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A NEURAL NETWORK MODEL FOR DAMAGE DETECTION OF EL-FERDAN BRIDGE

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ABSTRACT

This study presents an application of Artificial Neural Network (ANN) technique for the damage detection of El-Ferdan Bridge, Egypt. A finite element model of the bridge was constructed using the actual member sizes obtained from as-built drawings. Damage in a specific member was artificially simulated by reduction of the member cross-sectional area. Several damage conditions were assumed to cause reduction of 20, 40, 60, and 80 percent of the member's area and to occur in different members of the bridge. In each case, the corresponding static and dynamic properties of the bridge were obtained and fed to generalized feed forward ANNs with different learning rules. Several networks were designed to have different sets of network inputs including the static deflections of the bridge dick; the dynamic characteristics in terms of modal time periods of vibration; and a combination of both characteristics. In all cases the output layer consisted of two nodes representing the location of damage (member name), and the percentage of damage in that member. In each of these networks, several network topologies were examined including networks with one hidden layer and networks with two hidden layers, containing 5, 10, 15, 20, 25, 30, 35, 40, 45, and 50 neurons per layer. Sensitivity analysis results indicated the importance of the dynamic characteristics of the bridge for successful ANN predictions. Most successful network resulted in a 90.74% success in the prediction of the damage location together with a mean square error of 0.043 for the prediction of damage percentage. It is concluded that the ANN technique is very economic and accurate to be considered as an extra alternative for damage detection or structural health monitoring of large structures.

***Keywords*:** El-Ferdan Bridge; Damage detection; health monitoring; artificial neural networks; momentum; quick propagation.

1. INTRODUCTION

The ability to detect structural damage in a bridge well before it endangers the structure has been of interest to engineers for many years. Currently, bridge condition assessment is largely carried out by visual inspection at intervals of one to five years, followed by more detailed examination and analysis if necessary. Visual inspection of structural members depends on the human eye which is unparalleled in its ability to recognize significant patterns after a period of suitable training and experience. However, a human operator may not be effective in making decision by extracting relevant information from an overwhelming flow of data. Moreover, it is possible for significant damage to develope in the intervening period, putting structures at risk. There have been some disastrous failures of bridges due to undetected progressive damage in the past. Therefore there is considerable interest in continuous monitoring of bridges. While engineers keep an eye open on the natural world, groping for inspiration. Numerous engineering novelties track their origins into biological organisms. Mechanical inventions, like the airplane and the robots, as well as computational tools, like the Artificial Neural Networks (ANNs) and the Genetic Algorithms follow examples of the Nature.

ANNs mimic the operation of the human brain (nerves and neurons), and comprises of densely interconnected computer processors working simultaneously. A key feature of neural networks is that they are programmed to 'learn' by sifting data repeatedly, looking for relationships to build mathematical models, and automatically correcting these models to refine them continuously. Recent developments in ANNs have opened up new possibilities in the domain of inverse problems. For inverse problems like structural identification of large structures (such as bridges) where in situ measured data are expected to be imprecise and often incomplete, ANNs may hold greater promise.

Many investigators utilized the neural networks for damage detection of structures. For example, Luo and Hanagud,[1] developed a new Neuro-Fuzzy system, which was based on the steepest descent algorithm. Two procedures to improve the training performance were suggested. First, in order to avoid stopping of the algorithm in local minima, the learning rate was not only controlled by the error function but also by the error change. Second, a fuzzy controller that derived the learning rate was put into practice. This Neuro-Fuzzy concept was able to detect delaminations and stiffness losses in laminate beam specimens. Masri et al.,[2] focused on evaluating the efficiency of neural network for detecting modifications in the characteristics of the underlying physical system by using a multilayer feed forward network to map the excitation force, measured displacement, and velocity of a non-linear dynamic system to the system's acceleration. The input data, which were fed into the neural network, were experimentally recorded accelerations and white-noise force excitation. Outputs were numerically integrated velocity and displacements. Statistical parameters, like the dimensional standard deviation ratio were employed to evaluate damage in the structure. Yun and Bahng,[3] presented a method for estimating stiffness parameters of a complex structural system by using a back-propagation neural network. A substructural identification and a submatrix scaling factor were used to define the damage locations and scenarios. Yun et al.,[4] used the neural network technique to assess the damage of frame joint. Change on the joint fixity was simulated by reduction of the rotational stiffness of the spring as a damage scenario. A numerical simulation study on a 2-bay, ten story structure and a sub-structure technique was used to define the damage.

Sahin and Shenoi,[5] presented a multi layer perceptron (MLP) feed forward back propagation neural network, to quantification and localization of damage in a cantilever steel beam. A combination of global (changes in natural frequencies) and local (curvature mode shapes) were used as inputs. The damage scenarios were simulated on the finite element model and experimentally by reduction the local thickness of the selected element at different locations. Kao and Hung,[6] presented a novel neural network-based approach for detecting structural damage. The proposed approach involves two steps. The first step, system identification, uses neural system identification networks (NSINs) to identify the undamaged and damaged states of a structural system. The second step, structural damage detection, uses the aforementioned trained NSINs to generate free vibration responses with the same initial condition or impulsive force. Comparing the periods and amplitudes of the free vibration responses of the damaged and undamaged states allowed the extent of changes to be assessed. Furthermore, numerical and experimental examples demonstrated the feasibility of applying the proposed method for detecting structural damage.

Fang et al.,[7] explored the structural damage detection using frequency response functions (FRFs) as input data to a back-propagation neural network. A tunable steepest descent algorithm using heuristics approach, was used and it improved the convergence speed significantly without sacrificing the algorithm simplicity and the computational effort. With this basis, they implemented the neural network to the FRF based structural damage detection. The analysis results on a cantilevered beam showed that, in all considered damage cases including single damage and multiple-damage cases, the neural network could assess damage conditions with very good accuracy.

Yuen and Lam,[8] used a Bayesian probabilistic approach for smart structures monitoring (damage detection) based on the pattern matching approach utilizing dynamic data. ANNs were employed as tools for matching the damage patterns for the purpose of detecting damage locations and estimating their severity. An example using a five-story building was used to demonstrate the proposed methodology, which consists of a two-phase damage detection method and a Bayesian ANN design method. Adeli et al.,[9] developed a nonparametric system identification model to map the nonlinear relationship between the past observations and the future bridge response output using a hybrid neural network that incorporated several computing concepts.

Mehrjoo et al.,[10] presented a method for estimating the damage intensities of joints for truss bridge structures using a back-propagation based neural network. The technique that was employed to overcome the issues associated with many unknown parameters in a large structural system is the substructural identification. The natural frequencies and mode shapes were used as input parameters to the neural network for damage identification, particularly for the case with incomplete measurements of the mode shapes. Numerical example analyses on truss bridges were presented to demonstrate the accuracy and efficiency of the proposed method.

Bakhary et al.,[11] used the substructure technique together with a multi-stage ANN models to detect the location and extent of the damage. Modal parameters such as frequencies and mode shapes were used as inputs to ANN. A two-span continuous concrete slab structure and a three-story portal frame were used as examples. Different damage scenarios have been introduced by reducing the local stiffness of selected elements at different locations in the structures. The results showed that this technique successfully detected all the simulated damages in the structure. Liu et al.,[12] presented a structure damage diagnosis method combining the wavelet packet decomposition, multi-sensor feature fusion theory and neural network pattern classification. Vibration signals gathered from sensors were decomposed using orthogonal wavelet. Then the relative energy of decomposed frequency band was calculated. The input feature vectors of neural network classifier were built by fusing wavelet packet relative energy distribution of these sensors. Finally, with the trained classifier, damage diagnosis and assessment was realized. Results indicated that precise and reliable diagnosis information was obtained and the diagnosis accuracy was improved as well.

This study presents an application of the neural network technique for the damage detection of El-Ferdan Bridge, Egypt. For this, the bridge model has been simulated on finite element software utilizing as-built drawings of the bridge. Different damage scenarios and extents have been examined and the corresponding static and dynamic bridge properties have been obtained. Several generalized feed forward ANNs with different learning rules have been designed specially to solve such an inverse problem. All networks have been trained and tested and performance of different networks was compared. The most successful network was selected as a tool for damage detection of this important bridge.

2. DESCRIPTION OF EL-FERDAN BRIDGE

El-Ferdan swinging Bridge was chosen for damage detection. This specific bridge has several unique features. It is the largest swinging bridge in the world. Moreover, it is one of the most important infrastructures in the Sinai Peninsula crossing the Suez Canal. Furthermore, the bridge improved connections between Egypt and neighboring countries of Jordan and Saudi Arabia and it is one of a three connections between Africa and Asia.

The bridge provides alternate crossing for a single-track railway line with a gauge of 1435 mm or a two-lane road with a deck width of 9.2 m. The entire bridge structure is based on two identical swinging bridges, each with an overall weight of approximately 5,000 tones, positioned on the western and eastern banks of the Suez Canal. Both swing bridges have cantilever girders of 170 m and 150 m in length, whereby the longer of the two cantilever girders is swinging across the Suez Canal (see Figure 1). The overall spans of the bridge are 150, 340, and 150 meters, respectively.

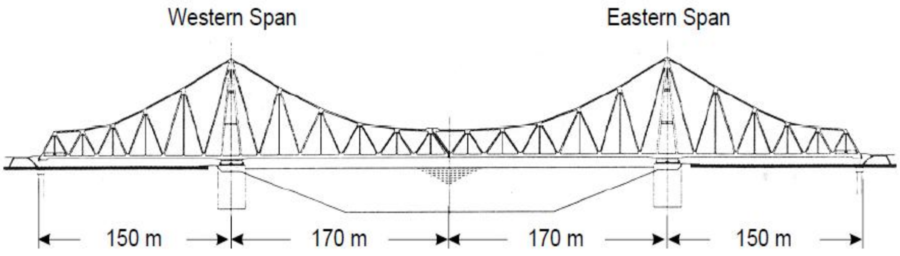


Fig. 1. Picture and a side view of El-Ferdan swinging bridge across Suez Canal, Egypt.

3. NEURAL NETWORK BASED MODELING

3.1. Input And Output Layers

In this study, several networks have been designed to have different sets of inputs to the networks. The first set uses only the static deflections of the 20 joints at the bridge dick as inputs to the neural networks. The second set uses the dynamic responses in terms of modal time periods of the first eight modes of vibration of the bridge. The third set uses both static deflections and natural periods of the bridge as input vector to the neural networks. In all cases the output layer consisted of two nodes representing the location of damage (member name), and the percentage of damage in that member.

3.2. Normalization Of Input And Output Data

Neural networks usually provide improved performance when the data lie within the range (0.0, 1.0). Because a sigmoid function is used, a slow rate of learning occurs near the end points of the sigmoid function. To avoid this, all input values and associated outputs were transformed to values ranging from 0.1 to 0.9 rather than from 0.0 to 1.0. The following equation was used

$$X_T = 0.1 + 0.8\left[\frac{X - X_{min}}{X_{max} - X_{min}}\right] \qquad (3.1)$$

where X_T is the normalized value, X is the original value, X_{max} is the maximum value of the attribute or output, and X_{min} is the minimum value of the attribute or output.

3.3. Training The Network

In a multilayer feed forward neural networks, training refers to the iterative process involving the presentation of training data to the network, the invocation of learning rules to modify the connection weights and, usually, the evolution of the network architecture, such that the knowledge embedded in the training data is appropriately captured by the weight structure of the network. During the training phase, the training data consist of input and associated output pairs representing the problem that need to be learned.

In this paper, the bridge consists of a total of 216 members on two parallel main girders each having 108 members. Due to the symmetry of the bridge on both plan and elevation, the damage scenarios were conducted for 54 cases only, where four damage percentages were assumed to occur in each case; which leads to a total of 216 data samples. A total of 162 data samples selected randomly were used during the training phase and the other 54 samples were reserved for the testing phase of the networks. This was conducted for all the three sets of networks described earlier in section 3.1.

3.4. Learning Algorithm

In this study, the training phase of ANNs is implemented by using the generalized feed forward networks, which is a generalization of the multilayer perceptions (MLPs) such that connections can jump over one or more layers (see Fig. 2). In theory, a MLP can solve any problem that a generalized feed forward network can solve. In practice, however, generalized feed forward networks often solve the problem much more efficiently. Moreover, two learning rules were used. These are the momentum and the quick propagation learning rules. For complete description of these learning rules, e.g. see Ref. 13.

3.5. Network Topology

Choosing a topology for a network is a difficult task. If the number of hidden units is too small, then the network may not be sufficient to develop the required internal representation of the problem and therefore may not be able to perform the necessary recognition. On the other hand, if the number of hidden units is too large, then the network can learn to give the correct classification for all the data in the training set but its performance would degrade in the testing set. This is the case of over fitting, where the network memorizes the training data rather than the pattern imbedded in the training data.

Since there is no direct and precise way of determining the most appropriate number of hidden layers and number of neurons to include in each hidden layer for a problem, a trial and error procedure is typically used to approach the best network topology for a particular problem. In this paper, in each of the three types of examined networks several network topologies were examined. These included networks with one hidden layer containing 5, 10, 15, 20, 25, 30, 35, 40, 45, and 50 neurons in the single hidden layer; and networks with two hidden layers containing 5, 10, 15, 20, 25, 30, 35, 40, 45, and 50 neurons in each hidden layer. The target network would be the smallest sized network that not only produces a minimum error for the training pattern but also gives a generalized solution that performs well on the testing pattern.

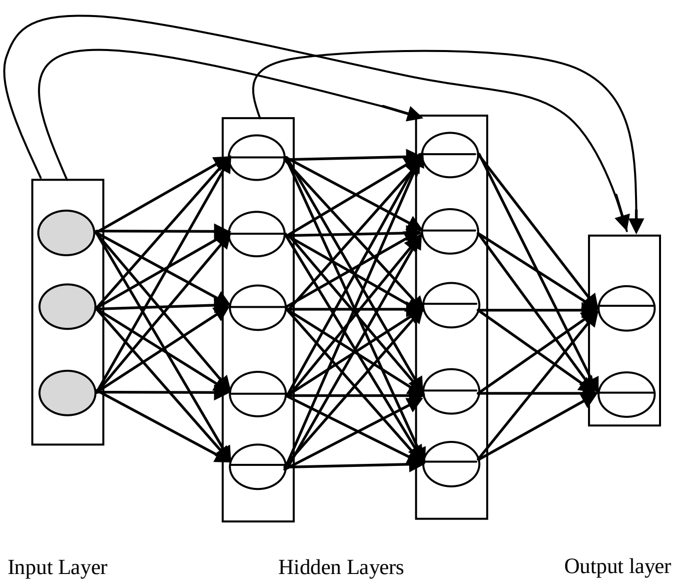


Fig. 2. Generalized feed forward neural network

3.6. Network error analysis

After an ANN model has been trained, validation of the network on the test patterns should be undertaken. The usual practice for ANN model validation is to evaluate the network performance measure using a selected error metric based on both training and testing data. The evaluation and validation of an ANN prediction model can be done by using common error metrics such as the Mean Squared Error (MSE). The definition for MSE is given in the following equation:

$$MSE = \frac{\sum_{j=0}^{p}\sum_{i=0}^{N}(d_{ij} - y_{ij})^2}{NP} \tag{3.2}$$

where p is the number of output processing elements, N is the number of exemplars in the data set, y_{ij} is the network output for exemplar i at processing element j , d_{ij} is the desired output for exemplar i at processing element j. A flow chart for the whole learning process that was conducted is shown in Fig. 3.

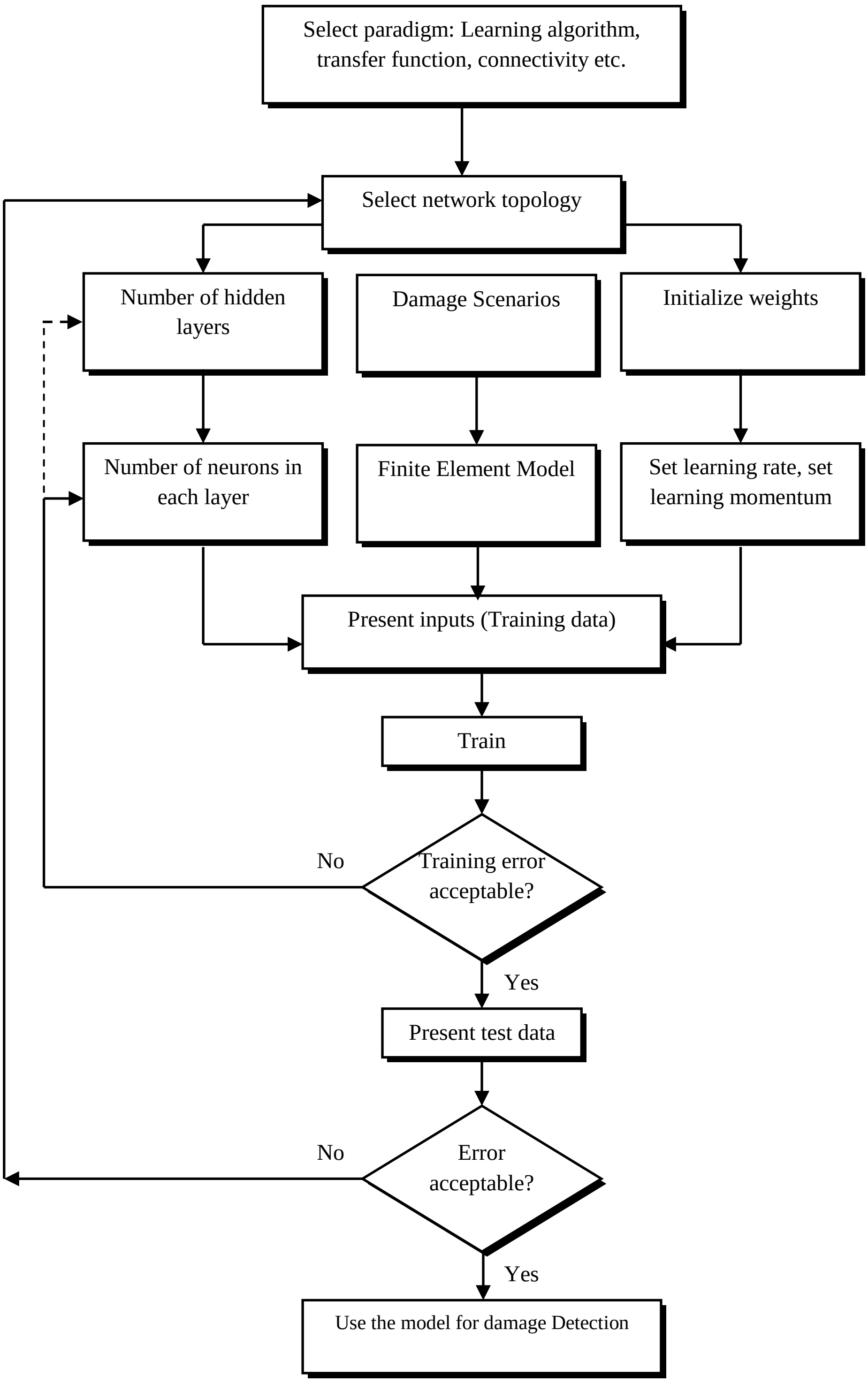


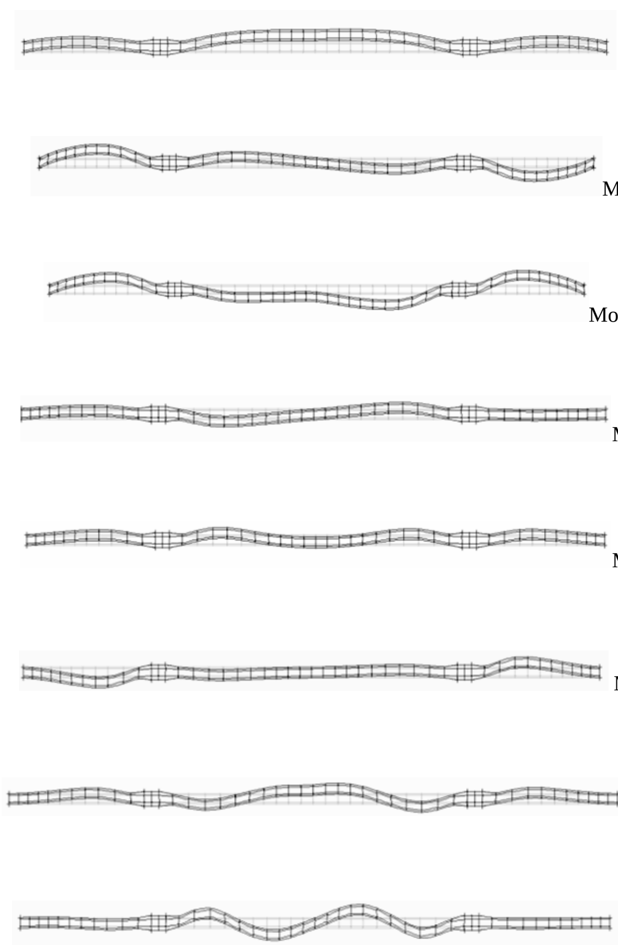
Fig. 3. Flow chart of for the learning process

3.7. Network sensitivity analysis

As a network is trained, it is important to know the effect that each of the network inputs has on the network output. This provides feedback as to which input channels are the most significant. Sensitivity analysis is a method for extracting the cause and effect relationship between the inputs and outputs of the network. The network learning is disabled during this operation such that the network weights are not affected. The basic idea is that the inputs to the network are shifted slightly and the corresponding change in the output is reported either as a percentage or a raw difference.

3.8. Preparation of data

A finite element model of the bridge was constructed using the actual member sizes used in construction of the bridge. It was then used to develop an understanding of the structural behavior and to establish correlations between specific member damage conditions and changes in the structural response. Damage was assumed to occur in different members of the bridge including top chord, bottom chord, diagonals and verticals. Damage in a specific member was artificially simulated by reduction of themember cross-sectional area. Several damage conditions were assumed to cause reduction of 20, 40, 60, and 80 percent of the member's area. Thus the finite element models were used as direct process models, proceeding linearly from causes of damage (change in the cross section of selected member) to effects on the structural response (static effects in terms of deflection of dick joints and dynamic effects in terms of modal time periods). The mode shapes for the case of undamaged bridge are shown in Fig. 4. Data extracted from the analysis were fed into several neural networks designed specially to solve such an inverse problem



Mode 1; T = 3.12 sec

Mode 2; T = 1.81 sec

Mode 3; T = 1.62 sec

Mode 4; T = 1.51 sec

Mode 5; T = 1.26 sec

Mode 6; T = 1.18 sec

Mode 7; T = 1.14 sec

Mode 8; T = 0.96 sec

Fig. 4. Mode shapes of undamaged bridge

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4. RESULTS AND DISCUSSION

Fig. 5. shows the percentage of success in prediction of the damage location of all the testing samples utilizing all designed networks. This is shown for one and two hidden layer networks. Moreover, the left and right graphs are plotted for the cases of using the momentum and the quick propagation learning rules, respectively. It is clear that using the momentum learning rule (left graphs) gives much better predictions than

using the quick propagation learning rule. Using the static properties only as inputs to the networks gives a poor prediction of the correct damage location. On the other hand, using the dynamic or the static plus dynamic characteristics of the bridge as inputs to the networks yields much better prediction of the damage location.

Best predictions are associated with the cases when both static and dynamic characteristics of the bridge are fed into the networks. Best performance was obtained by the network of topology 28-45-2 which uses both static and dynamic characteristics as inputs and has only one hidden layer. This network has a percentage of success of 90.74%. Moreover, the network of topology 8-40-2 which uses the dynamic characteristics only as inputs has a 79.63% percentage of success. Both networks were obtained utilizing the momentum learning rule.

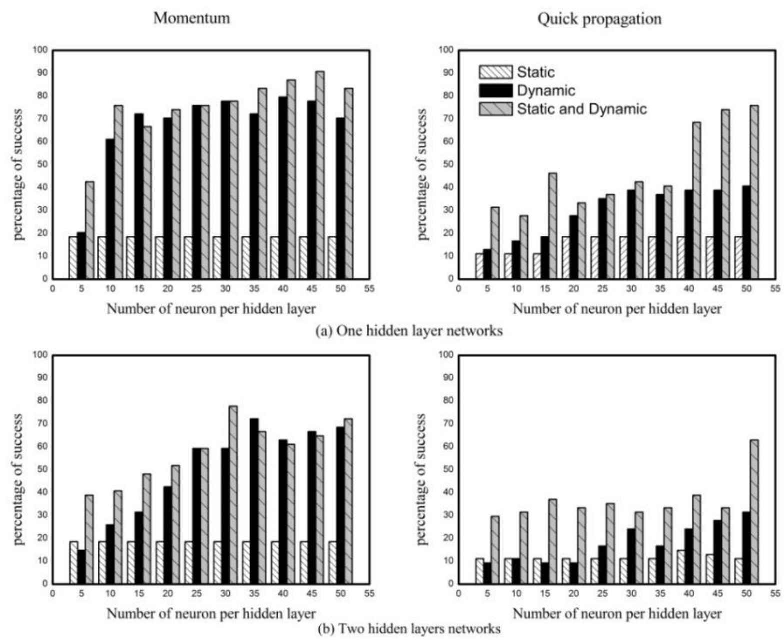


Fig. 5. Percentage of success in prediction of damage location
(a) One hidden layer networks; (b) Two hidden layer networks

Fig. 6. shows the mean square error (MSE) of the percentage of damage of all testing samples. The networks fed with the static properties only gives highest errors. Least errors were obtained in the case of single hidden layers using the momentum learning rule. Range of MSE in this case when the static and dynamic properties were fed into the network lies between 0.03 to 0.05, with a value of 0.043 for the selected network (28-45-2). Such small errors demonstrate the capability of the ANNs to predict the extent of damage in the damaged member.

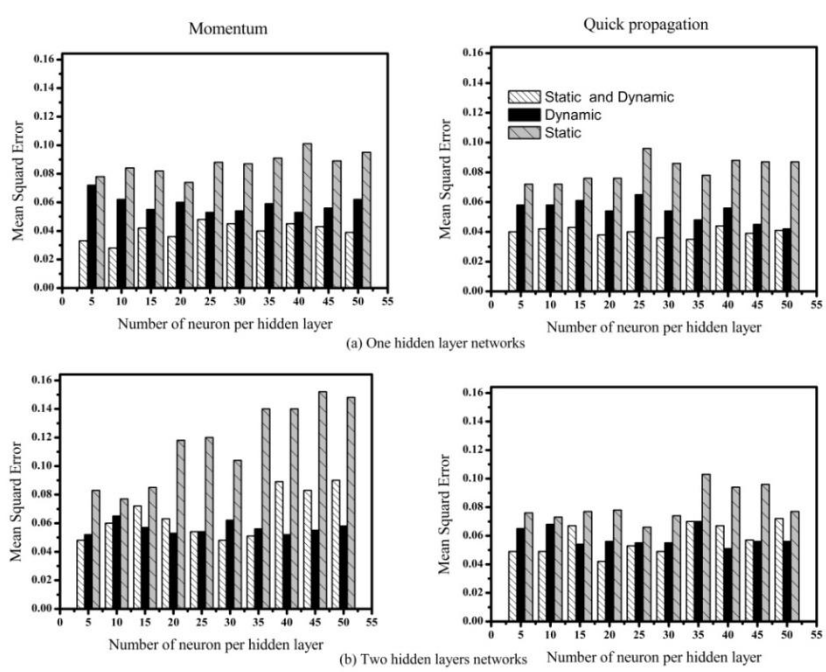
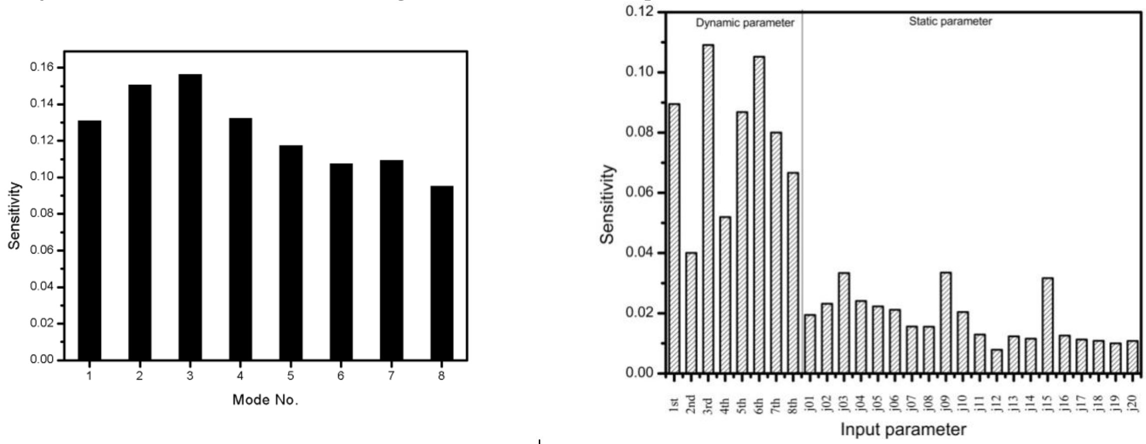


Fig. 6. Mean Squared Error for damage percentage
(a) One hidden layer networks; (b) Two hidden layer networks

To get an insight into the relative importance of different input parameters, a sensitivity analysis was conducted for the networks 8-40-2 which uses the dynamic parameters as inputs; and 28-45-2 which uses both static and dynamic parameters as inputs. Fig. 7. illustrates the results which indicate that for the case of dynamic properties used as inputs, relatively similar importance of different inputs is observed with sensitivity ranging between 10 and 15% for different inputs (modal periods). On the other hand for the case of dynamic and static properties used as inputs, the network is much sensitive to dynamic parameters than the static ones. It is observed that the dynamic parameters (8-parameters) have a sum of 63.4% of the sensitivity while the static parameters (20-parameters) have a sum of only 36.4% of the sensitivity. These results indicate the importance of the dynamic characteristics of the bridge for successful ANN predictions.



(a) network 8-40-2 (Dynamic properties used as inputs)

(b) network 28-45-2 (Dynamic and static properties used as inputs)

Fig. 7. Sensitivity results for different inputs (a) network 8-40-2 (Dynamic properties used as inputs); (b) network 28-45-2 (Dynamic and static properties used as inputs)

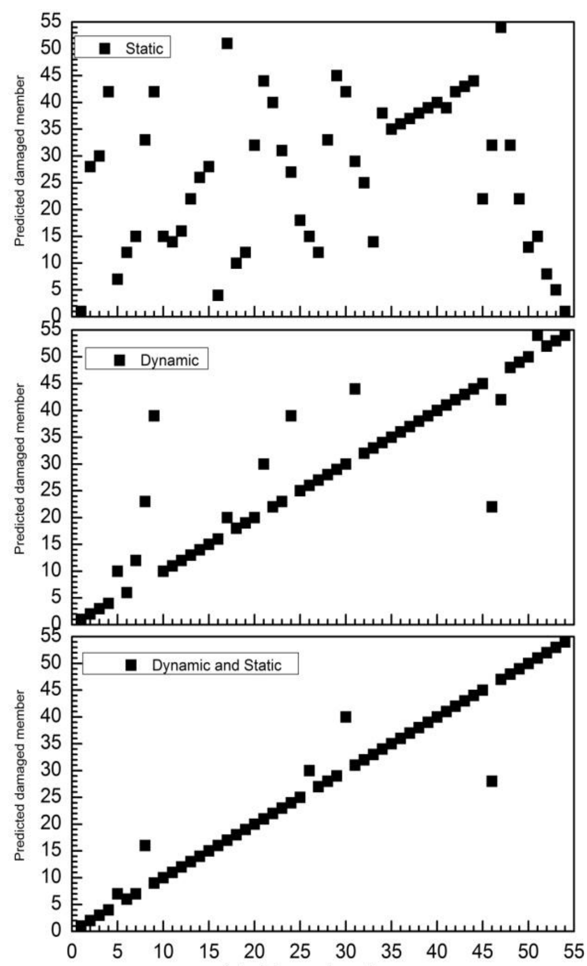


Fig. 8. Actual versus predicted damaged member in different networks.

Finally, three networks were selected and the relationship between the location of the actual and predicted damaged element are plotted in Fig. 8. The selected networks are networks 20-20-2, 8-40-2, and 28-45-2 which uses the static, dynamic, and static plus dynamic properties of the bridge as inputs, respectively. Clearly the prediction of the network that depends only on the static properties of the bridge is very poor. The network that uses the dynamic properties of the bridge gives reasonable predictions. Best predictions are obtained from the network that uses both static and dynamic properties of the bridge.

5. CONCLUSIONS

Based on the results obtained in this paper the following conclusions can be drawn.

1) Based on sensitivity analysis of different inputs, it was observed that the dynamic parameters (8-parameters) had a sum of 63.4% of the sensitivity while the static parameters (20-parameters) had a sum of only 36.4% of the sensitivity. These results indicate the importance of the dynamic characteristics of the bridge for successful ANN predictions.
2) Most successful network was 28-45-2 that uses both static and dynamic properties of the bridge. This particular network gave 90.74% success in the prediction of the damage location together with a mean square error of 0.043 for the prediction of percentage of damage.
3) Artificial neural networks hold a great promise for inverse problems like damage detection of large structures as in the case of the studied bridge. This technique is very economic and accurate enough to be considered as an extra alternative for damage detection or structural health monitoring of large structures.

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