

Research on Damage Identification Method of Civil Engineering Structure

Guanting She

Hefei University of Technology, Hefei, China

1393900945@qq.com

Keywords: Neural network, Damage identification, Engineering structure, Finite element simulation

Abstract: This paper analyzes and studies the change of dynamic characteristics of the structure by identifying the damage of the civil engineering structure. In recent years, due to the diagnosis and monitoring technology of structural dynamic characteristic parameters, the real-time diagnosis of various advantages has become a research hotspot in the current academic and engineering circles. At the same time, the neural network method in structural damage identification has received extensive attention and research. In this paper, the method of structural damage identification based on dynamic parameters and neural network is systematically studied.

1. Introduction

The biggest characteristic of artificial neural network is its strong adaptability. Artificial neural network automatically forms decision region through its own learning mechanism.^[1] Based on the characteristics of network learning and training rules of decision, can make full use of network status and related information data, from different state information about the value of each training to get a balanced convergence of these represent the network weights for a mapping relationship, and network can learn continuously, when the environment changes, the mapping relation can be adaptive, in an attempt to close to the progress of the object.^[2]

1.1 Classification of Artificial Neural Network

Artificial neural network has a variety of network models, which can be used to describe and simulate the biological nervous system from different angles and levels. Among them, the typical artificial neural network BP network model are as follows: (1), (2) the perceptron, (3) the linear neural network, and (4) the Hopfield model, the radial basis function network (5), (6) the organization network, using the network model can realize the function approximation, data clustering and pattern classification, optimization, etc.^[3-4]

1.2 Learning and Training Rules of Artificial Neural Network

In artificial neural networks, learning rules are an algorithm to modify the strength of the connection in order to obtain the structure of knowledge to adapt to the changes in the surrounding environment. Learning process can be divided into supervised process and unsupervised process. BP algorithm and ART theory are typical representatives. Have oversight process is through external teaching for learning, for a given input mode, when the actual output and the expected output of correct error, will be on automatic adjustment mechanism to adjust the corresponding network connection strength to reduce the error in the direction of change the connection weights, after many repetitions, and finally with the correct results within a certain range of error.^[5-7]

2. Structural Damage Identification Based on Neural Network

2.1 Numerical Simulation Analysis

Due to the large amount of experimental data needed for structural damage identification, the high cost of physical tests, and the difficulty in controlling and measuring some parameters in the

process of making test pieces, practical research on process structures is often restricted by many aspects. However, the method of experimental research on the model of engineering structure system, namely simulation technology, is not restricted by these problems, and becomes one of the effective methods for the damage diagnosis of engineering structure. In this example, the modal damage identification index and neural network are used to realize the identification, location and degree calibration of structural damage.

The plane element is used for the beam and the grid method is used for the numerical simulation of the dynamic analysis of the structural damage. Through finite element calculation, the first three frequencies of the plane element are shown in Table 1.

Table 1 the First Three Natural Frequencies of Intact Plane Element

Order number	Graphic unit
1	234.0953
2	855.0572
3	1348.426

2.2 Analysis of Simulation Results

Four working conditions of the structure were considered: nondestructive structure, 5mm damage at 100mm, 15mm damage at 100mm, and 5mm damage at 300mm. As can be seen in Figure 1 and Figure 2:

(1)The mode shape is not very sensitive to local damage; (2) Mode difference is a parameter that is more sensitive to local damage than mode shape. It can not only directly indicate the location of damage, but also qualitatively reflect the size of damage.



Fig.1 First Mode Mode Diagram of Various Working Conditions



Fig.2 Mode Difference Diagram

3. Analysis of Benchmark Problems in Structural Safety Monitoring

Structural damage detection and health diagnosis are widely used in civil engineering, and it is a promising field. Many scholars around the world have done a lot of research on structural damage detection and health diagnosis, and put forward many different theoretical methods and application technologies. However, people have been faced with a difficult problem, that is, a large number of research works have adopted different methods for different structures, resulting in the difficulty of comparison of various methods. Benchmark structure provides a platform for the unified evaluation of structural damage detection technology.^[7-9]

3.1 Finite Element Model of Benchmark Problem

Selection of units and models is the key to dynamic analysis of building structures. Among them, the strut system model can analyze the stress and failure state of the structure well. Therefore, based on the rod system model, this paper introduces the spatial beam element Beam4 spatial shell element Shell63 and the spatial rod element Link8.

The model is shown in Fig. 3. 3D beam element is used for frame column and frame beam, and 3D rod element is used for inclined brace. The floor is made of space shell units. Each node of the three elements has six degrees of freedom, that is, three translational degrees of freedom and three rotational degrees of freedom. The boundary condition is the column bottom consolidation, which limits all degrees of freedom.

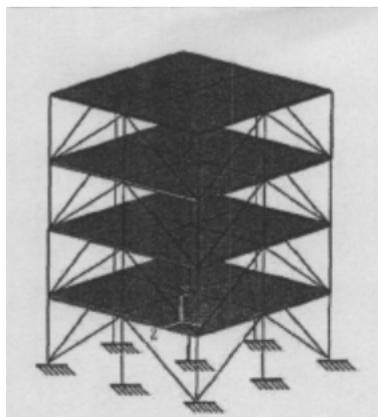


Fig.3 Schematic Diagram of the Model

3.2 Damage Identification Calculation and Analysis

Selection of characteristic parameters of network training is the key link. In this paper, input parameters that are sensitive to damage position but insensitive to damage degree are selected, such as the change ratio of two-order frequency, the square ratio of frequency change, and the regularized frequency change rate. For position recognition, the regularized frequency change rate of the first 6 orders NFCR., that is, the regularized frequency change rate of the first 6 orders of each sample is calculated with ANSYS6.0 as the input, and the number of output units is the number of layers, and each unit corresponds to a layer. When the output of the unit is 1, it means that the corresponding layer is damaged. When the unit output is 0, it indicates that the layer has no damage, the network learning parameter is $6 \times 4 \times 4$, and the error of training 10 steps reaches the ideal range.

6 damage modes are preset: the damage occurs when floors 1 and 2 are fully supported; 1, 3 floors all support; 14 floors fully supported; 2, 3 floors all support; 2, 4 floors all support; Floor 3 and 4 are fully supported. Each mode presets four damage levels of 20%, 50%, 70% and 90%, so there are 24 sets of data. At the same time, 72 groups of single-floor injuries in section 43.1 were also added into the training sample set as training data, so that a total of 96 groups of training data were obtained. A total of 8 groups of data were taken as the input parameters of the test data network, with the support stiffness of each layer reduced by 50% and 90%, as the regularization frequency change rate of the first 6 orders, and the output was the position of the damage layer. The learning parameters of the network are $6 \times 6 \times 4$, and the error of 32 training steps reaches the ideal range. In this training, the number of nodes in the hidden layer increased by 2, and the training step length increased a lot. The reason is that there are more injury modes that need to learn and memory damage.

4. Conclusion

With the rapid development of modal analysis technology, vibration testing technology and corresponding digital signal processing technology, the research progress of structural safety damage assessment has been greatly promoted, and a variety of damage diagnosis methods based on structural dynamic parameters have emerged. In many structural damage diagnosis methods, most of them focus on simple structures and ignore the influence of errors, which are far from the actual engineering structure damage diagnosis. This paper studies the application of artificial neural network in structural damage identification for specific engineering structures, and analyzes the influence of model error and measurement error on the identification results.

References

- [1] Civil structure condition assessment by a two-stage FE model update based on neural network enhanced power mode shapes and an adaptive roaming damage method[J]. *Engineering Structures*, 2020, 207:110234-.
- [2] N, Giordano, Luca F D , Sextos A . Out-of-plane closed-form solution for the seismic assessment of unreinforced masonry schools in Nepal[J]. *Engineering Structures*, 2020, 203(Jan.15):109548.1-109548.13.
- [3] Hussain, Shariq, Alam. Experimental and numerical studies for estimating coefficient of discharge of side compound weir[J]. *Canadian Journal of Civil Engineering*, 2019, 46(10):887-895.
- [4] Carl-Eric Hagendoft, Pär Johansson. Generic algorithm to assess moisture susceptibility of simplified wall assemblies[J]. *Canadian Journal of Civil Engineering*, 2019, 46.
- [5] Sakhakarmi S , Arteaga C , Park J W , et al. Automated Scaffolding Safety Analysis: Strain Feature Investigation using Support Vector Machines[J]. *Canadian Journal of Civil Engineering*, 2019, 47(8).
- [6] Sun M , Pan J , Bastard C L , et al. Advanced Signal Processing Methods for Ground-Penetrating Radar: Applications to civil engineering[J]. *IEEE Signal Processing Magazine*, 2019,

36(4):74-84.

[7] Ravinder R , Kumar A , Kumar R , et al. Irradiation - induced brittle - to - ductile transition in α - quartz[J]. Journal of the American Ceramic Society, 2020, 103(7).

[8] Alam. Seismic fragility assessment of multi-span concrete highway bridges in British Columbia considering soil–structure interaction[J]. Canadian Journal of Civil Engineering, 2021.

[9] Shao - Dong Shen, Pan P , Zhi - Zhou He, et al. Parametric analysis and new design formulas of a prefabricated energy - dissipating composite slotted shear wall[J]. Earthquake Engineering & Structural Dynamics, 2021.