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A Hierarchical Neural Network for Identification of Multiple Damage Using Modal Parameters

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Abstract. Artificial neural networks have been applied extensively in recent years due to their excellent performance in pattern recognition, which is useful for detecting damage in structural elements. The application of multiple damage cases by an ensemble neural network using dynamic parameters of structure is very limited. Therefore, in this paper, an ensemble neural network based on damage identification techniques was developed and applied for damage localization and severity identification of quad-point damage cases in I-beam structure. Experimental modal analysis and finite element simulation were carried out for I-beam with four-point damage cases to generate the modal parameters of the structure. Based on the results, it is found that the ensemble neural networks achieve a high detecting accuracy and good robustness of quad-point damage cases in I-beam structures.

INTRODUCTION

Damage detection at an early phase, is very important to avoid unexpected and catastrophic collapse and failures of structural systems. For proper functioning of the structure, damage should be detected, located and repaired if possible. Vibration-based methods are a global damage identification approach that has been considered for use on the dynamic properties of the structure to identify the location and severity of damage without prior information of the type or level of damage [1-2]. These approaches are based on the principle that a reduction in the structural stiffness produces changes in the modal parameters, such as the natural frequencies, mode shapes, and damping ratios.

In recent decades a significant amount of research has done on the Artificial Intelligence (AI) techniques to identify the damage in structures. ANNs are one of the artificial intelligence techniques with high capability and very low error rates in learning and modeling nonlinear complex functions [3-5]. ANNs inspired by the biological structure of the human brain and have learning capability. ANNs based on dynamic characteristics have been applied progressively for damage detection owing to their pattern recognition and information processing capabilities.

For example, dynamic characteristics of a steel-frame building to identify damage using ANN was applied by Chang et al [6]. In this study different levels of stiffness reduction are characterized for the natural frequencies and mode shapes. The results indicated that ANN-based damage detection approach is capable of detecting the damage with a high level of precision. Nick et al. [7] developed a two-stage method to locate and identify the damage in bridge structures using modal strain energy-based damage index method and ANN. The results showed proper accuracy proposed by ANN for identifying the damage magnitude and damage location in the structure.

A procedure to identify the damage in a steel beam using modal strain energy and ANN is developed by Tan et al [8]. In this research, firstly, the modal strain energy-based damage index for locating damage is applied, and then the damage index as input parameters for the ANN to identify the damage severity is used. The results demonstrated the

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accuracy of the proposed technique to detect damage in steel beams. Also, in recent years, several attempts have been made to assess damage in civil structures using the ANNs trained with vibration data [9-11].

The review of literature shows that the application of multiple damage cases by ANNs using the dynamic characteristics of structures is very limited and usually single damage cases are considered. The main focus of this study is to investigate the applicability of using ensemble neural networks trained with modal parameters for identification of the severity and location of quad damage cases in I-beam structure. A combination of natural frequencies and mode shapes are selected as the input parameters of ANNs and five individual neural networks corresponding to mode 1 to mode 5 are considered. Then, a method based on the ensemble neural network is proposed to combine the outcomes of the individual neural networks to a single network. Results of the study indicate that ensemble neural network based damage detection approach is capable of detecting the damage with a high level of accuracy.

Experimental study

In this study, one steel I-beam structure with a length of 3200 mm including a 100 mm overhang at both support ends was considered. The dimensions of the beam were consisted of flange width of 75 mm, section depth of 150 mm and thickness of 7 mm and 5 mm for the flange and web, respectively. In experimental modal analysis, the converted signals from the shaker and the accelerometers were analyzed and the modal parameters of the beams was determined. A photo of the test specimen is shown in figure 1. In this study, one I-beam structure was tested in its undamaged state and under different damaged states to determine the first five natural frequencies and mode shapes. In the first step, the modal testing was carried out using an intact structure in order to obtain the modal parameters. Subsequently, different fault scenarios were created by introducing different levels of severity at various locations along the structure. The results of the first five natural frequencies for the undamaged I-beams demonstrated that, in higher modes that were more difficult to obtain, the differences were more significant than in lower mode shapes that were easily obtained.

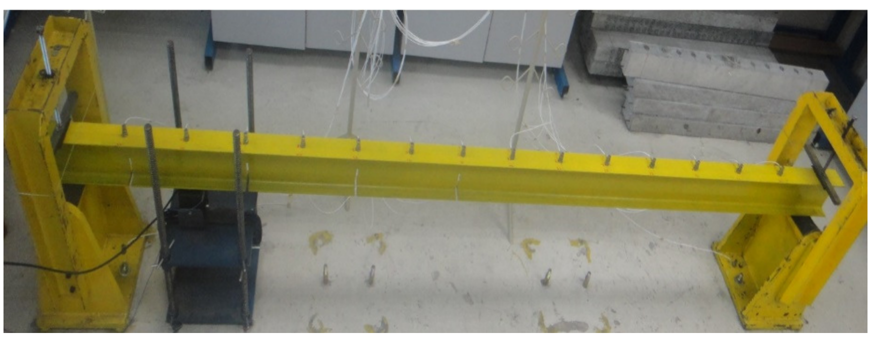

FIGURE 1. Test specimen.

In the experimental study, various damage scenarios were created in the structure. These scenarios were consisted of four locations of damage in the beam with 25 levels of severity for each location. The damage with 5 mm width and depth of 3 mm to 75 mm with an increment of 3 mm were gradually induced for each level of severity. Modal testing and experimental modal analysis for each case was done, individually. The locations of damages for the beam were at L/15,3L/15, 5L/15 and 7L/15 from the left support of the structure, as depicted in figure 2.

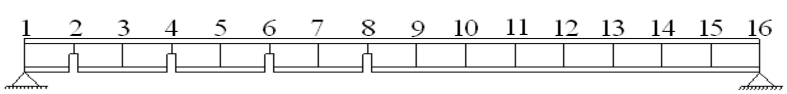

FIGURE 2. Location of quad damages in beam**.**

Damage was introduced in the form of a saw cut and a disk grinder was used to cut a slot at the aforementioned locations of the structure. The results of the extracted first five natural frequencies from the experimental modal analysis of the undamaged and all damaged states of the beam are illustrated in figure 3.

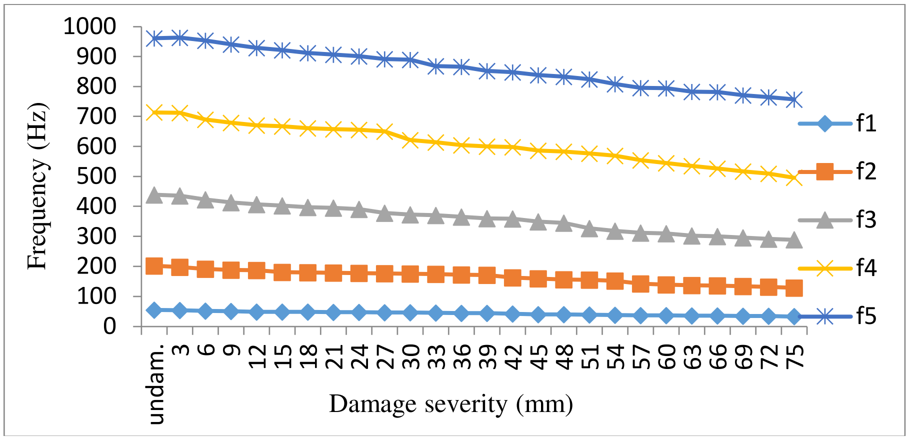

FIGURE 3. The first five natural frequencies with different damage severities

As shown in figure 3, when damage occurs, the dynamics of the structure was modified and the natural frequencies of all modes dropped. The maximum reduction of natural frequencies in this beam were 39.33%, 36.22%, 34.21%, 30.51% and 21.14% for mode 1 to mode 5, respectively. However, when damage was induced at four locations, a very large variation in the magnitude of the first five flexural modes was observed.

Numerical Study

The same damage scenarios described in the experimental analysis were created and finite element analysis of the undamaged structure was first carried out followed by the simulation of models under different damage scenarios to obtain the modal parameters of I-beam structure. To create a numerical model of the structure, Abaqus software (Release 6.14) was applied. The same dimensions of the I-beam according to the test specimen were considered in numerical modeling. The results of the first five natural frequencies for all damaged severities are demonstrated in figure 4.

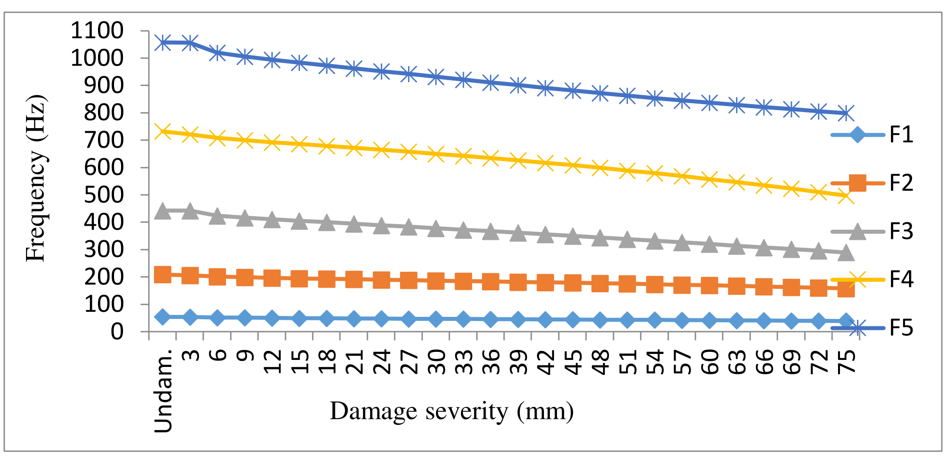

FIGURE 4. Influence of damage severities on natural frequencies

Looking at figure 4, after gradually modelling the damage from 3 mm to 75 mm, it was found that the natural frequencies dropped when damage was induced. These results were then used to verify the feasibility of ANN to detect the severity and location of the damages in the structure. Also, it was obvious that the mode shapes suffered major irregularities which were more marked in the damaged area of the structure. The percentage reduction of the natural frequencies for modes 1 to 5 were 27.64%, 24.4%, 34.5%, 32.05% and 24.45%, respectively. It can be pointed out that the simulated and experimental results showed very good agreement for the structure.

Structural damage identification using ANNs

The artificial neural networks are composed of several processing elements, namely neurons that are interconnected with each other. The neural network structure consists of an input layer, an output layer, and at least one hidden layer [12-13]. Multilayer feed forward neural network with backpropagation algorithm is the most applicable algorithm due to the mathematical design of the learning complex nonlinear relationships and applied in most civil engineering applications [14-15]. The damage identification procedure starts with designing several ANNs using the first natural frequency and all mode shape values at the points on the centerline of the beam for mode 1 to identify the damage characteristics of the I-beam. Therefore, the input layer of the ANN had 15 neurons comprising of one input, that was the first natural frequency and fourteen inputs corresponding to all the mode shape values of mode 1 at the points on the centerline of the beam. The output layer of the ANN had five neurons consisting of one neuron for severity and four neurons for locations of damage. The ratio of damage depth to the height of beam (d_d/h) and the ratio of damage location from the support to the length of beam for four different locations (l_{d1}/L, l_{d2}/L, l_{d3}/L, l_{d4}/L), were considered as damage severity and damage location indices, respectively.

In this section, for the severity identification, NeuroIntelligence software evaluates the training performance by the AE (Absolute Error), while for the location, the training performance is organized by the correct classification rate (CCR), which is defined as the ratio of the number of correctly recognized cases to the total number of cases. The network with the highest validation and testing CCR was selected as a best network to identify the four locations of damage. A network with the CCR value closer to 100 can identify the locations of damage more accurately than when the CCR value is lower than 100.

Based on the results, a network with two hidden layers with 7 neurons in layer 1 and 6 neurons in layer 2 was selected as the best network for identifying the severity and locations of damage in the I-beam structure. This architecture consisted of 15 neurons in the input layer that corresponds to the first natural frequency and fourteen inputs corresponding to all mode shape values of mode 1 at the points on the centerline of the beam, two hidden layers with 7 and 6 neurons and five neurons in the output layer correspond to severity and four locations of damage in the structure. The process of training was carried out individually for all modes by introducing a set of input-output vectors to the ANN architecture (15-7-6-5). The performance of individual networks for modes 1 to 5 are shown in table 1.

TABLE 1. Comparison of the individual and ensemble networks

Network	Performance for severity				Performance for locations (Mean CCR (%))			
	AE			C	L1	L2	L3	L4
	TRN	VLD	TST					
Mode 1	0.0201	0.0181	0.0245	0.9867	100	100	100	100
Mode 2	0.0045	0.0428	0.0386	0.9851	98.46	98.46	98.46	98.46
Mode 3	0.0031	0.0214	0.0298	0.9894	98.46	98.46	98.46	98.46
Mode 4	0.0028	0.0037	0.0145	0.9855	100	100	100	100
Mode 5	0.0024	0.0039	0.0115	0.9769	98.46	98.46	98.46	98.46
Ensemble	0.0068	0.0084	0.0096	0.9871	100	100	100	100

TRN: Training, VLD: Validation, TST: Testing, C: Correlation

It is clear from Table 1 that networks of modes 1 and 4 reached maximum performance (100% CCR). For the networks of modes 2, 3 and 5, some damage locations were inaccurately identified. In network of mode 2, the damage severities for all damage cases were successfully identified, but incorrect results in the damage location for some data with extra light damage cases had been obtained. The reason is that the vibrational data of these locations were less sensitive to mode 2. According to the results of mode 3, the severities were accurate for all damage cases with the MSE of 0.00382 and AE of 2.15% and 3% for validation and testing datasets. In this network, the value of correlation for the damage severity was 0.9894. This network produced good accuracy for location in all damage cases. A similar finding was demonstrated for outcomes of mode 5. The results demonstrate that the performance of training was very good and the ANN was able to provide maximum CCR between the modal parameters of I-beam structure and damage parameters. From the network performance, it is observed that the individual networks had identified the location of all four damage cases for training, validation and testing cases. To overcome the problem of incorrect results for extra light damage cases, the outcomes from the individual networks of modes 1 to 5 were combined using an ensemble network. In the ensemble network, the damage severities and locations identified by the ANN for all five individual networks were chosen as inputs, while the damage severity and four locations were the required outputs of the network. Therefore, the architecture of the ensemble network had 25 neurons which represent the severity and four locations of damage for each mode in the input layer and five neurons in the output layer. The architecture of the ensemble network is depicted in figure 5.

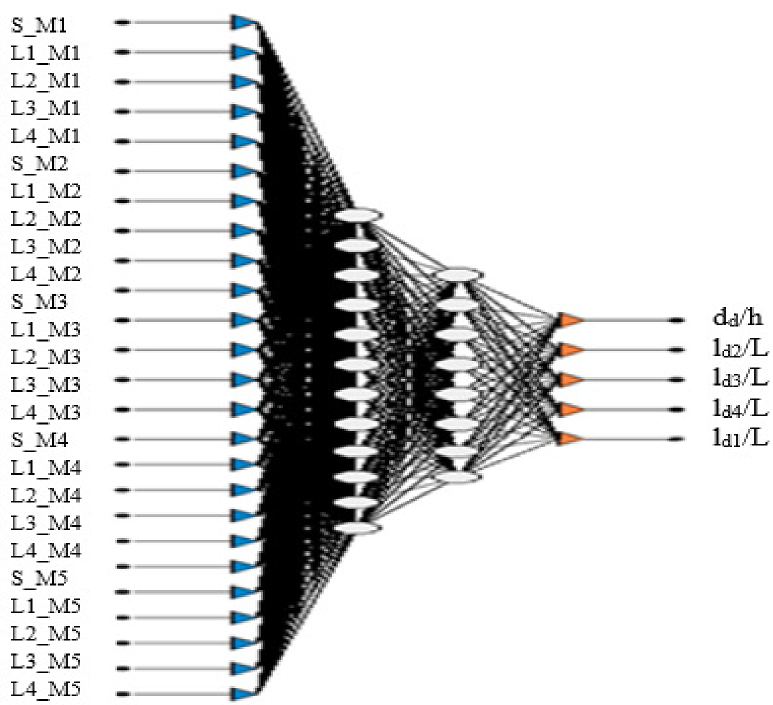

FIGURE 5. Final structure of the ensemble network for quad damage cases

From the training, testing and validation processes, the optimal structure was obtained with 2 hidden layers with 12 and 8 hidden neurons in the first and second hidden layers, respectively. The minimum MSE was found to be 0.003093 and the maximum value of correlation had been obtained. According to Table 1, the correlation of all datasets reached 0.9871 for the damage severity prediction. The values were 0.9885, 0.9684 and 0.9689 for training, validation and testing datasets, respectively.

The ensemble network reached a maximum performance of (100% MCCR) for all four damage locations. From the outcomes of damage severity, it is found that the best performances are achieved. The results showed that the ensemble network was very successful in identifying the severity of extra-light damage cases, which was a big drawback in individual networks. Based on the outcome, the errors in light and severe damage cases show a similar trend for all datasets. This means the minor errors were scattered between different damage cases. Also, the results of damage localization showed that the ensemble network provided a very good identification for the locations of damage. The impressive outcomes demonstrate that there is a good agreement between the modal characteristics of structures and the location of damage.

CONCLUSION

This study has been focused to the development and application of ensemble neural networks using modal parameters to identify damage severity and location in I-beam structures. A combination of natural frequencies and mode shapes for detecting damage produces more accurate results and has been used in this study. Experimental modal analysis and numerical simulations of I-beam with four-point damages are carried out to generate the modal parameters of the structure. The results indicated that numerical simulations were similar to the laboratory outcomes and good correlations were achieved. Results demonstrated that due to the presence of defect, the modal parameters of the damaged structure demonstrated a major deviation near the damage locations as compared to the undamaged structure. Also, the results showed that, the individual networks could identify the severity of damage with high level of accuracy, but were less accurate in identifying the location of damage.

To improve the capability of the damage identification for the structure, a method based on a neural network ensemble was proposed. In the ensemble network, five individual networks were trained, and the outputs were combined into a single network. The ensemble network has the advantages of all individual networks from different vibrational modes. The ensemble network provided the best network outcomes with accurate damage identification compared to individual networks. From the results of this research, it can be concluded that, the ensemble network was successful in identifying the severity and location of four damage cases with good agreement.

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