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Conventional Bridge Damage Identification Based on BP Neural Network

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Abstract. Aiming at the problem of insensitivity of damage identification in conventional bridges, the application of BP neural network in long-span bridges is studied, and it is extended to the field of damage identification of conventional bridges. The finite element models of three-span continuous variable cross-section box girders under intact and damaged conditions are established by Midas civil, and the eigenvalues of bridges under different conditions are analyzed. It is found that in conventional bridges, the sensitivity to structural damage is: mode > vertical displacement > natural frequency. The parameterized natural frequencies and modes of structures are used as input of BP neural network, and the damage location and degree are used as output to train the neural network. Then, the damage location and degree are identified under different working conditions, and the results show that the recognition effect is not satisfactory. Analyzing the reason, the natural frequency and modal shape of the structure will change when the conventional bridge is damaged, but the deformation value is very small. When training the BP neural network, it is easy to appear over-fitting, which results in poor recognition effect. Therefore, it is difficult to identify structural damage by using BP neural network through acquiring the characteristics of conventional bridges. It is still necessary to study appropriate damage identification parameters and methods that can be applied to conventional bridges.

1. Introduction

According to the proportion of dangerous bridges, conventional bridges are much higher than super-long-span bridges, and most of the bridges collapsed during operation are concentrated in conventional girder bridges[1]. The damage identification method based on neural network has been widely concerned and studied in engineering structures [2-5]. Taking three-span continuous variable cross-section concrete box girder as an example, this paper studies the application of neural network method in damage identification of conventional girder bridges, in order to promote the establishment of conventional bridge health monitoring system.

2. Paper Finite Element Model of Three-Span Continuous Variable Section Concrete Box Girder

Based on a three-span continuous variable cross-section box girder, this paper establishes a finite element model. The width of bridge deck is 6.5m, and the layout of bridge type is 37.5m+65m+37.5m=140m. Vehicle load grade: highway grade I; bridge seismic fortification intensity: VI; peak acceleration coefficient of ground motion is 0.05g. The top section of the pier is 3.5 m high, as shown in Figure 1. The beam end and mid-span section are 1.8m high, as shown in Figure 2. The finite element models of three-span continuous variable cross-section box girders based on Midas civil are presented in Figure 3, which are subdivided into left and right spans, middle piers and middle spans.

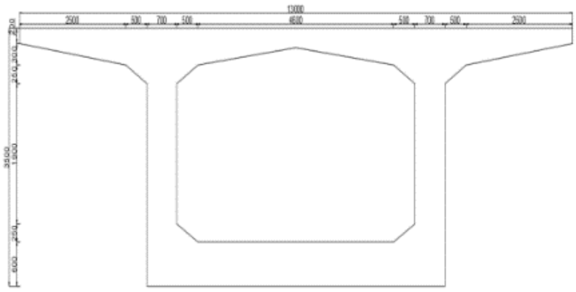

Figure 1. Pier Top section

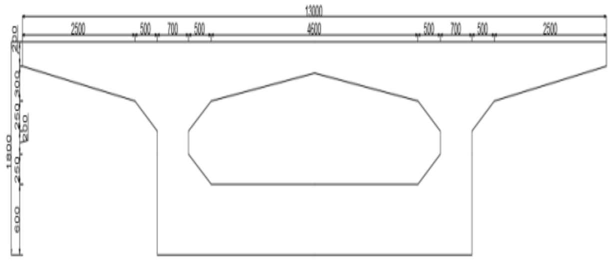

Figure 2. Beam End and Mid-span sections

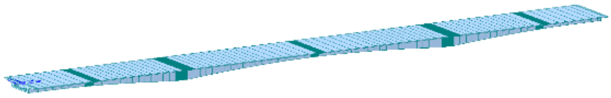

Figure 3. Finite element model of continuous variable cross-section box girder with three spans

3. Damage Simulation

Next, damage simulation of the three-span continuous variable cross-section box girder is carried out, which is divided into the selection of damage location and the simulation of damage degree. Damage mainly includes breathing crack, concrete carbonization, steel bar and concrete peeling, steel bar corrosion and so on. Under the action of reciprocating load of high-speed transport vehicle, when the damage of breathing crack reaches a certain degree, concrete will peel off steel bar, steel bar will be corroded, accompanied by fatigue damage, and ultimately fracture. In this paper, the damage locations are arranged in the middle of the left and right span, the top of the pier and the middle span, respectively. As shown in Figure 4, the shadow part is the location of the crack damage on the concrete beam bridge. The damage condition is divided into single position damage and double position damage. The single damage location is taken as the research object, and the damage condition is set as shown in Figure 5.

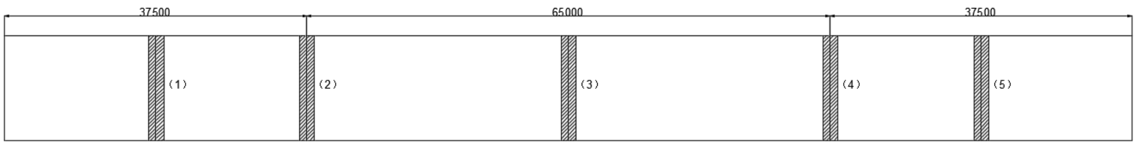

Figure 4. Crack damage of continuous variable section box girder (overlooking)

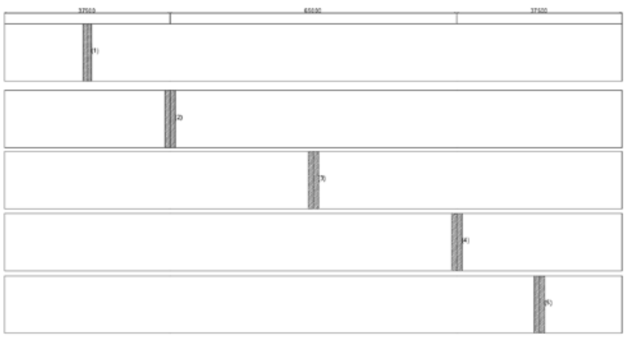

Figure 5. Single damage location

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Taking the top view of three-span continuous variable cross-section box girder, in order to facilitate the output of damage location identification, from the left span to the right span, the above five damage locations are sequentially arranged into 1-5, expressed by G1-G5. Generally, the crack damage of bar structure and frame structure can be simulated by changing the section area and elastic modulus of material. The crack damage of the bridge is simulated by changing the elastic modulus of the concrete of the three-span continuous girder bridge. In order to simulate different degrees of crack damage, the elastic modulus of C40 concrete is reduced to 90%, 85%, … , 25% , 20% respectively. Indicating that the degree of crack damage is 10%, 15%, 15%, … , 75% and 80%. D1 ~ D15 are used to express them respectively. D0 indicates that the structure is in good condition. The location and degree of damage can be expressed by D#-G#, for example, D1-G1 for 10% of the damage under condition 1.

4. Modal Analysis

After the damage of engineering structure, its dynamic characteristics will change accordingly. The change of structural dynamic characteristics can be represented by observing the change of natural frequencies and mode shapes of the structure. In order to observe this change more clearly and to study the sensitivity of natural frequencies to damage, the first 7 natural frequencies under different working conditions are selected. The natural frequencies and modes described in this paper refer to the vertical vibration of bridge structures. Taking D1-D15 working conditions under D0 and G1 as examples, the first eight natural frequencies of three-span continuous variable cross-section concrete box girders are shown in Table 1.

Table 1. First 7 Natural Frequencies of Bridge Structures under 15 Working Conditions of D0 and G1

Working Conditions	Frequency /Hz						
	1 order	2 order	3 order	4 order	5 order	6 order	7 order
D0	1.625732	3.325308	4.280689	5.567203	6.021167	7.704737	9.8668
G1-D1	1.625709	3.325237	4.280618	5.567173	6.021126	7.704722	9.866782
G1-D2	1.625696	3.325195	4.280576	5.567156	6.021103	7.704714	9.866772
G1-D3	1.625681	3.325149	4.28053	5.567136	6.021076	7.704704	9.86676
G1-D4	1.625664	3.325096	4.280477	5.567114	6.021045	7.704693	9.866746
G1-D5	1.625645	3.325036	4.280417	5.567089	6.021011	7.704681	9.866731
G1-D6	1.625623	3.324968	4.280348	5.567059	6.020971	7.704667	9.866713
G1-D7	1.625597	3.324888	4.280269	5.567025	6.020925	7.704651	9.866692
G1-D8	1.625567	3.324794	4.280175	5.566985	6.020871	7.704631	9.866668
G1-D9	1.625531	3.324683	4.280064	5.566936	6.020807	7.704609	9.866639
G1-D10	1.625488	3.324548	4.279929	5.566877	6.020729	7.704581	9.866604
G1-D11	1.625434	3.324381	4.279763	5.566803	6.020633	7.704546	9.86656
G1-D12	1.625366	3.32417	4.279552	5.566708	6.020511	7.704503	9.866504
G1-D13	1.625278	3.323894	4.279277	5.566581	6.020351	7.704445	9.86643
G1-D14	1.625156	3.323516	4.278901	5.566404	6.020133	7.704367	9.866328
G1-D15	1.62498	3.322969	4.278359	5.566138	6.019818	7.704252	9.866177

From Table 1, we can see that under the same damage condition, the natural frequency of concrete bridge structure increases with the increase of modal order; the natural frequency of concrete bridge structure decreases after damage occurs; after damage occurs, the higher-order frequency decreases more than the lower-order frequency, which indicates that the higher-order frequency change is more sensitive to structural damage. With the increase of damage degree, the natural frequency decreases, but the change is only about 3%.

When the structure is damaged, the mode shapes will change accordingly. The following is an illustration of the mode change under D0 and G1 conditions. For the convenience of viewing the changes of the modes of the damaged parts, the specific values will be shown in Table 2.

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Table 2. The first five modes of bridge structure under D0 and G1-D15

Working Conditions	Modal shape/m				
	1 order	2 order	3 order	4 order	5 order
D0	1.23E-05	2.73E-05	3.08E-05	9.34E-06	2.12E-05
G1-D15	1.3E-05	2.83E-05	3.17E-05	9.39E-06	2.40E-05
Variation	5.7%	3.7%	3%	0	13.2%

From the above table, it can be seen that the first five modes of bridge structure simulated by Midas are relatively small; the change of modes is more obvious than the change of natural frequencies after the damage of the structure, which shows that the modes are more sensitive to the structure, but the maximum change is about 10%. In addition, the displacement changes of damage location under simulated actual loads are obtained. The following examples are D0 and G1-D15, as shown in Table 3.

Table 3. Displacement of Damage Location of Bridge Structures under D0 and G1-D15

Working Conditions	Displacement /mm				
	Element 51	Element 52	Element 53	Element 54	Element 55
D0	-17.48258	-16.0755	-14.6374	-13.1805	-11.7218
G1-D15	-17.56168	-16.1459	-14.7006	-13.2368	-11.7713
Variation	0.452%	0.438%	0.432%	0. 427%	0. 422%
Working Conditions	Displacement /mm				
	Element 56	Element 57	Element 58	Element 59	Element 60
D0	-10.27559	-8.85377	-7.46141	-6.10481	-4.78921
G1-D15	-10.31793	-8.88987	-7.49163	-6.1294	-4.8084
Variation	0.412%	0.408%	0.405%	0.403%	0.401%

From Table 3, it can be seen that the absolute value of the vertical displacement of the damaged position increases under the action of environmental loads after the bridge is damaged. Compared with the natural frequencies and modes of the structure, the displacement change is not particularly sensitive to the damage of the structure at the same damage degree. The location and degree of damage can be predicted by placing displacement sensors on the bridge.

5. Damage Identification of Concrete Beam Bridge Based on BP Neural Network

5.1. Input and Output of Neural Networks

According to the results of finite element modal analysis, the change of natural frequencies of damaged structures is small, and only the change of higher natural frequencies is large. This paper expects to identify the damage location and the damage degree of bridge structure through BP neural network. When the damage degree is large, the modal shape of bridge structure changes about 10%, so the modal shape can be normalized as input parameters. Taking the first five modes of working condition G1-D15 as an example, the first step is to increase the mode value by five orders of magnitude for the convenience of the whole. Then the mapminmax function in MATLAB is used to normalize the mode and map it to the interval [-1, 1] as shown in Table 4.

Table 4. Normalization of modal mode shapes of bridge structures under G1-D15

Normalization	1 order	2 order	3 order	4 order	5 order
Pre-treatment	1.30	2.83	3.17	0.94	2.40
Post-treatment	-0.68	0.70	1.00	-1.00	0.31

After normalizing the first five modes of damage location of three-span continuous variable cross-section box girders under different working conditions, the damage response is taken as the input of

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the network and the output of the network. In this paper, it is expected that BP neural network can be used to identify the damage location and degree of bridge structure at the same time. The output of the network is parameterized to Ti, j (i = 1~5, j = 2~16). Five values of I correspond to the damage location of the bridge structure (damage location is 1, non-damage location is 0), and the corresponding damage degree of j to the bridge structure (near the preset damage level is 1, the others are 0). For example, the output vector of G1-D15 is shown in equation (1), which indicates that the damage location is in the middle of the left span and the damage degree is 80%.

$$T_{1,16} = \begin{bmatrix} 1 & 0 & 0 & \cdots & 1 \\ 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \end{bmatrix} \tag{1}$$

5.2. Construction of Network Structure

Any continuous function in the closed interval can be approximated by BP network with a single hidden layer, that is, a three-layer BP network can complete any mapping from n-dimension to m-dimension. Therefore, a three-layer BP neural network is constructed to deal with the non-linear mapping relationship between structural damage and structural modal. The difficulty of building BP neural network is to determine the number of neurons in the hidden layer, which generally needs the experience of the designer and many experiments to determine. It is difficult to find an ideal analytic formula to obtain. There is a direct relationship between the number of hidden layer units and specific problems, and between the number of input and output units. Too few hidden units will lead to poor fitting effect and poor recognition results; too many hidden units will lead to long learning time, but the error will not necessarily reduce, and may lead to poor fault tolerance, unable to identify samples that were not seen in the past. Therefore, it is necessary to determine the optimal number of hidden elements. In this paper, the initial number of hidden elements is determined according to the following formula (2), and then the optimal number of hidden elements is adjusted repeatedly.

$$n_1 = \sqrt{n+m} + a \tag{2}$$

Among them, n_1 is the number of hidden units and n is the number of input units. In this paper, let n = 15. m is the number of output neurons, m = 2 and a is the constant between [1,10]. After debugging, a = 5 is chosen in this paper. The number of hidden units n_1 is taken as an integer and eventually 10.

5.3. Network Training and Its Effect

Data from D1 to D14 under G15 are selected as training samples, and data from D15 under G1 to G5 are selected as test samples. Generally, the more damage cases are considered, the more training samples are obtained and the more accurate the recognition is, but the training samples will increase infinitely. In fact, the neural network has a strong generalization ability. As long as the training samples have a certain scale and high quality, it is not necessary to train all the samples.

In practical engineering, different network models can get different results of structural damage identification. The BP neural network with single hidden layer is simple to construct and easy to implement. It can approximate any non-linear continuous function. When training the BP neural network, the damage degree of each working condition is close (the damage degree increases from 10% to 5% as a gradient to 80%). The modal parameters simulated by the cable element have little difference under each working condition, and the over-fitting situation appears (as shown in Figure 6). The recognition result is quite different from the expected value.

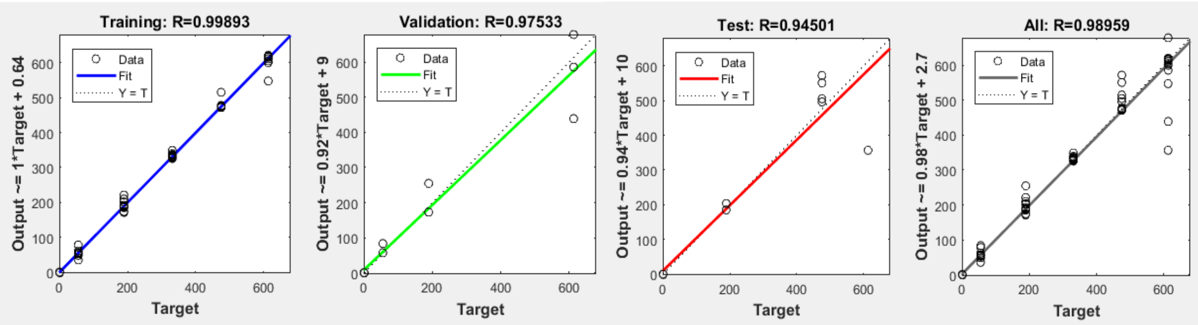

Figure 6. The fitting effect of BP neural network

6. Conclusion

In this paper, the finite element model is established to obtain the modal parameters under various working conditions, and the damage identification using neural network is still limited. When conventional bridges suffer from micro-damage, the change of modal parameters is very small, and the displacement and deformation of structures are very small. It is difficult to identify the damage. Only when there is a large damage in the bridge structure, can the damage be measured accurately. In the conventional bridge damage identification, how to accurately identify the damage degree by BP neural network is still a difficult problem.

7. Acknowledgments

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8. References

[1] C. Farrar, S. Doebling, D. Nix, Vibration-based structural damage identification, Philos. Trans. Roy. Soc. Lond. A: Math., Phys. Eng. Sci. 359(1778)(2001)131-149.
[2] Luca Facchini, Michele Betti, Paolo Biagini. Neural network based modal identification of structural systemsthrough output-only measurement. Computers and Structures 138 (2014) 183–194.
[3] Jordan C.Weinstein; Masoud Sanayei, M.ASCE; and Brian R.Brenner, F.ASCE. Bridge Damage Identification Using Artificial Neural Networks. J. Bridge Eng., 2018, 23(11): 04018084.
[4] HU Qin, XU Wei, GAO Fei, et al. Damage Identification of CA Mortar Layer of CRTS I Slab TrackBased on BP Neural Network[J]. Journal of Civil Engineering and Management, 2018, 35 (05): 87-93.
[5] LI Xue-song, MA Hong-wei, LIN Yi-zhou, et al. Structural damage identification based on convolution neural network[J]. Journal of Vibration and Shock, 2019, 38 (01): 159-167.