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Research on Structural Damage Identification of Truss Structure Based on EMD and Neural Network

Menghong Wang, Huan Lu* and Peiru Deng

School of Civil and Transportation Engineering, Beijing University of Civil Engineering and Architecture, Beijing, 100044, China

*Corresponding author's e-mail: luhuan3010@163.com

Abstract. In this paper, a method was proposed for damage detection of truss structures under natural excitation based on the combination of radial-basis function neural network and empirical mode decomposition (EMD). Firstly, EMD method was applied to decomposing the vibration response data of the rod end node into a series of IMFs (Intrinsic Mode Functions). For the structure's original response data, after using the EMD to decompose it, the damage information and other useful contents will be distributed into various IMFs. Using neural network's excellent feature of linear mapping, IMFs are put as an input into the neural network, and the output was compared with the ideal output, which reveals the damage status of the structure. In this paper, experimental analysis and numerical simulation were used to detect the damage conditions of single-damage condition and two different rods in the same truss structure. Good recognition results were obtained.

1. Introduction

During the service of these large span space truss structures, it is difficult to avoid the extreme environment of building material aging, earthquake and so on, or the structural damage caused by human factors during the design, construction or using. For those internal defects and minor damages that cannot be observed, after a long period of development and accumulation, the structure is likely to collapse suddenly under accidental strong external force. These structural defects that are not visually observed are most likely to be more harmful because of their concealed nature[1].

Based on the basic characteristics of EMD and radial-basis function neural network, a method for damage identification of truss structures is presented by combining these two methods[2]. The structural response signal containing damage information is decomposed into a series of eigenmode functions by EMD. The damage information can be highlighted in these IMF components. Then the damage feature vector is input into the radial basis neural network as the damage eigenvector, and the damage position and degree of the network frame structure can be obtained.

2. Basic theory

2.1. Radial-basis function network

Radial-basis Function Network is a three-layer forward artificial neural network: The first layer is the input unit layer and composed of external signal sensing units. They are responsible for receiving external signals. The second layer is the hidden unit layer, and the number of hidden layer units is determined by the problem handled by the network. The transform function contained in this layer is a nonlinear, non-negative function that is radially symmetrical and attenuated to the center node. The



third layer is the output unit layer to output the network response [3]. The calculation process of RBF is mainly the process of constantly adjusting the parameters such as the value of the center value of the basis function, variance, and the weight value of the network connection according to the input vector.

Learning methods usually have two stages: The first stage is the self-organizational learning stage, which is the process of finding the central value and variance of the basis function of the hidden layer unit. The second stage is the stage of supervised learning, which is the stage of forming the output layer connection weights[4].

Specific instructions are as follows:

(1) Learning function center value $t_i (i = 1, 2, \dots, I)$

The self-organizing learning process requires a clustering algorithm, and the more commonly used clustering algorithm is a mean clustering algorithm. Assume that there are I centers in the clustering algorithm. $t_i(n)$ is the central value of the n th iteration of the basis function, The calculation process is as follows:

Firstly, cluster center initialization. According to a priori knowledge, select I different samples in the sample set as the central value $t_i(0)$, where the number of iteration steps is 0. Secondly, enter the randomly selected training sample X_K into the network. Thirdly, determine which center value is closest to the training sample X_K selected in the previous step, That is to find $i(X_K)$:

$$i(X_K) = \arg \min \|X_K - t_i(n)\|, (i = 1, 2, \dots, I)$$

$t_i(n)$, is the i th center value at the n th iteration.

Fourthly, use the following formula to adjust the center value:

$$t_i(n+1) = \begin{cases} t_i(n) + \eta [X_K(N) - t_i(n)], & i = i(X_K) \\ t_i(n), & \text{other} \end{cases}$$

η , the step size and $0 < \eta < 1$.

Fifthly, determine whether all the samples have been learned. If the center value no longer changes, the calculation is completed. Otherwise, let a go to the second step and recalculate.

After the calculation is completed, t_i is the central value of the basis function.

(2) Learning variance $\phi_i (i = 1, 2, \dots, I)$

When the base function selects the Gaussian function:

$$G(\|X_K - X_i\|) = \exp\left(-\frac{1}{2} \sum_{i=1}^I \frac{\|X_K - X_i\|^2}{\sigma_i^2}\right), \quad i = 1, 2, \dots, I$$

$$\sigma_1 = \sigma_2 = \dots = \sigma_I = \frac{d_{\max}}{\sqrt{2I}}$$

I , the number of hidden layer units; d_{\max} , the maximum value of the difference between the selected central values.

(3) Learning connection weights w_{ij}

The connection weights are learned by the LMS method. After the output information of the hidden layer of the RBF network, the output layer uses the connection weight to carry out the weighted summation of the information. The real output of the network is:

$$Y(n) = G(n)W(n)$$

$$Y(n) = \{y_{ij}(n)\}, i = 1, 2, \dots, I. j = 1, 2, \dots, J$$

2.2. Damage identification method combining EMD with neural network

The Norden E.Huang proposed a method of processing non-stationary signals in 1998—Hilbert-Huang Transform, which uses IMF when dealing with non-stationary signal sources, that is, using EMD to decompose the original signal according to the size of the energy, and get a set of waveform sequences with different wavelengths and frequencies[5]. The original damage signal of the structure is decomposed by the EMD method[6]. The resulting IMF component contains structural damage information. With the strong pattern recognition ability of the neural network, the damage information in the IMF component can be mined[7].

In this paper, damage is defined as the complete breakage of one of the rods in the structure, and the vertical acceleration response time at each node under each operating condition is obtained by using the mode superposition method and the EMD decomposition program is used to decompose the time-response data under various operating conditions to obtain IMF components for constructing the neural network input vector. The node acceleration response data S in each sample is directly used as input vector input network to construct a RBF network Net_1; in addition, the acceleration response S is divided into the test sample and the training sample in the same manner for EMD decomposition. All the 10th-order components obtained by the decomposition are used as input vectors to construct another RBF network Net_2. Further, by examining the same damage condition, it is possible to compare the two methods.

3. Numerical simulation

3.1. Calculation model and incentive method

In this paper, the structure of the shell-shell truss structure is used for analysis. The model overview is as follows: Span is $3m \times 5m$. A total of 60 nodes and 174 rods. All rod materials use Q235, Section size is $\Phi 42mm \times 2.5mm$. The modulus of elasticity is $200Gpa$. The joints are hinged and the four supports are connected. The Midas-civil model is shown in figure 1. This article uses an angle steel model $L80 \times 8$. With the length of 0.5m, along the direction of travel, and 1.5m width transverse to the traveling direction, a four-wheeled vehicle weighing approximately 40kg is used to simulate mobile devices. The trolley is placed on the rail at the top of the truss and moves forward and backward to construct a random excitation.

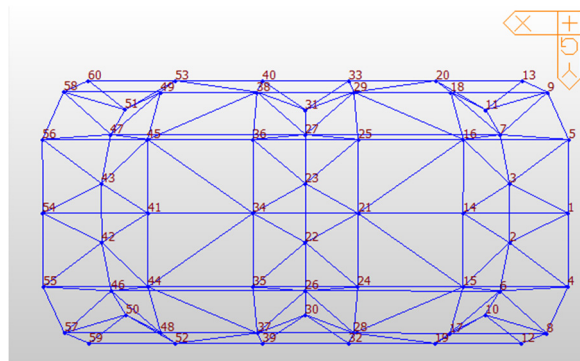


Figure 1. Midas-civil model.

First of all, the travelling speed of the car is defined to be 0.5m/s, and the diameter of the wheel is 0.1m. Then for each node on the track, the process of rolling the wheel on the track can be simplified to a time history function that a period of 0.4s and the peak value is 1/4 of the car's mass. In addition, two mass-ignoring orbits are added to the structure. The orbits are divided into a series of small cells according to the width of the wheel every 0.1m. The above-mentioned schedule function is applied to the nodes between the small cells. The four points at the same time as the four wheels of the trolley are used as a load group, moving from the leftmost to the right most of the structure in the order to move the group forward every 0.2s. Total time 0.8s.

3.2. Condition setting and identification

Condition1: The 67th member is completely damaged (reduced by 100% in stiffness) and the relevant node number is 24, 28; Condition 2: The 13th and 49th members are completely damaged (reduced by 100% in stiffness) and the relevant nodes are numbered as 7, 11, 21, and 25.

Due to limited space, and given the fact that the node identification value far from the damaged member is small, only the identification output result of the node near the damaged member is shown here. Table 1 shows the network output result of condition 1, where T_A is the RBF network output. The theoretical output value represents the actual damage of the structure; T_B is the RBF network output value when the IMF component is the input sample; T_C is the RBF network output value when the original acceleration response data is used as the input sample.

Table 1. No.67 chord recognition result.

Node	T_A	T_B	T_C	Node	T_A	T_B	T_C
15	0	0.0286	0.1216	26	0	0.0451	0.0052
16	0	0.0099	0.0878	27	0	0.0588	0.0475
17	0	0.0130	0.0515	28	1	0.9532	0.7921
18	0	0.0938	0.0179	29	0	0.0095	0.0843
19	0	0.0088	0.0804	30	0	0.0556	0.0587
20	0	0.0659	0.0166	31	0	0.0536	0.0996
21	0	0.0776	0.0176	32	0	0.0895	0.0165
22	0	0.0638	0.0427	33	0	0.0913	0.0360
23	0	0.0588	0.0063	34	0	0.0878	0.0083
24	1	0.9723	0.8243	35	0	0.0058	0.0108
25	0	0.0152	0.0627	36	0	0.0051	0.0177

The data in the table is represented as a histogram, as shown in figure 2 and the damage identification results of condition 2 is shown in figure 3.

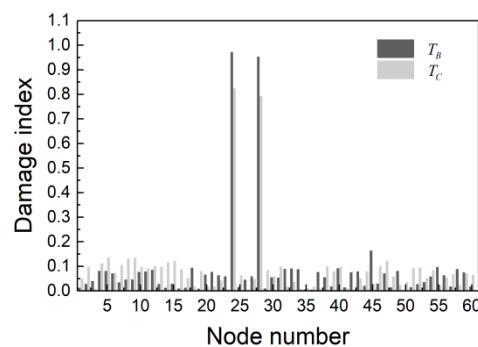


Figure 2. Comparison of damage identification results for 67th member.

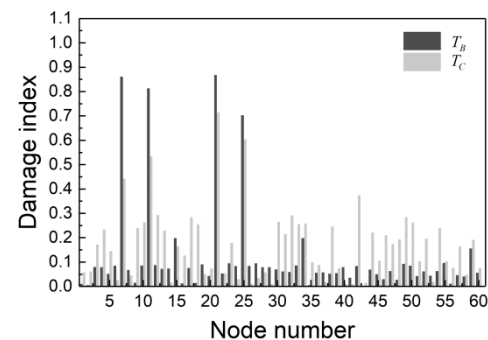


Figure 3. Comparison of damage identification results for 13th and 49th member.

From the above identification result, it can be seen that the network trained by the IMF as a data sample has a good recognition effect for the single-rod damaged conditions and the network trained by using the original data as a sample has a relatively poor accuracy and the error at the injury site is also more pronounced. Under multi-damage conditions, the two networks can identify the presence of the damage more accurately; but compared to single damage conditions, the accuracy of detection results is greatly reduced.

4. Test analysis

4.1. Model overview

The experimental model is constructed with reference to the numerical model. The dimensions of the model can be found from section 3.1 of this paper. The structural elements used for the tests were all

produced in advance at the truss factory in accordance with the predetermined size, and were installed on site in the structural laboratory. The site model is shown in figure 4.

4.2. External excitation setup and data acquisition

In order to genuinely simulate the role of the large-span network structure under the working environment, the task force designed a simple four-wheeled vehicle to run on the track welded above the structure to simulate the lifting equipment under real conditions, as shown in the figure 5. During the experiment, the manual traction cart runs running at a uniform speed in one direction on the track, and an accelerometer is used to collect the acceleration time-course response data during one-way operation of the trolley. According to the travel time of the car on the track, the sampling frequency of this experiment is set to 512Hz, and the sampling time is 10s.



Figure 4. Truss structure model.



Figure 5. Trolley on the grid structure.

4.3. Condition setting and damage identification

To verify the effectiveness of the neural network trained in the numerical simulation in the actual structure, the network trained in the simulation phase is directly used to identify the experimental data, and the following conditions are set: Condition I: The 34th web rod is completely damaged (the root bar is cut off), and the node numbers at the two ends are 7 and 16. Condition 2: The rods 34 and 35 are completely damaged. The two rods are adjacent web members. Among them, the two ends of the 34 rod are 7, 16, and 35, respectively. The nodes at the two ends are 3 and 16, respectively, and share node 16. The recognition results of these conditions as shown in figure 6 and figure 7.

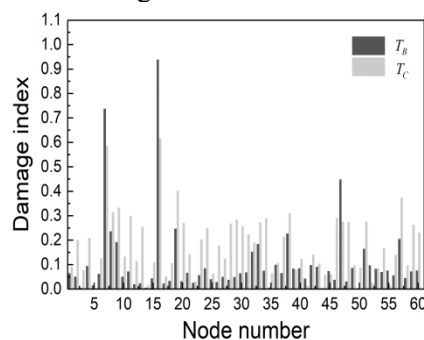


Figure 6. Comparison of damage identification results for 34th member.

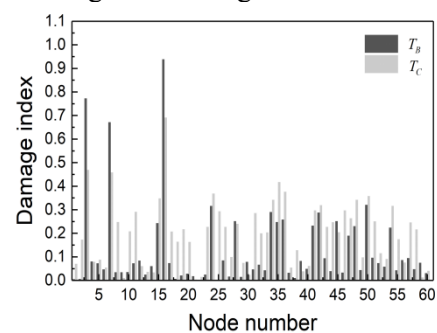


Figure 7. Comparison of damage identification results for 34th and 35th member.

From the recognition result of the operating condition, it can be seen that although there is a large error compared with the numerical simulation, the damage identification method based on the neural network can effectively identify the structural damage under the operating condition. The accuracy of the network based on the input of the IMF is obviously higher than that based on the original data. This further shows that the combination of the EMD and the RBF neural network has certain advantages.

5. Conclusion

This paper proposes a method for the damage detection of large-span network structures by combining radial basis neural network and empirical mode decomposition method. EMD-based method is first used through the numerical simulation and experimental analysis of the structure at the structural laboratory of BUCEA. The damage detection method combined with the neural network and the damage detection method of the simple neural network can successfully detect the damage location and damage degree. The main results are as follows:

(1) In order to reflect the improvement of the damage detection effect by combining the EMD method with the neural network, two types of networks have been set as reference in both the simulation and the experimental part. The first type is the network trained by using the IMF component obtained after EMD decomposition of the original data as the network input parameter; the second type is the network trained directly using the original data as the network input parameter.

(2) In order to simulate large-span truss structures with large-scale lifting equipment, such as industrial plants and maintenance workshops, and to simulate the role of large-span truss structures in the working environment as they are, the task force designed a simple four-wheeled vehicle in the structure. Run on the track above the welded to simulate the lifting equipment in real conditions.

(3) Both the simulation and the experimental results show that under single-damage condition, both types of networks can successfully detect the presence and location of damage; at the same time, the network based on the IMF data is superior to the one under any conditions.

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