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A Sensitivity Analysis on the Damage Identification Capability of Artificial Neural Networks

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Abstract: *Artificial neural networks (ANNs) have been applied extensively in recent years due to their excellent pattern recognition ability that is useful for structural damage identification purposes. When damage happens in a structure the consequence is a change in its modal parameters such as natural frequencies and mode shapes. Natural frequencies of a structure have a strong effect on damage and are applied as effective input parameters to train the ANN. In this research, a sensitivity analysis is implemented to investigate the sensitivity of the ANNs and to find the most accurate modal parameters as inputs to the network for the damage identification of structures.*

In this study, three different ANN using direct natural frequencies of the first five modes, the ratio of the first five frequencies for damaged and undamaged cases (fd/fu) and differences between frequencies before and after damage (Δf=fd-fu) were constructed and results of these networks were compared to find the best input parameters for damage identification and to assess the effect of different input parameters on the ANN performance. This sensitivity analysis was applied on the datasets from the experimental and numerical simulations of single damage of I-beam structures.

Keywords*:* *artificial neural networks (ANNs), damage identification, finite element, modal analysis, natural frequency, sensitivity analysis*

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I. INTRODUCTION

Damage in structures often leads to failure and can be defined as a weakening of the structure which may cause undesirable displacements, stresses or vibrations to the structure that negatively affects the functionality of the structure. Damage detection can increase safety, reduce maintenance costs and increase the serviceability of the structures. Thus, damage detection at an early phase, is essential to prevent sudden and catastrophic collapse and failures of structural systems [1-4].

Many techniques have been used to locate and identify damage in civil structures. The current non-destructive test (NDT) damage identification methods are based on visual inspections. The efficiency of these methods is restricted to the accessibility of the structural location in limited areas and relies on initial information concerning the likelihood of damage [5-6]. Therefore, the NDT damage identification methods are often insufficient for evaluating the condition of the structural systems especially when the damage is not observable. Vibration-based methods serve as both local and global damage identification approaches to identify the location and severity of damage. These methods are based on the principle that a reduction in the structural stiffness produces changes in dynamic characteristics, such as the natural frequencies, mode shapes, and damping ratios.

Most of the vibration-based damage identification approaches developed are considered as some form of pattern recognition exercise since they look for differences between two categories, e.g. before and after a structure is damaged or differences in damage levels. Artificial intelligence methods such as, artificial neural networks (ANNs) which parallel the remarkable capability of the human mind to reason and learn in situations with uncertainty and inaccuracy are very useful for solving inverse problems and have been used extensively for damage identification in structures with varied success [7-11].

ANNs have been applied extensively in recent years due to their capability in reliable damage identification, even when trained with incomplete and inadequate data, for the structural damage identification purpose. These capabilities make ANNs strong tools for the vibrational damage detection purpose. Many researchers have applied modal parameters as inputs of ANNs in structural damage identification. For example, a combination of natural frequency and mode shape for damage severity and location in a steel-frame building using the ANN technique was applied by Chang et al [12]. In this study various levels of stiffness reduction are characterized for the natural frequencies and mode shapes which equalize the damaged structure with specific damage locations and levels. Results showed that the ANN method is capable of detecting the damaged members with a higher confidence level and accuracy.

A procedure to identify the damage location and severity in a steel beam using modal strain energy and ANN is developed by Tan et al [13]. The findings of this research demonstrate the accuracy and efficiency of the proposed technique to detect damage in steel beams. Vibration data as inputs of ANNs are used in damage detection of beam-like structure by Aydin and Kisi [14-15]. In these studies, the first four natural frequencies of the structure are applied by ANNs. According to the results, ANN models can be applied in diagnosing multiple cracks in beam structures.

Application of ANNs for identifying crack growth direction in multiple cracks geometry is investigated by Gope et al [16]. In this research aluminium alloy with different damage locations are used and tests are carried out under static loading condition. Results showed that in multiple cracks analysis ANN is able to identify crack initiation direction with good accuracy. Fault diagnosis on beam-like structures from combination of natural frequencies and mode shapes using ANNs is studied by Hakim et al [17-18]. Achieved results showed that the ANN is efficient technique for damage identification on I-beam structure. Also many other research attempts to apply ANNs using modal parameters to identify damage in structural engineering [19-22].

In this research, a sensitivity analysis was implemented to investigate the sensitivity of ANNs to find the most accurate input parameters to the network for the damage identification of I-beam structures. In this study, three different ANN using direct natural frequencies of the first five modes, the ratio of the first five frequencies for damaged and undamaged cases (fd/fu) and differences between frequencies before and after damage (Δf=fd-fu) were constructed. Then the results of these networks were compared to find the best input parameters for damage identification and to assess the effect of different input parameters on the ANN performance. The experimental modal analysis and numerical simulations of I-beam structures were carried out to generate dynamic parameters of structures and also to investigate the applicability of ANNs for improved structural damage identification.

II. ARTIFICIAL NEURAL NETWORKS

ANNs are simplified models of the human brain and evolved as one of the most useful mathematical concepts which consist of many simple processing elements (neurons) and are highly interconnected with each other. They have the ability to learn from experience in order to improve their performance and to adapt themselves to changes in the environment [23-24]. They function to process information and establish complex and non-linear relationships by using certain rules and large sets of data to achieve suitable results. This makes ANNs a powerful tool for solving some of the complicated engineering problems.

ANNs can provide meaningful answers even when the data to be processed include errors or are incomplete and can process information extremely rapidly when applied to solve real problems [25-26]. As shown in Fig. 1, the architecture of ANN consists of an input layer, an output layer and at least one hidden layer. Signals are received at the input layer, pass through the hidden layer and reach the output layer. All neurons are interconnected to the neurons in the next layer through their weights.

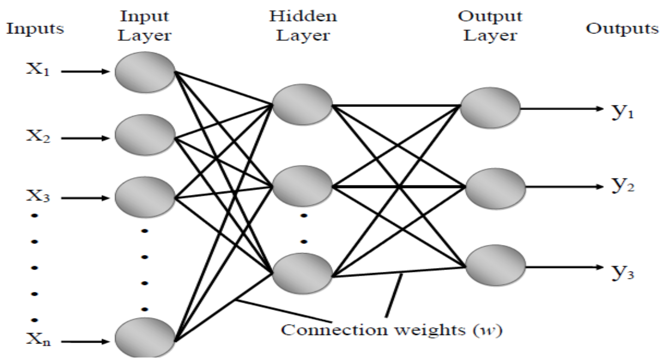

Fig. 1. Architecture of ANN

Backpropagation algorithm (BP) in multi-layer feedforward networks is the most applicable algorithm due to the mathematical design of the learning complex nonlinear relationships. This algorithm has a performance index, which is the least mean square error (MSE). In MSE algorithm, the error is calculated as the difference between the target output and the network output. Among various neural networks, multi-layer perceptron (MLP) is most commonly used in structural damage identification.

III. DAMAGE DETECTION STRATEGY AND EXPERIMENTAL SET UP

When there is damage in a structure, the stiffness in general will reduce. Since the natural frequencies of a structure depend on stiffness, the natural frequencies will also reduce when there is damage. In this study, natural frequencies of steel I-beam structures are applied as input parameters used to train the ANN. To identify the natural frequencies, experimental modal analysis and finite element simulation were performed with different damage scenarios. In this study, four identical healthy steel I-beam with a length of 3200 mm including a 100 mm overhang at both support ends were considered. The dimensions of beams included a flange width of 75 mm, section depth of 150 mm and thickness of 7 mm and 5 mm for the flange and web, respectively. The experimental test set up of the beam is illustrated in Fig. 2.

Fig. 2. Experimental set up

In the modal testing, the beam structures were excited by a shaker and input force measured by force transducer, which was mounted on the top of shaker at a certain reference point and the responses of the structures were measured by accelerometers. In the experimental modal analysis, the converted signals from the shaker and the accelerometers were analyzed and the modal parameters of the beams were determined. For measuring, the test grid model was chosen to have 48 points in three sets between two supports at both ends of the model.

Sixteen accelerometers were used to record the response of the specimen. The accelerometers have a sensitivity range from 95 mV/g to 100 mV/g. The time history signals of the shaker were amplified and the response signals were processed using a multi-channel signal analyzer. For each modal test, the sampling rate was set to 5.14 kS/s. In the frequency domain, this corresponds to a frequency bandwidth of 2000 Hz with 6401 FRF data points. Therefore, the frequency resolution of 0.31 Hz per data point was achieved in this study.

The acquired response time history signals were then converted into the frequency spectra domains using the Fourier transform. By dividing the Fourier transform signals of the accelerometers (output signals) by the Fourier transform signal of the shaker (input signals), the FRFs were obtained. After the raw data were measured and saved using the acquisition software, modal analysis software was then used to calculate the frequency domain data (FRFs) and execute the modal analysis. FRFs were obtained, and the modal parameter containing natural frequencies and mode shapes were extracted from the FRFs by a curve fitting technique. In short, from the experimental modal analysis, the dynamic properties of the beams including FRFs, natural frequencies and mode shapes were determined at each undamaged and damaged state. In this study, four I-beam structures were tested in its undamaged and under different damaged states to determine the first five natural frequencies.

VI. EXPERIMENTAL MODAL ANALYSIS

Each of the four I-beams was tested individually in its datum state to determine the dynamic characteristics of the structure. Table 1 lists the first five natural frequencies for the undamaged I-beams. From Table 1, it can be seen that although the beams were identical, there were differences in their modal parameters.

Table 1 First five natural frequencies of undamaged beams

Frequency / Beam	F1 (Hz)	F2 (Hz)	F3 (Hz)	F4 (Hz)	F5 (Hz)
B1	56.21	202.01	440.95	709.42	951.21
B2	55.88	198.56	439.47	713.31	947.11
B3	55.74	206.16	440.26	716.21	967.21
B4	54.55	202.47	440.58	715.95	963.94

In addition, in higher modes like modes 4 and 5 that were more difficult to obtain, the differences were more significant than in lower modes that were easily obtained. In the experimental study, various damage scenarios were created in the test structures. These scenarios consisted of eight locations with 25 levels of severity for each location. Four beams consists B1 to B4 were considered as single damaged at locations L/2, 2L/15, 4L/15 and 6L/15 away from the left support of the beams, respectively. Damage was inflicted by introducing a slot by grinding at different locations of the structure. The twenty-five damage cases 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 and the modal testing for each case was done, individually.

The outcomes from the experimental modal analysis of damaged beams were obtained and are explained in this section. The results of the extracted first five natural frequencies of all the undamaged and damaged states for beam B1 are depicted in Fig. 3. This Figure shows that, the natural frequencies decrease with the increase in the extent of damage. For this reason, natural frequency can be applied as an indicator for damage identification in the beam structure.

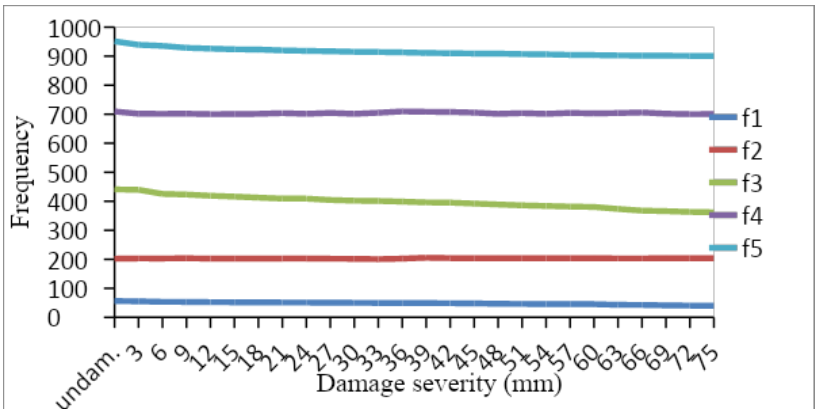

Fig. 3. Influence of damage severities on the natural frequencies (beam B1)

From Fig. 3, after gradually inducing damage from 3 mm to 75 mm, the natural frequencies decreased with the severity level. In beam B1 where the damage was located at the mid-span of the beam, the natural frequencies of modes 1, 3 and 5 were the most affected. According to the results, the maximum reductions of the natural frequency were 29.48%, 1.71%, 17.88%, 2.55% and 5.33% for mode 1 to mode 5, respectively. However, the values of the natural frequencies of the second and fourth modes were affected only slightly. To offer an explanation, in beam B1, where damage was inflicted at mid-span (which is the node point for modes 2 and 4), only minor changes had been observed for these two modes.

The same experimental procedure as explained for beam B1 was repeated for beams B2 to B4. In beam B2, the natural frequencies were evaluated through all the damage severities and a very clear reduction on the magnitude of all the first five natural frequencies was observed when damage was inflicted to the structure. The maximum reductions of the natural frequency were 9.65%, 21.72%, 12.45%, 10.30% and 3.8% for mode 1 to mode 5, respectively. In beam B3, the maximum reduction of the natural frequency was 14.42%, 22.11%, 2.58%, 1.57% and 3.18% for mode 1 to mode 5, respectively. Results show that the variation of the natural frequencies for the third and fourth modes is minor changes. The reason is that the location of damage is very close to the node points of modes 3 and 4, so only minor changes for these modes can be observed.

In beam B4, an important reduction of the magnitude of the first to fourth natural frequencies is observed when damage is induced, but there is only slightly difference on the natural frequencies for different severities of damage in mode 5. The maximum reductions of the natural frequency were 26.27%, 9.55%, 9.04%, 13.14% and 1.47% for mode 1 to mode 5, respectively.

V. NUMERICAL SIMULATION

In this section, finite element simulation of undamaged model and with different damage scenarios using Abaqus (Release 6.14) is presented. Same dimensions and material properties of the I-beam according to the test specimens were considered in numerical modelling. The element type for the finite element model used was Solid C3D8, which is an eight-nodded linear three-dimensional solid brick element. Solid elements, which are the standard volume elements of Abaqus software can be composed of a single homogeneous material and are more accurate compared to other elements. The I-beam model was simulated in its undamaged state to determine the first five flexural natural frequencies as shown in Table 2.

Table 2 Frequencies of the first five flexural modes (undamaged beam)

Mode 1 (Hz)	Mode 2 (Hz)	Mode 3 (Hz)	Mode 4 (Hz)	Mode 5 (Hz)
54.39	209.01	443.13	732.84	1058

The same damage scenario as described in experimental section was considered in numerical modelling. The twenty-five damage severities were individually modelled, for each beam. The numerical results of all damaged states for beams B1 to B5 showed that the influence of damage was not the same for all five natural frequencies and was related to the location and extent of damage.

The natural frequency results of beams B1and B2 showed a very clear reduction of the magnitudes in all the first five modes when damage was inflicted at L/15 and 2L/15 of the beam span. Also, beam B3 was modeled at different stages of damage severities to determine the dynamic properties. Based on the results, clear reductions in natural frequencies were observed. From the numerical results of beam B4, a clear reduction of the magnitude of modes 1 to 4 was observed when damage was induced. Also, the results show slight changes in the shape of mode 5 after the 75 mm damage.

A correlation analysis is presented to show the strength of the relationship between the finite element modelling and experimental modal analysis results of the I-beam structure. The relative percentage error between the first five natural frequencies achieved from the experimental modal analysis and simulated results of the structure were applied to check their correlation, as Eq. (1).

$$f_{rpe} = \frac{\left| f_{\exp} - f_{num} \right|}{f_{\exp}} * 100 \tag{1}$$

In Eq. (1), f_{rpe} is the relative percentage error, f_{exp} is the natural frequency of the tested structure and f_{num} is the natural frequency of the numerical model. Comparison of the natural frequencies between the experimental and numerical results show that in beams B1 and B4, the maximum relative error was under 8%, except for mode 5 with about 12.5%. In beams B2 and B3 the maximum relative error for modes 1, 3 and 4 was less than 4%, which shows a good correlation between the numerical and experimental results. The results of experimental modal analysis and numerical simulation will be used as training data for the ANN. By incorporating the training data, ANN will be able to give outputs in terms of damage severity using the five first natural frequencies.

VI. DAMAGE IDENTIFICATION USING ANN

In this study, three different ANN using direct natural frequencies of the first five modes, the ratio of the first five frequencies for damaged and undamaged cases (f_d/f_u) and differences between frequencies before and after damage ($\Delta f=f_d-f_u$) were constructed and results of these networks were compared to find the best input parameters for damage identification and to assess the effect of different input parameters on the ANN performance. Various damage scenarios were imposed to the structures. These scenarios consisted of four locations with twenty-five levels of severity for each location. The twenty-five damage severities corresponded to a ratio of damage depth to the height of beam (d_d/h), as shown in Table 3.

Table 3 Ratio of damage depth to the height of beam (d_d/h)

Cut slot (mm)	d_d/h	Cut slot (mm)	d_d/h	Cut slot (mm)	d_d/h
3	0.02	**30**	0.20	**57**	0.38
6	0.04	**33**	0.22	**60**	0.40
9	0.06	**36**	0.24	**63**	0.42
12	0.08	**39**	0.26	**66**	0.44
15	0.10	**42**	0.28	**69**	0.46
18	0.12	**45**	0.30	**72**	0.48
21	0.14	**48**	0.32	**75**	0.50
24	0.16	**51**	0.34	-	
27	0.18	**54**	0.36		

d_d/h: Ratio of damage depth to height of beam

The four damage locations were at L/2, 2L/15, 4L/15 and 6L/15 of the span length. These locations corresponded to the ratio of damage location from support to the length of beam (l_d/L), as shown in Table 4.

Table 4 Ratio of damage location from the support to the length of beam (l_d/L)

Damage location (l_d)	l_d/L	Damage location (l_d)	l_d/L
L/15	0.067	**5L/15**	0.333
2L/15	0.133	**6L/15**	0.400
3L/15	0.200	**7L/15**	0.467
4L/15	0.267	**L/2**	0.500

In this study, to train the ANN using the feedforward BP algorithm, initially an input vector comprising of the first five frequencies , or the ratio of the first five frequencies for damaged and undamaged cases (fd/fu) or differences between frequencies before and after the damage (Δf=fd-fu) was fed to the input layer. These input vectors produce a set of output. The difference between the given output and the target output is the error, which will propagate through the network in backward step. The training process is successfully completed, when the iterative process has converged. The ANN model was then chosen based on statistical results such as the Absolute Error (AE), Mean Squared Error (MSE) and coefficient of determination (R^2). During the training, the MSE will be minimized, and consequently the output of the ANN will be closed to the target output. An accurately trained ANN gives successful damage identification when a new sample is given as input. The details are given in the following sections.

6.1 First five frequencies as input parameters

The data from the first five natural frequencies of beams B1 to B4 were used to identify the severity of a single damage. Once the network is trained using the training data, it is ready to identify the severity of damage in the structure. The values of the damage index corresponding to each set of natural frequencies have been fed to the network as desired outputs.

For the damage severity identification, the outcome of the proposed ANN will be an array with 6 elements, which contains five inputs and one output. i.e.,{Nf_1, Nf_2, Nf_3, Nf_4, Nf_5, d_d/h}. The output is the ratio of damage depth to the height of structure (d_d/h). The training process continues to update and adjust the weights of the ANN until the network can produce satisfactory outputs compared to the target values. Many architecture networks having different conditions were conducted, trained and tested using available datasets. According to results, in architectures with one hidden layer, the MSE is lower than other networks with two hidden layers. After trying different networks with one or two hidden layers and taking into consideration the network error, it was decided to have one hidden layer in the architecture of the ANN. However, in a network with one hidden layer, good convergence had been achieved and the BP was limited to one hidden layer, which yielded a total of three layers. It is important to note that utilizing more than one hidden layer in the network makes the computation process complicated and expensive in terms of time.

Also results showed that with the increase of the hidden neurons, the training error is reduced, but there should be a critical number of hidden neurons for minimizing the error. The reason is that, with too many hidden neurons, a network can simply memorize the correct response to each pattern in its training set instead of learn a general solution. So, in this study with the increasing number of hidden neurons, the MSE is decreased, but variations in the MSE values for more than 10 neurons are insignificant. Therefore, the network architecture comprising of five neurons in the input layer corresponds to the five first frequencies, with one hidden layer with ten neurons and one neuron in the output layer corresponds to the severity of damage in the structure. The final architecture for this network is depicted in Fig. 4.

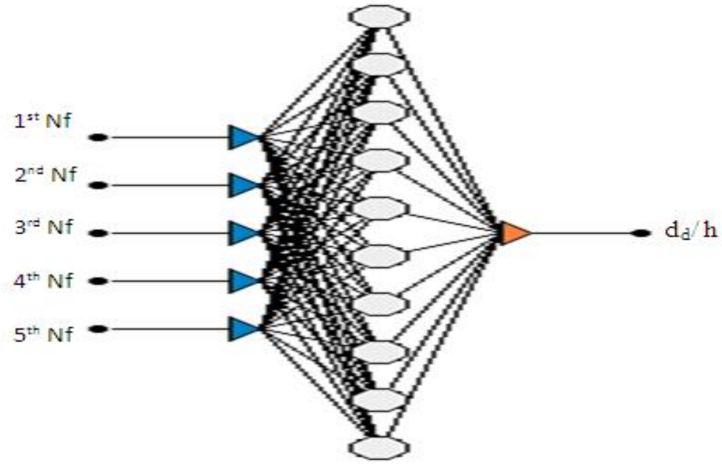

Fig. 4. Final architecture of ANN using the first five natural frequencies

One of the problems that happen during the training of the ANN is called overfitting. During the overfitting, the error on the training set is driven to a very small value, but when new data are presented (validation set) to the network, the error is large. It means that the network has memorized the training samples, but it has not learned to generalize to new conditions. The validation set was applied as a further check for the generalization of the network and to examine the accuracy of the selected architecture. The plot of predicted damage severity by the ANN for validation sets against the actual data is shown in Fig. 5.

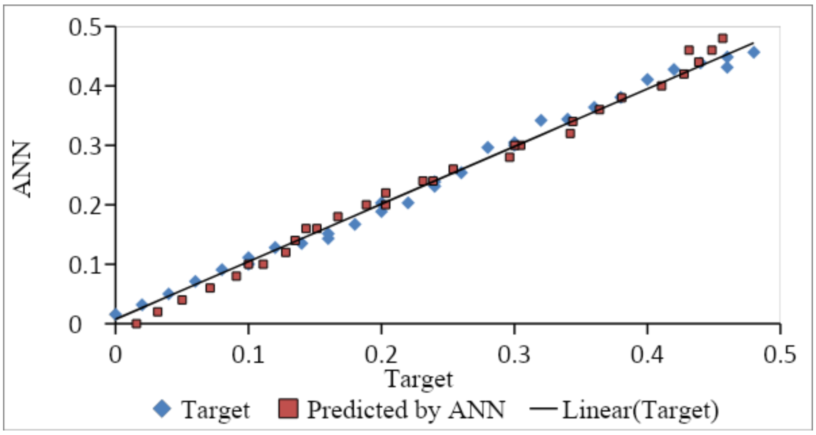

Fig. 5. Damage severity identified by ANN and actual values (validation data)

It is clear from Fig. 5 that there is a good agreement between the results identified and target results. These results demonstrate that the ANN was successful in training the relationship between the input and output data with AE of 1.7% for the validation datasets. The testing set was used to visually inspect the performance after training. After the network was trained, the testing of the ANN was carried out to assess the confidence in the performance of the trained network. In this step, the trained network was tested with data, which were not present in the training datasets. After training, the network has learnt the samples and when tested with new data, it should be able to identify the severity of damage with an acceptable error.

The ANN was successful in identifying the severity of damage with AE of 1.55% for testing sets and it was very close to the actual output. This is apparent from the results that the network with the architecture of 5-10-1 produced the best outcomes for damage severity when compared to other networks and selected as the optimal network for damage severity identification.

6.2 Ratio of the first five frequencies of damaged and undamaged

In this section, the ratio of the first five natural frequencies of damaged and undamaged (fd/fu) was applied to identify the severity of damage. Similar procedure was performed and the process of training for different architectures of the ANN was implemented until the network can produce acceptable outputs compared to the target values.

According to results, the network comprising of five neurons in the input layer corresponding to the ratio of the first five frequencies of damaged and undamaged (f_d/f_u) as inputs, one hidden layer with 13 neurons and one neuron in the output layer corresponding to severity of damage was chosen. This network is then tested with both validation and testing datasets. The ANN could identify the severity of damage with the AE of 2.34%, 3.17%, and 2.67%, for training, validation and testing datasets, respectively. This network (5-13-1) had minimum MSE i.e. 0.002157 and maximum correlation i.e. 0.9619 compared to other networks. The correlation value was 0.9749 and 0.9188 for the training and validation datasets, respectively.

Results showed that when the ratio of damaged and undamaged frequencies was used as the input parameters, the network performance was reasonably good, but provided large AE for validation and testing datasets. The performance of this network in terms of the correlation for the training datasets was 0.9749, while the values for validation and testing datasets were 0.9188 and 0.9489. However, the results of damage severities when the ratio of damaged and undamaged frequencies was used as input parameters of ANN, gave less accurate results in identifying damage severity.

6.3 Differences between frequencies before and after damage

Differences between the first five frequencies before and after the damage (Δf=fd-fu) as input parameters were applied to identify the severity of a single damage in this section. According to results, an architecture comprises of five neurons in the input layer corresponding to the differences between the first five frequencies before and after the damage (Δf=fd-fu) as input parameters, one hidden layer with 11 neurons and one neuron in the output layer corresponding to the severity of damage in the structure had minimum AE for the validation and testing datasets and was selected as the optimal architecture. The selected network (termed as 5-11-1) has the MSE of 0.008936 and the maximum correlation i.e. 0.9579. The AE for training, validation, and testing was 3.76%, 4.6%, and 4.37%, respectively. Results showed that the outcomes were poor when the differences of damaged and undamaged frequencies were applied as the inputs of the ANN. The correlations of this network were 0.9705, 0.9469 and 0.9395, for training, validation, and testing sets, respectively, simultaneously indicating the low performance of this network.

6.4 Comparison of sensitivity analysis results

Three different architectures for the ANN according to three different input parameters were constructed and the results for them were discussed. The summary of the sensitivity results is compared and tabulated in Table 5. As can be seen, the outcomes of the network using direct natural frequencies show the lowest MSE and AE for all three datasets. Also, the correlation of all datasets was 0.9965, while this value for other networks was 0.9619 and 0.9579.

Table 5 Comparison of sensitivity analysis results

Inputs	Design	MSE	AE			Correlation			
			TRN (%)	VLD (%)	TST (%)	All data	TRN	VLD	TST
f	5-10-1	0.000329	1.50	1.69	1.55	0.9965	0.9976	0.9839	0.9844
f_d / f_u	5-13-1	0.002157	2.34	3.17	2.67	0.9619	0.9749	0.9188	0.9489
Δf	5-11-1	0.008936	3.77	4.59	4.37	0.9579	0.9705	0.9469	0.9395

TRN: Training sets, VLD: Validation sets, TST: Testing sets

The large error for the other two networks may be due to the reason that the trained network was unable to learn and find the relationship between inputs and output sufficiently from the training datasets of (fd/fu) and Δf. Therefore, the sensitivity analysis indicates that using direct natural frequencies of the structure gave the most significant effect on the identified damage severity while the ratio of the natural frequencies for damaged and undamaged cases (fd/fu) and differences between frequencies before and after damage (Δf=fd-fu) left a respectively moderate and small impact on the damage severity of the structures.

VII. CONCLUSIONS

In this research, a sensitivity analysis was implemented to investigate the sensitivity of the ANNs and to find the more accurate input parameters to the network for the damage identification purpose. The inputs to the network included the first five natural frequencies of the I-beam structures, which were extracted from the modal testing and finite element simulation.

In this study, three different ANN using direct natural frequencies of the first five modes, the ratio of the first five frequencies for damaged and undamaged cases (f_d/f_u) and differences between frequencies before and after damage ($\Delta f=f_d-f_u$) were constructed and results of these networks were compared to find the best input parameters for damage identification and to assess the effect of different input parameters on the ANN performance.

According to the results from the sensitivity analysis, using direct natural frequencies of the I-beam structure had the most significant effect on the identified damage severity than the ratio of natural frequencies for damaged and undamaged case (fd/fu) and differences between frequencies before and after the damage (Δf=fd-fu). Based on the sensitivity analysis, the ANN was quite sensitive to modal data.

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