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An Ensemble Neural Network for Damage Identification in Steel Girder Bridge Structure Using Vibration Data

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Abstract Damage detection has the ability to prevent the occurrence of unpredictable failures and increase the serviceability of structures. Vibration-based damage detection methods are due to the fact that the damages will change the dynamic characteristics of a structure, such as natural frequencies, mode shapes and damping ratios. Resultantly, structural capacity is usually impacted, which subsequently, adversely affects performance. Fortunately, artificial neural networks (ANNs) have emerged as one of the most powerful learning tools, inspired by biological nervous systems. Unsurprisingly, the said technique has been applied for structural damage identification in the past decades. Relatedly, the objective of this study was to investigate the potential of ensemble neural network-based damage detection techniques in a scaled steel girder bridge structure using dynamic parameters. Experimental and finite element analyses of the structure were performed to generate modal parameters and study the efficiency of the ensemble neural networks in order to improve structural damage identification. Pursuant to the damage identification results, the ensemble ANN-based damage identification method was able to detect and locate damage with a high level of accuracy.

Keywords Damage Identification, Ensemble Neural Network, Finite Element Analysis, Vibration Parameters, Modal Analysis

1. Introduction

It is general knowledge that severe damage to structures can deteriorate their structural stability and lead to major disasters, and as such, it is necessary to detect the location and size of any damage as early as possible. Early detection and monitor of structural damage can help to maintain the structure in due time, and this is extremely important to prevent sudden and catastrophic collapse, thus preserving the service life of civil structures. Indeed, structural health monitoring (SHM) methods have been applied to evaluate the condition of structures, and one of the most important aspects in SHM is damage detection. Structural damage detection is the identification of damage presence and its location as well as the extent of damage imposed to the structure.

Vibration-based SHM methods have been widely studied as a promising alternative for effective structural damage detection. The basic notion of the vibration-based method is that damage will induce measureable alterations in the vibrational parameters of structures, such as natural frequencies and mode shapes. Therefore, damage can be detected by observing these structure characteristics [1-4].

Artificial neural networks (ANNs), which simulate the human nervous system to learn in situations with uncertainty and inaccuracy, are very useful for solving inverse problems, and have been commonly used for structural damage detection in the past decades with varied success [5-6]. These capabilities make ANN a flexible and powerful machine learning technique for vibrational damage detection purpose. Several reviews of vibration-based damage detection method for different structures have been carried out and the damage identification algorithms as well as their advantages and drawbacks have been discussed [7-9].

Numerous applications of damage detection applying ANNs have been reported in the literature. For example, Nick et al. [10] developed an approach to locate and assess damage severity in bridge structures using modal strain energy and ANN. The results showed suitable precision proposed by the ANN when evaluating damage severity as well as accurate performance of the suggested approach.

In addition, a procedure to identify the damage location and its severity in steel beams using both modal strain energy and ANN was developed by Tan et al. [11]. In their study, the damage index was used as input parameters for the ANN to identify the damage in the structure. The said research demonstrated the accuracy of the proposed technique to detect damage in steel beams. Besides that, Chang et al. [12] used ANN to identify damage in a steel-frame building by observing its dynamic parameters. In the said research, various stiffness reductions were considered for modal parameters of the structure. Results demonstrated that the ANN was able to identify the damaged parts with a high level of precision.

Gu et al. [13] also offered a damage detection method using artificial neural networks, to evaluate the changes in modal frequencies due to damage inflicted by temperature variations. It was ascertained that the incorporation of the suggested ANN with novelty detection presented a robust method to identify damage severity, regardless of temperature variation. Moving on, vibration data, as inputs of ANNs, were used in the damage detection of a beam-like structure by Aydin and Kisi [14]. In their study, the first four natural frequencies of the structure were used by ANNs, and it was discovered that ANN models could be applied to diagnose cracks in beam structures.

In another research, Zheng et al. [15] implemented a numerical model to analysis and generate the first five modal frequencies of a beam structure to train a neural network with two outputs, namely delamination size and location of damage. The results demonstrated that the ANN was successful in identifying the location of delamination with a high level of accuracy. Suffice to say, in recent years, the interest of applying ANNs using modal parameters to SHM has increased, and several attempts have been made to assess damage in civil structures using ANNs trained with vibration data [16-20].

Despite the incredible efforts by researchers, there are still outstanding needs, e.g., to locate and evaluate the severity of damage in girder bridge steel structures using ensemble neural networks. Hence, the main concentration in this present work was to investigate the possibility of using ensemble neural networks, which were trained with vibrational modal parameters acquired from experimental and numerical analysis of undamaged and damaged scaled girder bridge structure. Natural frequencies and mode shapes of the structure were chosen as the input factors of the ANNs to identify the location and evaluate the severity of the structure. In this study, five different ANNs, representing mode 1 to mode 5, were trained. Subsequently, an ensemble artificial neural network was implemented to take advantage of several parallel networks computing instead of the individual network computation. The feasibility of this approach was proved through its implementation to different damage detection scenarios.

2. Artificial Neural Networks

Artificial neural networks (ANNs) are advanced information processing model, inspired by biological nervous systems, which have the ability to pattern recognition, classification, and nonlinear modeling [21]. An ANN is a mathematical model of the biological neuron, which is applied to process nonlinear relations between independent and dependent variables in parallel. ANNs can develop their own algorithm and provide significant answers using the given input and output data [22]. The basic structure of an ANN consists of an input layer, an output layer, and at least one hidden layer. Figure 1 shows a 3-layer typical architecture of a neural network.

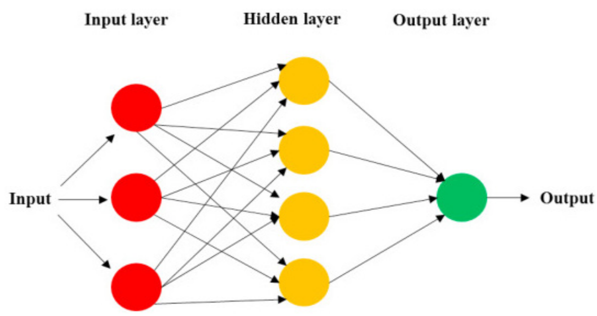

Figure 1. The architecture of three-layer ANN model

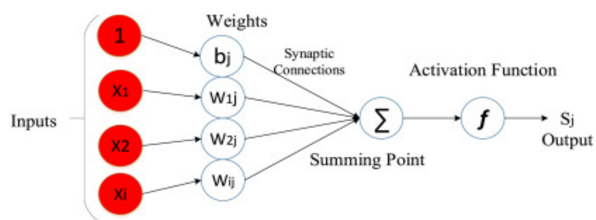

Figure 2. The diagram of an artificial neuron [22]

Based on Figure 2, each neuron has a synaptic weight. These weights are adjusted by training algorithms. Each neuron sums the weighted inputs and maps the summation by an activation function [23-24]. Multi-layer feedforward neural network with backpropagation algorithm is by far the most extensively used due to the advantages of accuracy and versatility to solve complex problems. It is applied in most civil engineering applications [25-27]. The statistical index of mean square error (MSE) is the performance index of backpropagation algorithm. When the input datasets are provided to the ANN, the outputs are compared with the targets, while minimizing the error rate. This process is repeated until a bias value that gives a more accurate prediction is obtained. Once a minimum value of MSE is attained, the training stops and the trained network is then used to test a set of new datasets.

One of the main advantages of neural networks is their capability to generalize. The generalization of ANN refers to the ability to handle unseen data. The performance of ANNs is mostly dependent on their generalization capability. Relatedly, ensemble neural network is one of the promising methods to develop the generalization ability of a network. Ensemble neural networks were formally proposed and established by Hansen and Salamon [28]. They proved that they can perfect the generalization power of ANNs by training a specific number of individual networks and synthesizing the outputs of each neural network [29]. Ensemble neural network has exhibited improved performance when compared to a single network in most cases. The basic idea of ensemble neural network is illustrated in Figure 3. Any type of vibration characteristics can be used as inputs for ANNs, and when the networks are properly trained, damage identification is fast and mathematical models are not required.

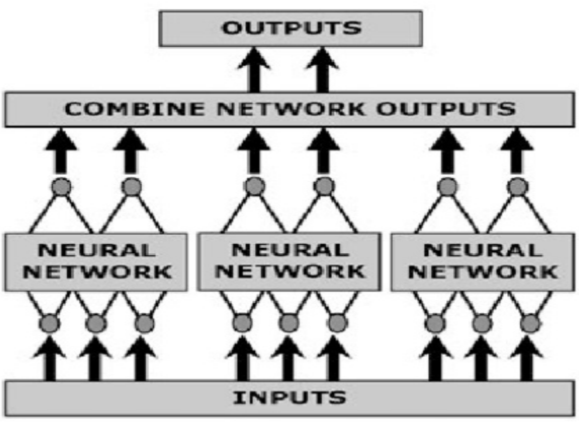

Figure 3. The basic idea of ensemble neural network

3. Experimental Modal Analysis

Experimental modal analysis (EMA) is an easy-to-operate method, which is used to extract the structural dynamic characteristics of a structure, such as natural frequency, damping ratio, and modal shape, by exciting the structure artificially [30]. In this section, the experimental considerations of the modal analysis procedure are described. In this study, a model of a steel girder bridge was used as a specimen for experimental testing. This model was consisted of a steel plate with dimensions of 1200 mm, 210 mm, and 5 mm in length, width, and thickness, respectively.

Three stiffeners were fixed along the length of the steel plate with dimensions of 1200 mm by 50 mm by 5 mm in length, height, and width, respectively. The distance between each stiffener was 70 mm, while the distance between the stiffener and the edge of the plate was 35 mm. In modal testing, the scaled girder bridge structure was excited, and the responses of the structure were determined by accelerometers. Meanwhile, in the EMA, the transformed signals from both the shaker and accelerometers were analyzed, and the modal characteristics of the structure were determined. The girder bridge and its test set up are illustrated in Figure 4. Fourteen accelerometers in each set were used to record the specimen response.

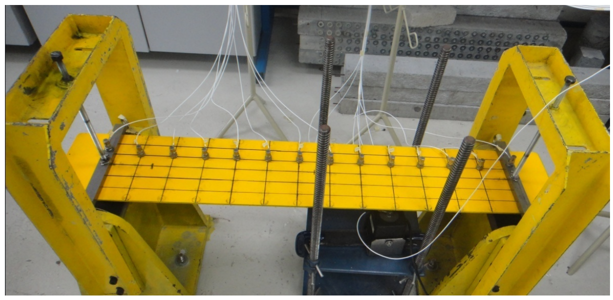

Figure 4. Test setup

To identify the dynamic properties of the steel girder bridge, modal testing was carried out. In the first step, the modal testing was performed using an intact girder bridge in order to obtain the modal parameters. Subsequently, different damage scenarios were formed by presenting various levels of severity at different locations on the structure. In the experimental analysis, the converted signals from the accelerometers were analyzed, and the dynamic characteristics of the structure were determined. In short, from modal testing, the modal parameters of the steel girder bridge, were determined at both undamaged and damaged state. In this study, the scaled steel girder bridge structure was tested in its datum state and under different damaged states to determine the dynamic characteristics of the structure, consisting the first five natural frequencies and mode shapes. Table 1 shows the first five modal frequencies of the undamaged girder bridge.

Table 1. Natural frequencies from EMA for undamaged structure

Location	Mode 1	Mode 2	Mode 3	Mode 4	Mode 5
L/13	117.57	174.32	348.81	424.55	695.41
2L/13	116.48	173.82	346.69	423.49	694.67
3L/13	115.39	172.45	347.15	421.65	693.11
4L/13	112.41	171.89	346.45	423.05	695.40
5L/13	110.41	177.2	352.50	428.05	701.40
6L/13	106.37	172.91	345.87	421.65	692.23
L/2	105.85	174.89	347.81	423.18	696.16

In the next step, different scenarios consisted of seven locations of damage with 25 different severities for each location were applied to the girder bridge structure. A total of 175 single damage cases were investigated. The locations of damage were at L/13th, 2L/13th, 3L/13th, 4L/13th, 5L/13th, 6L/13th, and L/2th of the span length. Twenty-five levels of damage severity, which had a fixed width of 5 mm and depth ranging from 2 mm to 50 mm with a gradual increment of 2 mm, were inflicted on the structure. Damage was induced by presenting a slot by grinding from the bottom of the middle stiffener of the structure. A similar methodology (as aforementioned) was applied in the damage case. Damage was initiated from the soffit of the middle stiffener at L/13th of the span length, and the experimental modal analysis for all damage severities was done. For each level of damage severity, five modal frequencies were identified. Based on the results, damage can affect the frequency response of the structure. The results showed that an increase in the severity level of damage leads to a decrease in structural frequency. Results also showed some changes in the magnitude of the mode shapes with different severities of damage.

4. Finite Element Analysis

The same scenarios of damage, presented in the experimental section, were created, and finite element simulation was performed to obtain the modal parameters of the steel girder bridge structure. To create a numerical model of the tested steel girder bridge deck, Abaqus software (Release 6.14) was used. The same dimensions of the girder bridge (as the test specimen) were considered in the numerical modeling. In the first step, the bridge model was simulated in its undamaged state to determine the magnitude of the first five natural frequencies and mode shapes. Table 2 lists the first five natural frequencies of the undamaged girder bridge.

Table 2. Natural frequencies from FEA for undamaged structure

Number of mode shape	Mode 1	Mode 2	Mode 3	Mode 4	Mode 5
Natural Frequencies (Hz)	128.9	165.1	389.8	451	755.3

In the next step, the same damage scenario for the girder bridge, as described in the experimental modal analysis (EMA), was simulated. Damage was modeled from the soffit of the middle ripe. The damage severities were induced damage, with 2 mm length, 5 mm thickness, and depths of 2 mm to 50 mm, with increments of 2 mm. Each damage severity was modeled individually. In addition, the numerical modal analysis was performed for all the damaged girder bridge models. For each damage severity, the results of the first five natural frequencies and mode shape magnitudes were recorded. Figure 5 shows the first five frequencies for one damage case from the numerical simulation at L/13 of the span length.

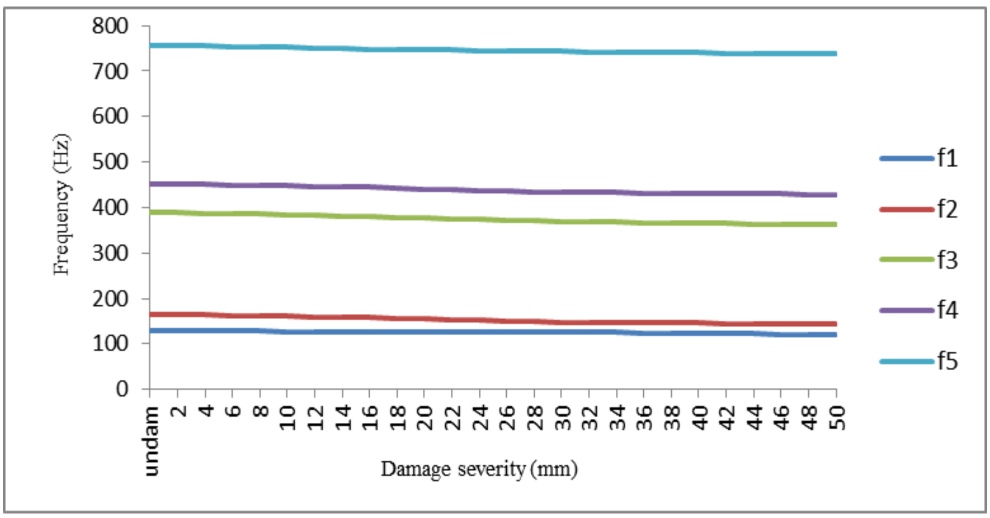

Figure 5. Effect of damage severity on the first five natural frequencies (L/13)

Looking at Figure 5, after gradually modeling the damage from 2 mm to 50 mm, it was found that the natural frequencies dropped when damage was inflicted. These results were then used to verify the feasibility of ANN to identify the severity and location of the damages in the girder bridge structure. A correlation analysis was introduced to show the correlation between the numerical simulation and experimental analysis results, as expressed in Eq. (1).

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

where f_{rpe} = relative percentage error, $f_{\exp}$ = natural frequency from experimental modal analysis, and f_{num} = natural frequency of the simulated model. Based on the correlation outcomes, the variations of the percentage relative error of mode 1 for all seven damage locations were between 10-12%. Also, the maximum value of error was less than 7% for mode 2 at all damage locations, which showed good correlation between the simulation and experimental results.

The maximum relative error was 9-11% for mode 3, smaller than 9% for mode 4, and between 10-11% for mode 5, which showed reasonably good correlations between the numerical simulation and experimental results. Therefore, it could be concluded that the simulated girder bridge could be applied as an acceptable representation of the tested structure in this study.

5. Structural Damage Identification Using ANNs

In this section, the development of neural networks for damage assessment in a scaled steel girder bridge deck was investigated. Damage datasets were obtained from both the experimental analysis and numerical simulation of the structure. They were then applied for the training purpose using the backpropagation algorithm. At first, five single networks representing mode 1 to mode 5, were considered to identify the severity and location of the damage. Several numbers of ANNs, using the first natural frequency and all mode shape values, were constructed to identify damage severity and location of the structure. In this study, 364 different datasets from both intact and damaged structures were gathered from the experimental modal analysis and numerically simulated model. The distributions of the input datasets were performed into training (256 datasets; 70%), validation (54; 15%), and testing (54; 15%). As mentioned earlier, seven locations with 25 severities for each location were given to the test structure. The damage severities corresponded to a cross-section of the loss of the second moment of area (I), as demonstrated in Table 3.

Table 3. The damage severities corresponded to the loss of the second moment of area (I)

Severity (mm)	I (%)	Severity (mm)	I (%)
undamaged	0	26	88.94
2	11.5	28	91.48
4	22.1	30	93.6
6	31.85	32	95.33
8	40.73	34	96.72
10	48.8	36	97.8
12	56.1	38	98.61
14	62.67	40	99.2
16	68.55	42	99.59
18	73.78	44	99.82
20	78.4	46	99.94
22	82.44	48	99.99
24	85.94	50	100

The output parameters of the ANN were the ratio of the cross-section loss of the second moment of area for damaged to undamaged cases, representing the severity of the damage. Meanwhile, the ratio of the damage location from the support to the length of the deck represented the location of damage. The values of the damage severity index based on different damage severities are presented in Table 4.

Table 4. Different values of damage severity index

Severity (mm)	Damage Index	Severity (mm)	Damage Index
undamaged	1	26	0.1106
2	0.885	28	0.0852
4	0.779	30	0.0640
6	0.6815	32	0.0467
8	0.5927	34	0.0330
10	0.5520	36	0.02195
12	0.439	38	0.0138
14	0.3733	40	0.0080
16	0.3145	42	0.0041
18	0.2622	44	0.0017
20	0.2160	46	0.0005
22	0.1756	48	0.00006
24	0.1406	50	0

Furthermore, the values of the damage location index corresponded to the different locations of steel girder bridge structure are shown in Table 5.

Table 5. Different values of damage location Index

Damage location	Damage Index for the location (l_d/L)
L/13	0.077
2L/13	0.154
3L/13	0.231
4L/13	0.308
5L/13	0.385
6L/13	0.462
L/2	0.50

The architecture of the first individual neural network consisted of 13 neurons in the input layer representing the first natural frequency and twelve mode shape values of mode 1 at the points on the deck of the steel girder bridge structure. Thus, the inputs and outputs of the neural network for mode 1 could be expressed as the following:

$$\{f_1, \phi_{1,2}, \phi_{1,3}, \phi_{1,4}, \phi_{1,5}, \phi_{1,6}, \phi_{1,7}, \phi_{1,8}, \phi_{1,9}, \phi_{1,10}, \phi_{1,11}, \phi_{1,12}, \phi_{1,13}, DI, l_d/L\}$$

The procedure of training was performed by the backpropagation algorithm, and was continued and repeated until the error between the actual and identified output by the ANN reached a minimized value. As mentioned previously, modal frequencies as the input parameters for the ANN model were vary in different ranges of magnitude for different modes. In such cases, the input values with large magnitude dominate the input values with small magnitude value. To overcome this difficulty, the input and output data were normalized between the prescribed intervals which were [-1,1]. Therefore, in this work, the transfer function in the hidden layers and output layer was the hyperbolic tangent, as this type of transfer function was more suitable for damage identification problems.

Different architectures using Alyuda NeuroIntelligence software (version 2.2) with the different number of hidden units and hidden layers were trained. The architectures were evaluated using the validation and testing datasets. Generally, the network, which gives the least MSE during validation, will be chosen as the optimal network to identify the damage parameters. After adjusting the weights of the ANN in the process of training, the network should be able to identify the location and severity of the damage using new datasets with an acceptable error. Therefore, the validation and testing of the ANN were performed to prevent over-fitting and examine the precision of the chosen architecture for damage identification of the structure. In this research, a network with the architecture of 13-7-4-2 obtained a minimum MSE with a high correlation compared to the other networks. Besides, both good convergence and best performance were achieved. The architecture for the artificial neural network is illustrated in Figure 6.

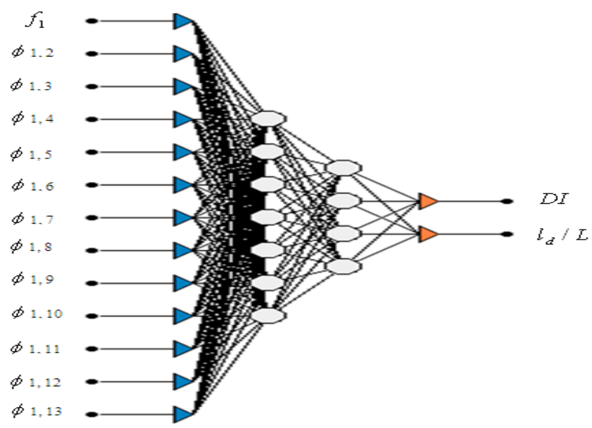

Figure 6. The ANN architecture for the first mode of the girder bridge

Therefore, the said architecture was produced the best predictions for damage identification of the girder bridge structure. The same architecture (denoted as 13-7-4-2) was applied to identify damage for modes 2 to 5. To improve the applicability of the ANNs, a new mapping topology, termed as "ensemble neural network", was used to fuse the information from the single networks. The damage identification values were fused as an ensemble network to identify damage in the structure. The architecture of the ensemble neural network consisted of ten input neurons representing the severity and location of damage for each mode of individual network, and two output neurons representing damage severity and damage location of the structure. Different ANN architectures were trained to modify their connection weights. This was done until the network could identify the outputs with an acceptable precision. As shown in Figure 7, the final architecture of ensemble network had 2 hidden layers with 6 and 4 neurons in the first and second layers, respectively.

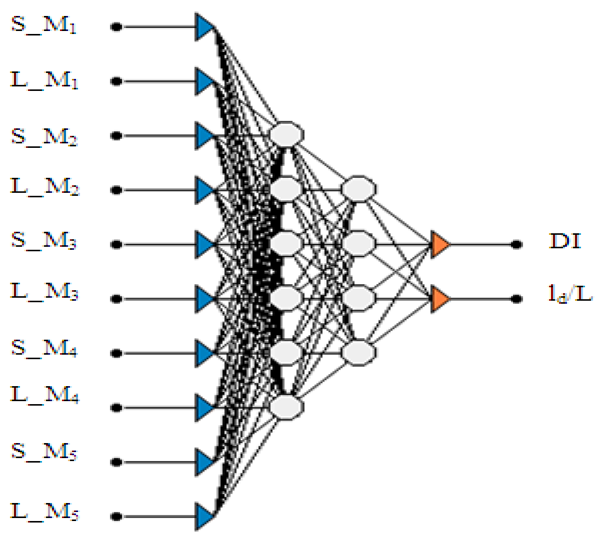

Figure 7. Ensemble neural network architecture for the girder bridge

The performance of the ensemble network, in terms of the correlation and absolute error (AE) for all three datasets of the training, testing, and validation, is summarized in Table 6.

Table 6. Performance of the ensemble network

Datasets	AE		Correlation	
	Severity	**Location**	**Severity**	**Location**
All	0.007368	0.008049	0.9915	0.9899
Training	0.007243	0.007861	0.9922	0.9916
Validation	0.007569	0.008275	0.9846	0.9852
Testing	0.007648	0.008438	0.9831	0.9805

Also, the results of the damage severity and location through the ensemble neural network have been compared with the actual values and illustrated in Figures 8 and 9, respectively.

According to Table 6 as well as Figures 8 and 9, the correlation of all datasets for damage severity was 0.9915 for the ensemble network. Finally, the architecture of 10-6-4-2 was selected for the ensemble network. The performance of the single neural networks was compared with the ensemble network in Table 7. As it is shown in Table 7, the MSE of the ensemble network was smaller than all single networks. Based on Table 7, the results for the network of modes 1 and 4 demonstrated the smallest error for damage severity and shown the best outcomes, compared to the other networks.

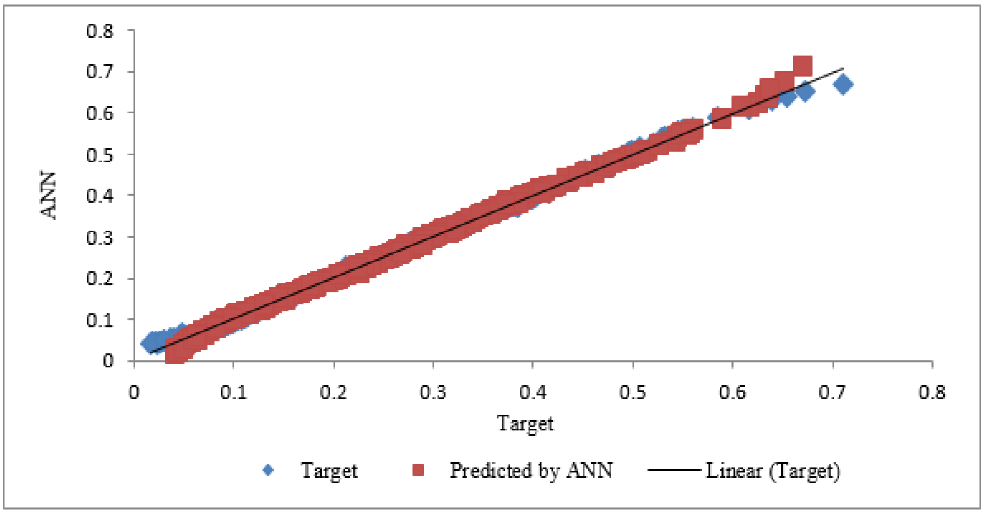

Figure 8. Damage severity through the ensemble neural network

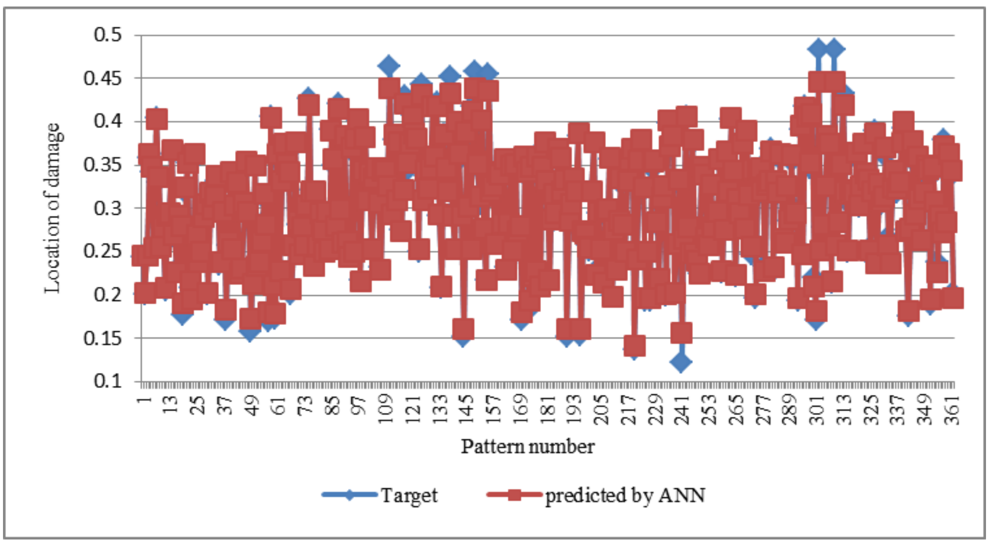

Figure 9. Damage location through the ensemble neural network

Table 7. Performance of the selected individual and ensemble neural network

Network	Design	Iteration	MSE	AE (TRN)	AE (VLD)	AE (TST)	Correlation	
							Severity	Location
Mode 1	13-7-4-2	23741	0.00055	0.0215	0.02591	0.0274	0.9891	0.9965
Mode 2	13-7-4-2	20540	0.00036	0.0358	0.03846	0.0238	0.9861	0.9684
Mode 3	13-7-4-2	25785	0.00062	0.0418	0.04236	0.0423	0.9823	0.9643
Mode 4	13-7-4-2	20001	0.00062	0.0460	0.03316	0.0331	0.9879	0.9735
Mode 5	13-7-4-2	14381	0.00174	0.0512	0.04849	0.0485	0.9783	0.9576
Ensemble	10-6-4-2	15293	0.00017	0.0082	0.00843	0.0084	0.9915	0.9899

Additionally, in term of damage localization, the individual networks of modes 1, 2, and 4 produced a better performance, than that of the networks for modes 3 and 5. Indeed, some of the incorrect locations of damage cases in mode 3 could be due to the environmental uncertainties during the experimental analysis of the structure. Also, the poor efficiency of mode 5 was due to the difficulties in extracting higher mode shapes during the modal analysis of the girder bridge structure.

It is also significant to note that some individual networks were very good in assessing damage severity, but poor in detecting the location of the damage. For example, the network of mode 1 could evaluate the severity of the damage, with an absolute error (AE) of 1.85% for testing sets, while it was less accurate in damage localization, with an absolute error of 2.75% for the testing sets. Finally, the outcomes of the ensemble network provided better results, in comparison to all the individual networks, for both damage severity and location of the girder bridge. The good results further demonstrated the effectiveness of the ensemble network to prevent inaccurate outcomes from the individual neural networks and provide better results.

6. Conclusions

Vibration-based damage detection approaches can be applied to identify defect in a structure, as its dynamic parameters shift with physical alterations in the structure. Artificial Neural Networks (ANNs) have received great attention for use in identifying damage in civil structures based on dynamic modal parameters. Therefore, in this research, the development of ensemble neural networks, using vibration modal parameters of a scaled girder bridge structure, was studied. Numerical simulation and experimental analysis of the scaled girder bridge, with regards to the different scenarios of damage, were performed to produce the vibrational modal characteristics of the structure. The correlation results showed the compatibility of both the numerical model and tested structure.

To ascertain the location and severity of the damage cases, five single artificial neural networks, representing mode 1 to mode 5, were constructed. Then, an ensemble neural network was suggested to fuse the results of the individual networks into a single framework. From the results, it was observed that the ensemble network identified most of the damage cases in the steel girder bridge with a high degree of precision, which reiterated the effectiveness and applicability of the network to identify the severity and location of damage. The good outcomes of the ensemble neural network demonstrated the efficiency of this approach to prevent less accurate results from single neural networks and deliver better outcomes. Therefore, the investigated method could serve as a reliable technique for the identification of damage in civil structures.

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