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INVESTIGATION OF NATURAL FREQUENCIES REDUCTION, AN APPROACH TO DAMAGE DIAGNOSIS IN STRUCTURES

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Abstract

This paper present an approach based on reduction of natural frequencies of structures in order to identification of damage. In the proposed method, the crack identification procedure consists of three steps. Firstly, using finite element method, three natural frequencies of a variable cross-section beam for different cracks depth and locations are obtained. In the second step, two types of networks are created and trained. The neural networks inputs are first three natural frequencies and the outputs of first and second networks are corresponding locations and cracks depth, respectively. In third step, some of natural frequencies of variable cross-section beam with distinct crack conditions are applied as inputs for trained neural networks. Finally obtained results of two types of neural networks are compared with each other.

Keywords: Natural frequency reduction; finite element method; damage diagnosis; modal analysis

1. Introduction

A lot of studies have been done on non-destructive estimation methods. The non-destructive methods used so far can be divided in four groups.

The first group includes methods that determine if there is a specific fault in the structure or not [1, 2]. The second group includes methods not only capable of identifying the fault but also locating it [3-5]. The third group includes methods capable of specifying more information about the fault, like the depth [6-9], and the fourth group contains methods that can even estimate the effect of the fault on the structure.

In recent years investigators have shown great interest in vibration analysis method and so there are a lot of investigations in this area. Dimarogonas reviewed methods of investigating cracked structures in 1996 [10]. Crack causes a local flexibility in the structure which affects the dynamic behaviour. For example it reduces the natural frequencies and changes the mode shapes. Analyzing these effects can be used for crack detection [11]. Dimarogonas et al. modeled a crack using local flexibility and calculated the equivalent stiffness utilizing fracture mechanics [12, 13]. Adams et al. developed an experimental technique to estimate the location and the depth of a crack based on the changes of the natural frequencies [14]. In another investigation Dimarogonas presented methods which relate the depth of the crack to the changes of the natural frequencies when the crack location is known [15]. These methods can be used to identify cracks in different structures. Gudmunson presented a method to predict the changes of the natural frequencies caused by faults such as cracks, notches, etc [16]. Masoud et al. investigated vibrational characteristics of a fixed-fixed beam with a symmetric crack considering coupling effect of crack depth and axial load [17]. Shen et al. presented a method based on minimizing the difference between the measured data the data obtained from an analytical data to identify cracks in an Euler-Bernoulli beam [18].

In this paper the parameter used to identify the fault is natural frequency. This is because of the fact that measuring natural frequency is cost effective [20], and can be done in most structures [11]. A new technique used frequently for damage identification in recent years is neural network. Wu et al. used back propagation neural network to identify the fault location in a simple frame [21]. Kao and Hung presented a two step method for identifying cracks based on neural network. First step was to identify damaged and undamaged system situations. Second step was fault detection in structures. In this step a trained neural network was used to produce free vibration response of the system and finally a comparison was made between the results to evaluate changes in amplitude and periods [22]. Chen et al. worked on using neural network for fault detection in engineering structures in case the excitation signal is not available [23]. In recent years some studies have been done on multi-crack detection of structures. Sekhar summarized different studies on double/multi-cracks and the respective influences, identification methods in vibration structures as beams, rotors, pipes etc [24]. Lee used finite element method to solve forward problem in a multiple cracked beam. The inverse problem was solved iteratively for the locations and sizes of the cracks using the Newton-Raphson method [25]. Patil and Maiti detected multiple cracks by frequency measurements. Their procedure gave a linear relationship explicitly between the changes in natural frequencies of the beam and the damage parameters [26]. Mazanoglu et al. performed a vibration analysis of multiple cracked non-uniform beams by the Rayleigh–Ritz approximation method [27]. Binici proposed a parametric study in order to investigate the effect of cracks and axial force levels on the eigenfrequencies [28]. A new method for natural frequency analysis of beam with an arbitrary number of cracks has been developed by Khiem and Lien on the bases of the transfer matrix [29]. Ertugrul et al. analyzed the vibrations of cracked beam as a result of impact shocks to obtain information about the location and depth of cracks in cracked beams [30]. This paper probes a procedure for identification of crack in non-uniform beam. The procedure has three steps. In first step, three natural frequencies of a non-uniform beam for various locations and sizes of cracks were calculated by **F**inite **E**lement **M**ethod (**FEM**). In second step, two RBF and two BEP neural networks were created and trained. The inputs of neural networks were first three natural frequencies and the outputs of first and second RBF and BEP neural networks were corresponding locations and depth of cracks, respectively. Also In third step, some of natural frequencies of non-uniform beam with distinct crack conditions used as inputs in trained neural networks. Finally calculated results of two types of neural networks were compared with each other.

2. Modal Analysis Using Finite Element Method
3.

The considered structure is a cantilever variable cross-section beam with material and geometrical characteristic that are tabulated in Table 1. A schematic view of assumed cracked beam is shown in Fig. 1.

Table 1. Beam Characteristics

Density (Kg/m^3)	Poisson Ratio	Elasticity Modulus (GPa)	Length (mm)
7860	0.3	210	240
Thickness (mm)	**Depth at the Fixed End (mm)**		**Truncation Factor**
12	20		0.5

The natural frequencies of the considered cracked beam were obtained by using modal analysis and for this target, FEM has been applied. In this article about 700 eight nodes 2D elements have been used for modal analysis.

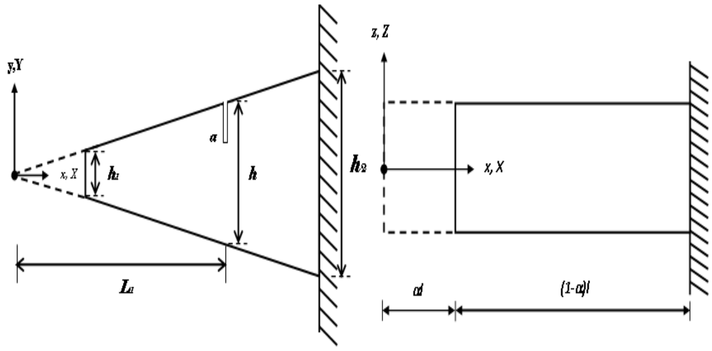

Fig1. Beam geometry

This element is defined by eight nodes which have two degrees of freedom at each node includes translations in the nodal *x* and *y* directions. Dimensions of elements varied from 0.002 at region far from cracks to 0.00055 at vicinity of cracks. A meshed view of the cracked structure is illustrated in Fig. 2 and Fig. 3.

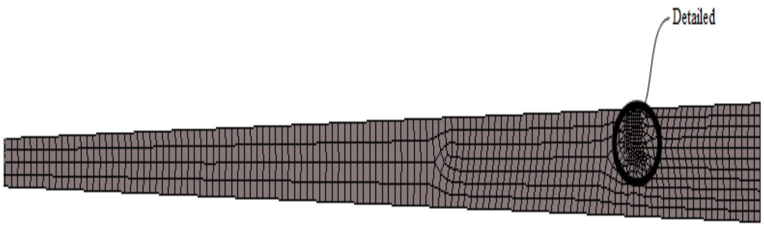

Fig2. Typical finite element discretisations

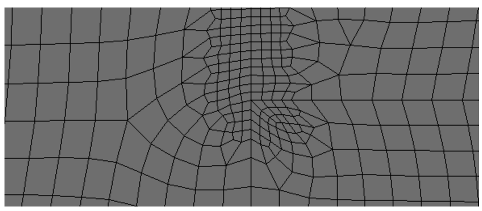

Fig 3. Detailed of typical finite element discretisations

For validation of FEM calculated results of present paper, three natural frequencies of the structure were calculated for some different conditions of crack and then they were compared with the corresponding results that presented in reference [31]; (See Table 2). The crack location and depth in Table 2 were presented in non-dimensional form. The non dimensional location is the location of crack divided by lengths of beam. Also non-dimensional depth is depths of crack divided by depths of the beam.

Table 2. Comparison of FEM results between the present work and Reference [31].

Condition		1	2	3
Crack Location		0.6	0.6	0.8
Crack Depth		0.3	0.5	0.5
Natural Frequencies. Present Work (HZ)	f_1	313.99	313.09	279.28
	f_2	1457.60	1398.20	1384.70
	f_3	3558.10	3218.50	3338.50
Natural Frequencies Reference [31] (HZ)	f_1	313.61	312.74	280.68
	f_2	1456.09	1398.41	1383.58
	f_3	3551.35	3215.78	3320.60
Error (%)	f_1	0.12117	0.11191	0.498789
	f_2	0.1037	0.015017	0.08095
	f_3	0.19007	0.08458	0.53906

The obtained results display that FEM analysis has been done with the maximum error about 0.54%. In Table 2, f_i represent the i^{th} natural frequency of cracked beam.

4. Artificial Neural Network

In this section the process of crack detection has been performed by using finite element method and two distinct types of artificial neural network including RBF and BEP neural networks. Neural networks have been trained using obtained data from finite element method.

5. Back-Error Propagation Neural Network

The most popular type of neural network is multi-layer feed forward (MLFF). A schematic diagram of typical BEP neural-network architecture is shown in Fig 4. The network usually consists of an input layer, some hidden layers and an output layer. The back-error propagation is the most widely used learning algorithm. The back-propagation neural network was proposed by McClelland and Rumelhart [32] in a ground-breaking study originally focused on cognitive computer science.

In this paper the structure of neural network includes three layers: the input layer, hidden layer, and output layer.

The variable M shows the total neuron number in the input layer, variable N shows the total neuron number in the hidden layer, and the variable L shows the total neuron number in the output layer. Values w_{MN} are the weights between the input and the hidden layer. Values w_{LN} are the weights between the hidden and the output layer. The operation of back error propagation is consisting of three steps:

1- Feed-forward step:

$$v_j = w_{LN}(n).u_{j+1}(n); \tag{1}$$

$$o_j(n) = \varphi(v_j(n)) = \frac{2}{1+\exp(-v_j(2n))}; \tag{2}$$

Where, o_j is output, u_j is input, u_{j+1} is output of hidden layer and φ is a transfer function.

2- Back-propagation step:

$$\delta_j(n) = e_j(n).\varphi'(v_j(n)) = (d_j(n) - o_j(n))o_j(n)(1 - o_j(n)); \tag{3}$$

Where, δ_j represents the local gradient function, e_j shows the error function, o_j means the actual output and d_j is desired output.

3- Adjust weighted value:

$$w_{NM}(n+1) = w_{NM}(n) + \Delta w_{NM}(n) = w_{NM}(n) + \eta\delta_j(n).o_j(n); \tag{4}$$

where η is the learning rate. Repeating these three steps results to the value of the error function will be zero or a constant value.

In this paper two BEP neural networks are employed for prediction of location and depth of crack respectively. These networks consist of one input layer with 3 neurons, one hidden layer with 20 neurons and one output layer with two neurons. The inputs of BEP neural networks were first three natural frequencies of different conditions of cracks and output were locations of cracks.

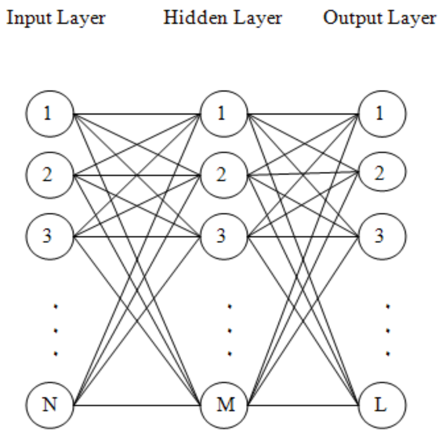

Fig 4. Schematic diagram of typical BEP neural-network architecture

6. Radial Basis Neural Network

The structure of RBF is shown in Fig5. It includes four layers, the input layer, hidden layer, summation layer and output layer. In this study two RBF were used to detect the number of cracks in structure. The inputs of RBF were first three natural frequencies of different conditions of cracks and output were locations of cracks.

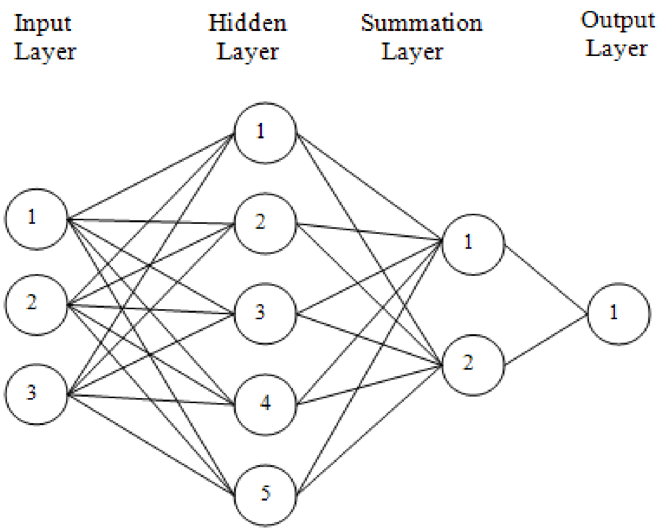

Fig 5. Schematic diagram of radial basis neural network

7. Results

The predicted values of locations and depths of cracks have been compared with the actual values in Table 3.

Table 3. Comparison of predicted and actual depths and locations of cracks

Number	1		2	
Parameter	Depth	Location	Depth	Location
Actual	0.3	0.7	0.5	0.7
Predicted (BEP)	0.310	0.717	0.515	0.716
Error (%) (BEP)	3.48	2.57	3.14	2.36
Predicted (RBF)	0.294	0.735	0.525	0.682
Error (%) (RBF)	1.94	5.12	5.12	2.45

8. Conclusion

This paper, presented a procedure based on RBF and BEP for identification of crack in variable cross-section beam. In the proposed procedure, first of all, three natural frequencies of a variable cross-section beam for different locations and depths of cracks were obtained using FEM and then RBF and BEP neural networks were trained. Finally trained ANNs were used to predict the characteristics of some cracks on mentioned beam and the results of the RBF and BEP neural networks were compared with each other which both of them were in good agreement with actual data.

References

[1] Vandive, J.K., Detection of structural failures on fixed platforms by measurement of dynamic responses, Proceedings of the 7th Annual Offshore Technology Conference, Houston, Texas, 1975.
[2] Crohas, H. and Lepert, P., Damage detection monitoring method for offshore platforms is field tested, Oil& Gas J., 80, 94-103, 1982.
[3] Cawley, P. and Adams, R.D., The location of defects in structures from measurements of natural frequencies, J. Strain Anal., 14, 49-57, 1979.
[4] Pandey, A.K., Biswas, M. And Samman, M.M., Damage detection from changes in curvature mode shapes, J. Sound Vib, 145, 321-332, 1991.
[5] Chance, J., Tomlinson, G.R. and Worden, K., A simplified approach to the numerical and experimental modeling of the dynamics of a cracked beam, Proceedings of the 12th International Modal Analysis Conference, Honolulu, Hawaii, 1994.
[6] Stubbs, N. And Osegueda, R., Global non-destructive damage evaluation in solids, Int. j. analyt. exp. modal anal., 5, 67-79, 1990.
[7] Wu, X., Ghaboussi, J. and Garrett, J. H., Use of neural networks in detection of structural damage, Comput. Struct., 42, 649-659, 1992.
[8] Kaouk, M. and Zimmerman, D.C., Structural damage assessment using a generalized minimum rank perturbation theory, AIAA J., 32, 836–842, 1994.
[9] Kim, J.T. and Stubbs, N., Model uncertainty and damage detection accuracy in plate-girder bridges, J. Struct. Eng., 121, 1409-1417, 1995.
[10] Dimarogonas, A.D., Vibration of cracked structures: a state of the art review, Eng. Fract. Mech., 55, 831-857, 1996.
[11] Douka, E., Loutridis, S. and Trochidis, A., Crack identification in beams using wavelet analysis, Int J Solids Struct., 40, 3557-3569, 2003.
[12] Dimarogonas, A.D., Vibration Engineering, West Publishers, St Paul, Minesota, 1976.
[13] Paipetis, S.A. Dimarogonas, A.D., Analytical method in rotor dynamics, Appl. Sci. London,1986.
[14] Adams, A.D. and Cawley, P., The location of defects in structures from measurements of natural frequencies, J. Strain Anal., 14, 49-57, 1979.
[15] Chondros, T.G. and Dimarogonas, A.D., Identification of cracks in welded joints of complex structures, J. Sound Vib., 69, 531-538, 1980.
[16] Goudmunson, P., Eigenfrequency change of structures: a state of the art review, Eng. Frac. Mech., 55, 831-857, 1982.
[17] Masoud, A., Jarrad, M.A. and Al-Maamory, M., Effect of crack depth on the natural frequency of a prestressed fixed-fixed beam, J. Sound Vib., 214, 201-212, 1998.
[18] Shen, M.-H. and Taylor, J.E., An identification problem for vibrating cracked beams, J. Sound Vib., 84, 150-457, 1991.
[19] Liang, R.Y., Hu, J. and Choy, F., Theoretical study of crack-induced eigenfrequency changes on beam structures, J. Eng. Mech., 118, 384-396, 1992.
[20] Kim, J.-T. and Stubbs, N., Crack detection in beam-type structures using frequency data, J. Sound Vib., 259, 145–160, 2003.
[21] Wu, X., Ghaboussi, J. and Garret, J.H., Use of neural networks in detection of structural damage, Comput. Struct., 42 , 649-659, 1992.
[22] Kao, C.Y. and Hung, S.L., Detection of structural damage via free vibration responses generated by approximating artificial neural networks, Comput. Struct., 81, 2631-2644, 2003.
[23] Chen, Q., Chan, Y.W. and Worden, K., Structural fault diagnosis and isolation using neural networks based on response-only data, Comput. Struct., 81, 2165-2172, 2003.

[24] A.S. Sekhar, “Multiple cracks effects and identification,” *Mech syst signal proc.*, vol. 22, pp. 845-878, May. 2008.
[25] J. Lee, “Identification of multiple cracks in a beam using natural frequencies,” *J. Sound. Vib*., vol. 320, pp. 482-490, Feb. 2009.
[26] D.P. Patil, and S.K. Maiti, “Detection of multiple cracks using frequency measurements,” *Eng. Fract. Mech.*, vol. 70, pp. 1553-1572, Aug. 2003.
[27] K. Mazanoglu, I. Yesilyurt, and M. Sabuncu, “Vibration analysis of multiple-cracked non-uniform beams,” *J. Sound. Vib.*, vol. 320, pp. 977-989, May. 2009.
[28] B. Binici, “Vibration of beams with multiple open cracks subjected to axial force,” *J. Sound. Vib,* vol. 287, pp. 277-295, Oct. 2005
[29] N.T. Khiem, and T.V. Lien, “A simplified method for natural frequency analysis of a multiple cracked beam,” *J. Sound. Vib.*, vol. 245, pp. 737-751, Aug. 2001.
[30] E. Cam, O. Sadettin, and L. Murat, “An analysis of cracked beam structure using impact echo method,” *NDT. E. Int.*, vol. 38, pp. 368-373, Jul. 2005.
[31] Chaudhari, T.D., Maiti, S. K.: Modelling of transverse vibration of beam of linearly variable depth with edge crack. Eng. Fract. Mech, 63, 425-445, 1999.
[32] McClelland, J.L. and Rumelhart, D.E., Parallel distributed processing: Explorations in the Microstructure of Cognition, Volumes I and II, MIT Press, Cambridge, Massachusetts, USA, 1986.