 60 members was used as the input of the network for training and testing. Follow the identification criteria for location and degree. The identification results are shown in Table 1. Three sets are randomly selected from the 121-dimensional input data.Because the amount of data is too large, listing data will take up a lot of space.Now the results are drawn into a line chart, which can intuitively show the output of the test data, to know its output. The error of the actual situation. The results of the three groups of single damage tests are plotted as a graph, the horizontal axis represents the unit number, and the vertical axis represents the network output. The network's training and test statistical analysis of single damage is shown in Figure 2:

Table 1: Statistical results of test data for three input dimensions of single damage

Test sample	Input dimension	Judging criteria	Judging criteria	Correct rate(%)
363	121	Positioning	363	100
		$0.8y \le \bar{y} \le 1.2y$	334	92
	90	Positioning	354	98
		$0.8y \le \bar{y} \le 1.2y$	144	40
	60	Positioning	340	94
		$0.8y \le \bar{y} \le 1.2y$	59	14

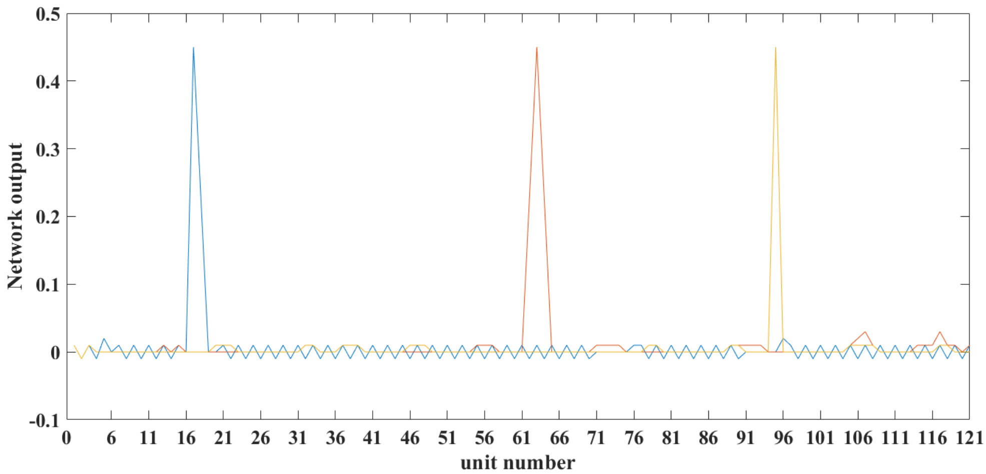

Figure 2: Statistical results of test data for three input dimensions of single damage

As can be seen from Table 1 and Figure 2, when all modal strain energy differences of 121 members are used as input, the accuracy of damage identification is the highest, and the location of the damage can be made 100%, and the degree of damage identification is as high as 92. %. When the input dimension is 90, the positioning accuracy is 98%, but the recognition of the damage degree is only 40%. When the input dimension is 60, the positioning accuracy is as high as 94%, but the recognition of the damage degree is only 14%.

(2) Statistical analysis of training and testing of the two injuries by the network

Select 10 units, numbered 7, 14, 23, 34, 39, 51, 57, 71, 82, 98, and make a combination of these 10 rods. There are a total of $C_{10}^{2}=45$ types of double damage positions and the degree of damage. It is a random combination of 50%, 60%, 70%, and 80%. There are a total of 4 × 4 = 16 types, so there are a total of 45 × 16 = 720 sets of data. 100 sets are randomly selected as test data, and the remaining 620 sets are used as training data. From the comparison of the test results of the three dimensions of the single damage, the best identification effect can be obtained by using the modal strain energy difference of 121 elements as the input, so the double damage uses 121 dimensions. The output results of the test data are shown in Figure 3 according to the identification criteria.

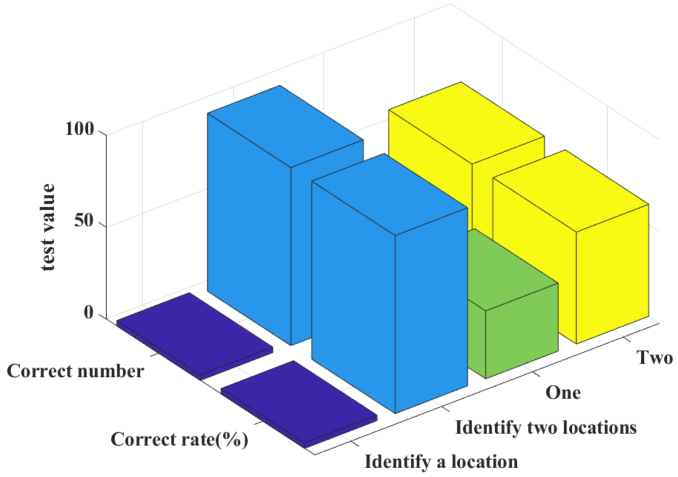

Figure 3: Statistical analysis of training and testing of the two injuries on the network

From the results in Figure 3, we can see that the recognition of double injuries only identified one location accounting for 3%, the remaining 97% could identify two locations, 37% identified only one degree of injury, and 61% identified two degrees of injury.

4.2 Network Test for Three Damages and Calculation of Multi-Hidden Layer Network

(1) Statistical analysis of the network's three damage tests

The combination of the three damage positions has $C_{25}^{3}=2300$ in total, and only simulates one degree of damage. All damage levels are 50%. The main purpose is to identify the three damage positions. Is 1. From these 2300 groups of data, 100 groups were randomly selected as test data, and the remaining 2200 groups were used as training data. The output results of the test data according to the identification criteria are shown in Figure 4.

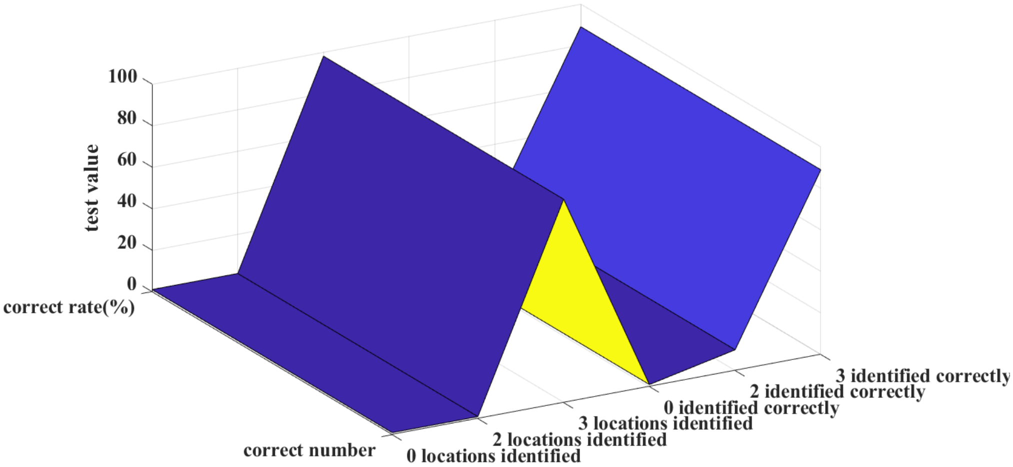

Figure 4: Statistical analysis of the test results of the network with three damages

It can be seen from Figure 4 that when the damage location is increased and only one degree of damage is set, the location of the damage can be almost 100% identified, and the accuracy rate is also high.

(2) Multi-Hidden layer network computing

In theory, a single hidden layer BP neural network can solve all mapping problems.When selecting a network, a single hidden layer is generally preferred.The network performance is adjusted by changing the number of nodes in the hidden layer. This section trains as A network with double hidden layers is compared with a single hidden layer network. This section uses single damage data.The input layer of the network is a modal strain energy difference of 121 elements. The number of nodes in the first hidden layer is 50, the number of nodes in the second hidden layer is 80, and the output layer represents 121 cells. In the case of damage, the network structure is shown in Figure. The comparison of the test results of the single hidden layer network and the double hidden layer network is shown in Figure 5.

From the comparison results in Figure 5, it can be seen that the recognition effect of a single hidden layer is significantly better than that of the double hidden layer. For simple mapping problems, the single hidden layer of the BP neural network can be solved. The performance of the network may not be as good as a single hidden layer, which may be caused by overfitting the data.

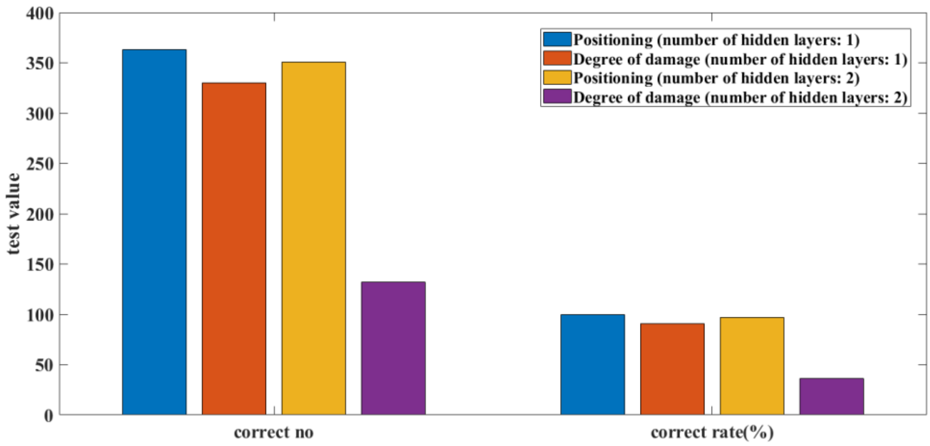

Figure 5: Test results of single hidden layer network and double hidden layer network

5. Conclusions

(1) Based on the statistical analysis method based on structural damage identification, experiments have shown that low-order modal strain energy differences can identify single damage, and the location of multiple damages can sometimes not be fully indicated. The degree of calculation based on the formula is based on the result of the first step of identifying the position, the calculation formula of the degree ignores the influence of the damaged member adjacent to the member, the calculation result is not accurate, and can only be used as a reference.

(2) In this paper, the modal strain energy difference (first-order mode) is used as the input of BP neural network, and the output of the network is used to display the damage. This paper simulates a single damage, two damages, and three damages of the steel frame. For the single damage, the modal strain energy differences of the first 121, 90, and 60 units are taken as the input of the BP neural network to discuss the impact of different input dimensions on the test results; for double damage, 620 training samples are taken; for more complex ones for three injuries, three different training samples were taken in turn. It also defines the standards for identifying test data correctly and makes statistics on the test data. And train a multi-hidden layer network, compared with the single hidden layer network, explore the impact of the number of hidden layers on the network performance.

(3) The method proposed in this paper uses modal strain energy as the input of BP neural network to identify damage. The effect of numerical simulation is ideal, but when it is applied in practice, it needs to consider the actual situation and the ideal situation of computer simulation differences in data. In actual damage detection, because the experiment is expensive and takes a long time, it is difficult to collect enough sample data. Therefore, obtaining a large number of sample data requires numerical simulation to establish a dynamic model of the damaged structure and reduce the simulation. Errors from experimental data, so how to incorporate structural damage mechanisms into dynamic models is also the focus of research.

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