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Structural damage detection of steel bridge girder using artificial neural networks and finite element models

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Abstract. Damage in structures often leads to failure. Thus it is very important to monitor structures for the occurrence of damage. When damage happens in a structure the consequence is a change in its modal parameters such as natural frequencies and mode shapes. Artificial Neural Networks (ANNs) are inspired by human biological neurons and have been applied for damage identification with varied success. Natural frequencies of a structure have a strong effect on damage and are applied as effective input parameters used to train the ANN in this study. The applicability of ANNs as a powerful tool for predicting the severity of damage in a model steel girder bridge is examined in this study. The data required for the ANNs which are in the form of natural frequencies were obtained from numerical modal analysis. By incorporating the training data, ANNs are capable of producing outputs in terms of damage severity using the first five natural frequencies. It has been demonstrated that an ANN trained only with natural frequency data can determine the severity of damage with a 6.8% error. The results shows that ANNs trained with numerically obtained samples have a strong potential for structural damage identification.

Keywords: artificial neural networks (ANNs); finite element; damage detection; backpropagation algorithm; natural frequency

1. Introduction

Damage in structural systems is defined as any reduction in stiffness and mass that negatively affects the functionality of structures, affects the serviceability and safety which may finally lead to failure. There are four levels of damage identification consisting of determination of the presence of damage in the structure, determination of damage location, determination of the severity of damage and prediction of the remaining service life of the structure (Rytter 1993). Recently soft computing techniques such as artificial neural networks (ANNs), genetic algorithm (GA) and fuzzy logic have been used extensively for damage assessment with varied success. In this study the application of ANNs in structural damage detection is considered.

ANNs are powerful tools used to solve many real life problems that are inspired by the human brain which has been applied to damage identification and is considered to be a strong method in the field of structural dynamics. For example, Mehrjoo *et al*. (2008) focused on reporting damage of joints in two truss bridge structures using ANNs. Natural frequencies and mode shapes were

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applied as inputs to the ANN for damage identification. Applicability and efficiency of the ANN to determine the severity and locate damage of the joints in truss bridges was proven in this study. Park *et al*. (2009) proposed a sequential methodology for damage detection in beams using time-modal features and ANNs.

Damage detection of a cracked column using ANN was studied by Yau (2005). In this study, the first natural frequency of a cracked column under different compression loads were calculated by an analytical method and applied as inputs and the crack size, crack location and the compression load of the column were chosen as outputs of the ANN. The authors, according to the results of testing patterns on a numerical example of a trained ANN found that BPNN is a useful tool for predicting the applied compressive force to the column, and the crack size-location on the cracked column. Natural frequencies were used to detect the location and depth of cracks in a clamped-free beam and a clamped-clamped plane frame by Suh *et al*. (2000), who presented a technique of combining neural network with a genetic algorithm for damage assessment.

Damage assessment of a bridge structure was carried out based on the estimated modal parameters using ANN by Lee *et al*. (2002). As inputs to the neural networks, the ratios of the resonant frequencies before and after damage and the mode shapes after damage were used. The predicted damage locations and severities were found to compare well with the imposed damages on the structure.

Also many other research efforts attempted to apply ANNs to identify damage in structural engineering (Rosales *et al*. 2009, Stull and Earls 2009, Inglessis *et al*. 2002, Ramadas *et al*. 2008, Lam and Ng 2008, Zapico *et al*. 2003, Ni *et al*. 2006, Lu and Tu 2004).

This paper focuses on a numerical modal analysis based on a finite element simulation used to generate modal parameter data to train ANN for the purpose of damage severity prediction. In this work the finite element modeling of a bridge girder structure using DIANA (Release 9.3) as a robust and efficient software package is presented. Several damaged scenarios are created and the numerically obtained natural frequencies of the first five modes of the undamaged and damaged bridge model have been successfully applied as the training samples for the ANN.

2. Artificial neural networks

ANNs are usually employed when the relationship between the input and output is complicated or if the application of another available method takes a large amount of computational time and if the effort is very expensive. It requires suitable input parameters, good data selection for training and suitable computational algorithms, so that it is able to learn complicated relationships between inputs and outputs with a high precision (Mohammadhassani *et al*. 2013a, 2013b, Hakim *et al*. 2011, Nam *et al*. 2009).

ANNs operate as a black box and are powerful tools for capturing and learning significant data in structures. Neural networks can provide meaningful answer even when the data to be processed includes errors or are incomplete and can process information extremely rapidly when applied to solve real world problems.

As shown in Fig. 1 a typical neural network has three layers: the input layer, the hidden layer and the output layer. Each neuron in the input layer represents the value of one independent variable. The neurons in the hidden layer are only for computational purposes. Each of the output neurons computes one dependent variable. Signals are received at the input layer, pass through the hidden layer, and reach the output layer.

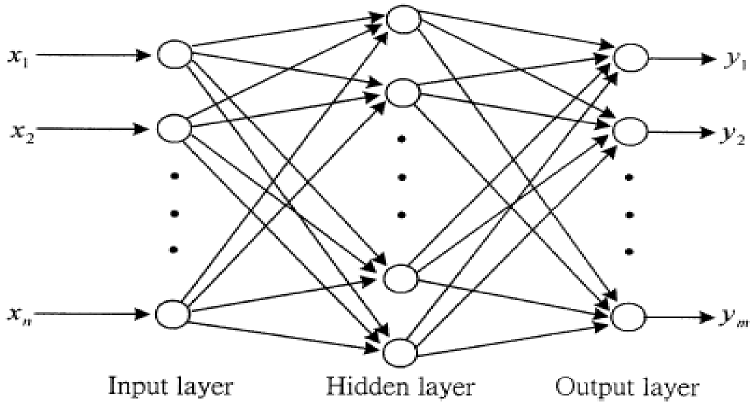


Fig. 1 Typical BP neural network

Amongst various ANNs, the Multi-Layer Perceptron (MLP) is the most commonly used in structural identification problems (Wu *et al*. 2002, Xu *et al*. 2002). The reason is that MLP networks have been used successfully for many different problems and can approximate any continuous multivariate function to any degree of accuracy (Funahashi 1989, Hornik *et al*. 1989). In MLP neurons, each layer is connected to all the neurons in both the previous and the subsequent layer. Backpropagation is one of the best-developed algorithms that can train multilayer perceptron networks (Kim *et al*. 2009, Noorzaei *et al*. 2007, Fonseca and Vellasco 2003, Leu *et al*. 2004). The backpropagation algorithm has a performance index, which is the least Mean Square Error (MSE) (Hagan *et al*. 1996, Noorzaei *et al*. 2008). MSE is the sum of the squares of the errors between the actual outputs from the training set and the computed outputs is minimized iteratively. In this study, the error incurred during the training is calculated in Eq. (1).

$$MSE = \frac{1}{Q}\sum_{K=1}^{Q} e(k)^2 = \frac{1}{Q}\sum_{K=1}^{Q} (t(k) - a(k))^2 \tag{1}$$

In this equation, $e(k)$ is the calculated error in k^{th} neuron, $t(k)$ is the exact output in k^{th} neuron, $a(k)$ is the network output in k^{th} neuron and Q is the number of training patterns. The least mean square error algorithm adjusts the weights and biases of the network so as to minimize this mean square error.

3. Damage detection strategy and finite element modelling

In this work it is proposed that the first five natural frequencies are applied as inputs of the ANN for the prediction of damage severity. To identify the natural frequencies as dynamic properties of the bridge girder, finite element analysis with different damage scenarios was performed. In the first stage, numerical modeling was performed using an undamaged bridge girder in order to obtain the modal frequencies. Later, numerous damage scenarios were created by introducing different severities of damage at different locations along the bridge girder. Results of the numerical modal analysis will then be used as training data for the ANN algorithm. By incorporating the training data, the ANN will be able to give outputs in terms of damage severity using the five first natural frequencies.

The model as shown in Fig. 2 contains a plate with dimensions 1200 mm length including a 100 mm overhangs at both support ends and 210 mm and 5mm in width and thickness, respectively. Three stiffeners as shown in this figure were fixed along the length of the plate with dimensions of 1200 mm by 50mm by 5mm representing length, width and height, respectively. The modulus of elasticity of the steel, the Poisson's ratio and the density were, 2.1×10^{11} kg/m^2, 0.2 and 7850 kg/m^3, respectively. The element type for the finite element model used is an eight-nodded isoparametric three dimensional solid brick element (DIANA 9.3). It is based on linear interpolation and Gauss integration. This element type have translations in the nodal *x*, *y* and *z* directions.

The mesh configuration of the bridge girder model is shown in Fig. 3. The FE model consists of 14744 nodes and 7200 elements. With this mesh configuration, the bridge girder model has 44232 degrees of freedom (DOF).The geometry of the finite element model bridge girder contains 44 points, 88 lines, 55 surfaces and 10 bodies. The support conditions in one side are considered as fixed for x, y and z directions, but on other side only y and z are fixed and x direction is free.

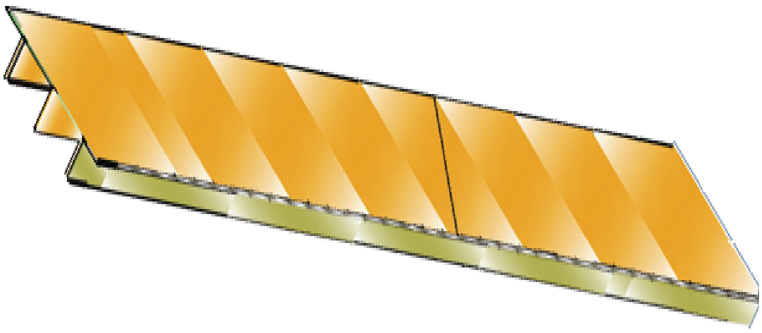


Fig. 2 Bridge girder geometry

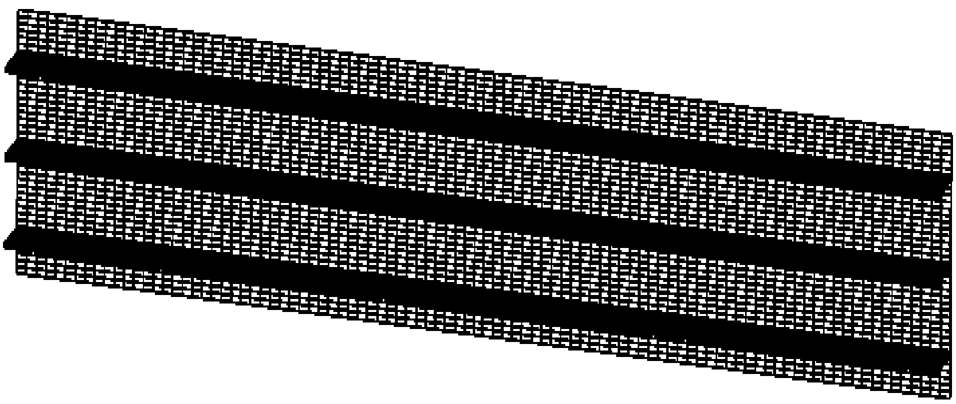
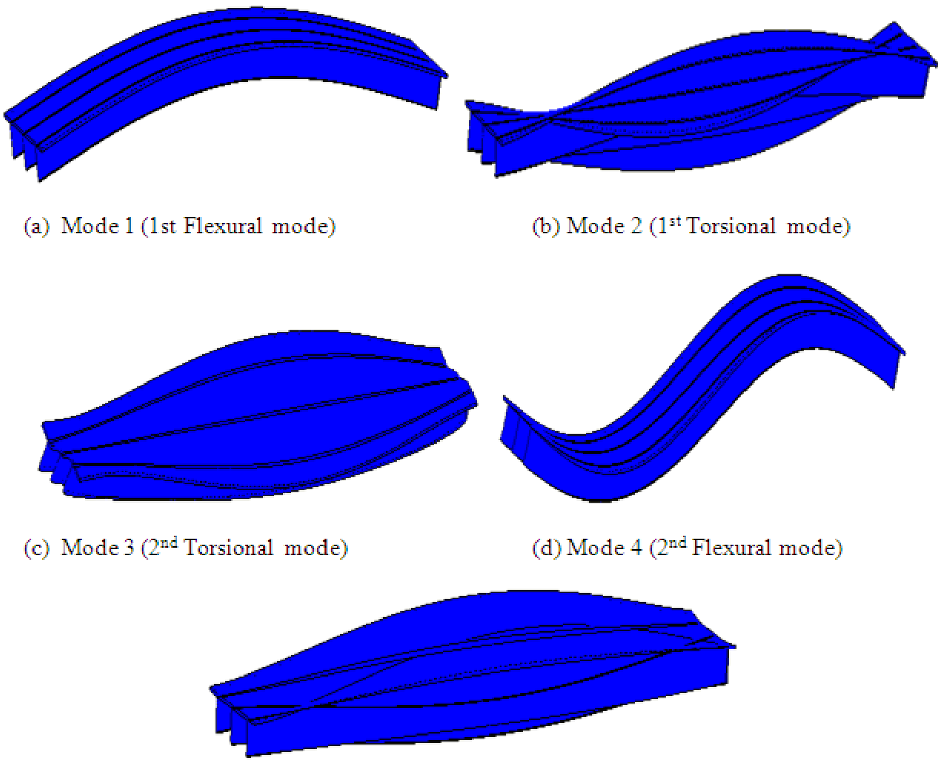


Fig. 3 Finite element modeling of bridge girder

Table 1 Frequencies of the first five modes at undamaged state

Mode 1 (Hz)	Mode 2 (Hz)	Mode 3 (Hz)	Mode 4 (Hz)	Mode 5 (Hz)
129	165	255	391	452



(a) Mode 1 (1st Flexural mode)

(b) Mode 2 (1st Torsional mode)

(c) Mode 3 (2nd Torsional mode)

(d) Mode 4 (2nd Flexural mode)

(e) Mode 5 (3rd Torsional mode)

Fig. 4 Modes shape for undamaged cases

Table 2 Cross-section loss of the second moment of area (I) with different damage severity

Cut slot (mm)	I (%)	Cut slot (mm)	I (%)
2	11.5	18	73.78
4	22.10	20	78.40
6	31.85	22	82.44
8	40.73	24	85.94
10	48.80	26	88.94
12	56.10	28	91.48
14	62.67	30	93.60
16	68.55	-	-

The bridge model was simulated in its undamaged state and under different damaged states to determine the first five natural frequencies. Table 1 lists the first five natural frequencies for the undamaged bridge girder.

The mode shapes for the first five modes of the undamaged state of the bridge girder model is shown in Fig. 4.

In this study various damage scenarios were simulated. These scenarios consisted of seven locations with fifteen severities for each location. The seven damage locations were at L/13, 2L/13, 3L/13, 4L/13, 5L/13, 6L/13 and L/2 of the span length. These damage severities correspond to a cross-sectional loss of the second moment of area (I) as shown in Table 2.

Table 3 shows the first five frequencies for a damage case from the numerical simulation at 4L/13 and it is obvious that the natural frequencies drop when damage is induced. These results will be used for training ANNs for damage severity.

4. Damage detection using ANNs

In this study, different sets of data from the undamaged and damaged scaled down steel girder bridge deck were collected from the numerical modal analysis. These data were gathered for damage severity of the steel bridge girder, containing the first five natural frequencies. Different neural network models were conducted trained and tested using these available data.

In this research, the feed forward backpropagation algorithm for the ANN training was selected. At first an input vector comprising the first five natural frequencies is fed to the input layer. This

Table 3 Natural frequencies of the first five modes for damage at 4L/13

Cut slot (mm)	N.F 1	N.F 2	N.F 3	N.F 4	N.F 5
2	128.7	164.4	390.1	450.4	754.7
4	128.3	163.6	388.8	449.8	753.6
6	127.9	162.8	387.5	449.1	753.2
8	127.2	161.6	386.7	448.3	752.7
10	126.9	160.4	385.8	447.5	751.6
12	126.7	159.5	383.6	446.8	750.3
14	126.3	158.4	381.7	445.3	749.5
16	126.2	157.5	379.9	444.2	748.3
18	125.8	156.7	378.5	442.6	747.6
20	124.9	155.2	377.5	441.7	747.1
22	124.4	153.8	375.8	439.7	746.5
24	124.3	152.6	373.7	438.6	744.9
26	123.6	151.5	371.8	437.6	744.2
28	122.9	150.8	370.6	436.3	743.4
30	121.7	149.6	369.9	434.7	743.1

*N.F: Natural Frequency

input vector produces a set of outputs. The difference between the given output and the target output is an error, which will propagate through the network in a backward step. During this process, the mean square error (MSE) is minimized, and consequently the ANN output will be close to the target output. An accurately trained ANN gives successful predictions when a new sample is given as the input.

The output parameter of the ANN is the damage index (DI), representing the severity of damage. This damage index is a ratio of the cross-sectional loss of the second moment area for the damaged to the undamaged case. The value of damage index based on different damage severity is demonstrated in Table 4.

The network was trained using Matlab 7.11 (R2010b). Once the network is trained using training data, it is ready for the prediction of the severity of damage in the structure. Data sets from the numerical model were used for the training and testing of the network.

In this research, 400 different sets of data from the undamaged and damaged steel girder bridge deck was collected from the numerical modal analysis. These data were gathered for the damage severity of the structure containing the first five natural frequencies. Divisions of the datasets were carried out randomly into the training and testing datasets. Out of the 400 datasets, 280 (70%) were used as training datasets, while the remaining datasets (30%) were used for the testing phase (120 datasets).

This data was normalized between -1 and 1 and fed to the input neurons. The values of the damage index corresponding to each set of natural frequencies were also fed to the network as the desired outputs. The training process was then stopped when the maximum number of iterations reached 50000 or the mean square error (MSE) of the network for the training set reached 0.008.

During the training of the ANN, the best network with the optimum parameters such as, connectivity weights, biases, number of hidden layers, number of neurons in each layer, type of activation function in the hidden and output layers were determined. Also the rate of learning and momentum values are specified. In this study, many architectural networks having different conditions were determined. After trying out different networks with one and two hidden layers and while taking into consideration network error, in a network with one hidden layer, a good convergence was achieved.

Determining the hidden neurons in each hidden layer is the next step. The effect of different numbers of hidden neurons on the MSE was investigated. It was demonstrated that by increasing

Table 2 Cross-section loss of the second moment of area (I) with different damage severity

Cut slot (mm)	DI*	Cut slot (mm)	DI*
2	0.8850	18	0.2622
4	0.7790	20	0.2160
6	0.6815	22	0.1756
8	0.5927	24	0.1406
10	0.5520	26	0.1106
12	0.4390	28	0.0852
14	0.3733	30	0.0640
16	0.3145	-	-

* DI: Damage Index

the hidden neurons, the training error is reduced, but there is a critical number of hidden neurons that exists for minimizing the error rate. 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 learning a general solution.

Therefore a network with architecture 5-14-1 is selected as the best possible architecture in this study. This architecture comprises of five neurons in the input layer corresponding to the five first natural frequencies, one hidden layer with fourteen neurons and one neuron in the output layer corresponding to the severity of damage in the steel bridge girder. In summary, in order to have minimum compatibility costs with a high accuracy, the number of hidden neurons in the hidden layer is fixed to 14.

In this network the Hyperbolic Tangent Sigmoid function was applied to the hidden and output layer as activation functions and the constructed ANN had a learning rate of 0.15 and 0.65 for the momentum yielded with minimum error.

Training of this architecture was continued up to 50000 iterations and the average percentage of the training error reached 6.8%. After that, the network was saved and the corresponding connectivity weights were saved. A comparison of the predicted damage severity by the ANN and target values from the numerical analysis is depicted in Fig. 5.

The correlation coefficient (R^2) gives an indication of the accuracy of the trained network, having a value between 0 to 1. If the correlation coefficient is close to 1, it shows how successful the training was. Smaller MSE and larger R^2 mean a better performance. The selected network was capable of providing a good correlation between the natural frequency information and the extent of damage in terms of the damage index for a given set of natural frequencies. This network had a minimum MSE of 0.00785 and a maximum correlation of 0.981 compared to the other networks with different architectures.

According to the results, the correlation coefficient (R^2) reached 0.941 for the tested data set. The testing results were very close to the actual output and demonstrated that the ANN was successful in training the relationship between the input and output data with an acceptable error.

After the network was trained, the testing set is used to avoid over-fitting and to assess the confidence in the performance of the trained network. At this stage, the trained network is tested

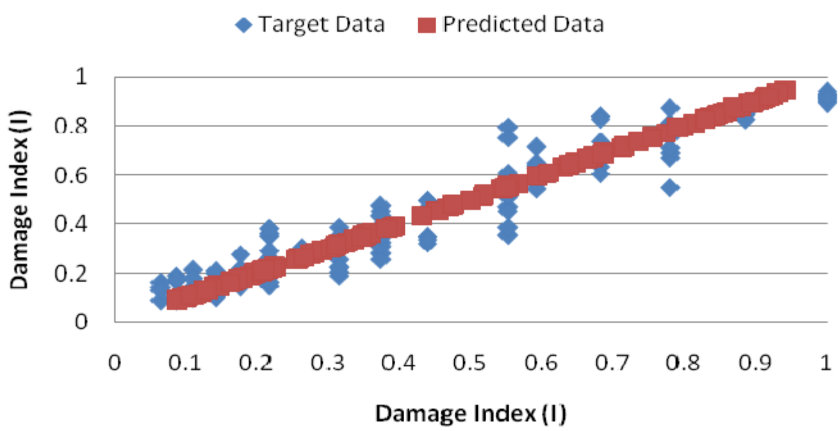


Fig. 5 Comparison of damage severity identified by ANN and target data for training sets

with the data, which was not present in the training data set. After training, the network learned the samples and when tested with the new data, it should be able to identify the severity of damage with an acceptable error. Comparisons between the predicted damage severity and the target data for the testing data sets are shown in Fig. 6. From this figure it can be seen that there is a good agreement between the predicted values and the experimental data. The ANN was successful in predicting the severity of damage with an average percentage error of 8.25% for the testing sets which was close to the actual output.

The results were also seen to be quite reasonable and the testing sets error had very similar characteristics without over fitting. In this study, the ANN predicted the damage severity with an error of 6.8% and 8.25% respectively for the training and testing sets.

4. Damage detection using ANNs

Deterioration and reduction in structural stiffness, produces changes in dynamics properties, such as the natural frequencies and mode shapes. In this study, neural networks are applied to extract knowledge from the natural frequencies of damaged structures at different locations. Details of the study using ANNs for the prediction of damage severity in a model steel girder bridge were described.

The dynamic tests carried out on the damaged and undamaged test structure showed that a reduction in stiffness during the damage which led to a reduction in natural frequencies for different modes. The numerically generated natural frequencies of the first five modes of the undamaged and damaged bridge model were successfully applied as the training samples for the ANN.

According to the results, the ANN was able to predict the damage severity with an average percentage error of 6.8 % and 8.25%, respectively for training and testing. Also, the results show a highly acceptable coefficient of correlation between the identified and numerical data and imply that the developed ANN model can be applied as a very good tool for the identification of damage severity in the bridge girder model. Therefore, it can be concluded that ANN trained with just

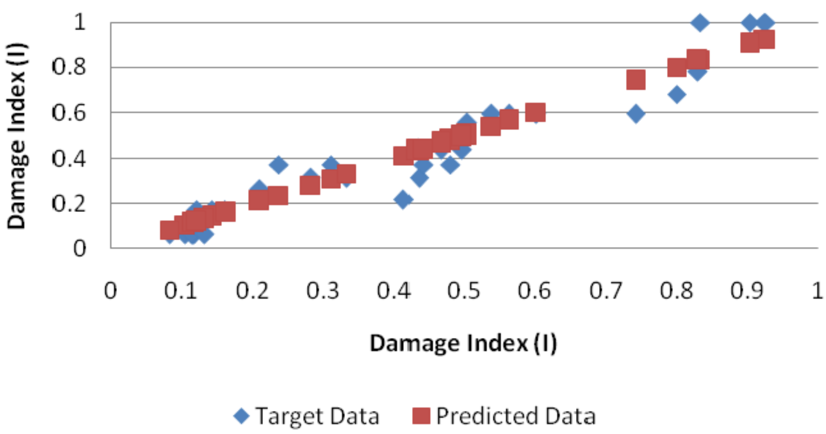


Fig. 6 Comparison of damage severity identified by ANN and target data for testing sets

natural frequencies obtained from a numerical modal analysis as inputs can very well be applied to evaluate the severity of damage in a structure.

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References

Fonseca, E.T. and Vellasco, P.G.S. (2003), “A path load parametric analysis using neural networks”, *J. Construct. Steel Res.*, **59**, 251-267.

Funahashi, K. (1989), “On the approximate realization of continuous mappings by neural networks”, *Neural Networks*, **2**(3), 183-192.

Hagan, M.T., Demuth, H.B. and Beale, M.H. (1996), Neural Network Design, PWS Publishing Company, Boston, MA, USA.

Hakim, S.J.S., Noorzaei, J., Jaafar, M.S., Jameel, M., Mohammadhassani, M. (2011), “Application of artificial neural networks to predict compressive strength of high strength concrete”, *Int’l J. Phys. Sci. (IJPS)*, **6**(5), 975-981.

Hornik, K., Stinchcombe, M. and White, H. (1989), “Multilayer feed forward networks are universal approximator”, *Neural Networks*., **2**(5), 359-366.

Inglessis, P., Medina, S., Lopez, A., Febres, R. and Lopez, J.F. (2002), “Modelling of local buckling in tubular steel frames by using plastic hinges with damage”, *Steel Composite Struct., An Int’l J.*, **2**(1),57-65.

Kim, H., Cui, J., Seo, H.Y. and Lee, Y.H. (2009), “Iterative neural network strategy for static model identification of an FRP deck”, *Steel and Composite Struct., An Int’l J.*, **9**(5), 445-455.

Lam, H.F. and Ng, C.T. (2008), “The selection of pattern features for structural damage detection using an extended Bayesian ANN algorithm”, *J. Eng. Struct.*, **30**(10), 2762-2770.

Lee, J.W., Kim, J.D., Yun, C.B., Yi, J.H. and Shim, M. (2002), “Health-monitoring method for bridges under ordinary traffic loadings”, *J. Sound Vib.*, **257**(2), 247-264.

Leu, S.S. and Loch, S. (2004), “Neural-network-based regression model of ground surface settlement induced by deep excavation”, **13**(3), 279-289.

Lu, Y. and Tu, Z. (2004), “A two-level neural network approach for dynamic FE model updating including damping”, *J. Sound Vib.*, **275**(3-5), 931-952.

Mehrjoo, M., Khaji, N., Moharrami, H. and Bahreininejad, A. (2008), “Damage detection of truss bridge joints using artificial neural networks,” *J. Expert Sys. Appl.*, **35**(3), 1122-1131.

Mohammadhassani, M., Nezam Abadi-Pour, H., Zamin Jumaat, M., Jameel, M. and Arumugam, A.M.S. (2013a), “Application of artificial neural network (ANN) and linear regressions (LR) in predicting the deflection of concrete deep beams”, *Computer and Concrete,* **11**(3). [In Print]

Mohammadhassani, M., Nezamabadi-Pour, H., Jumaat, M., Jameel, M., Hakim, S.J.S. and Zargar, M. (2013b), “Application of the ANFIS model in deflection prediction of concrete deep beam”, *Struct. Eng. Mech.*, **45**(3), 323-336.

Nam, K.K., Haeng, L.S., Sup, J.K. (2009),” Prediction on the fatigue life of butt-welded specimens using artificial neural network”, *Steel Composite Struct., An Int’l J.*, **9**(6), 557-568.

Ni, Y.Q., Zhou, X.T. and Ko, J.M. (2006), “Experimental investigation of seismic damage identification using PCA-compressed frequency response functions and neural networks”, *J. Sound Vib.*, **290**(1-2), 242-263.

Noorzaei, J., Hakim, S.J.S. and Jaafar, M.S. (2008), “An approach to predict ultimate bearing capacity of surface footings using artificial neural network”, *Indian Geotech. J.*, **38**(4), 515-528.

Noorzaei, J., Hakim, S.J.S., Jaafar, M.S., Abang, A.A.A. and Thanoon, W.A.M. (2007), "An optimal architecture of artificial neural network for predicting of compressive strength of concrete", *Indian Concrete J*., **81**(8), 17-24.

Park, J.H., Kim, J.T., Hong, D.S., Ho, D.D. and Yi, J.H. (2009)," Sequential damage detection approaches for beams using time-modal features and artificial neural networks", *J. Sound Vib*., **323**, 451-474.

Ramadas, C., Balasubramaniam, K., Joshi, M. and Krishnamurthy, C.V. (2008), "Detection of transverse cracks in a composite beam using combined features of lamb wave and vibration techniques in ANN environment", *Int'l J. Smart Sens. Intellig. Sys*., **1**(10), 970-984.

Rosales, M.B., Filipich, C.P. and Buezas, F.S. (2009), "Crack detection in beam-like structures", *Eng. Struct*., **31**(10), 2257-2264.

Rytter, A. (1993), "Vibration based inspection of civil engineering structures", Ph.D. Thesis, Department of Building Technology and Structural Engineering, Aalborg University, Denmark.

Stull, C.J. and Earls, C.J. (2009), "A rapid assessment methodology for bridges damage by truck strikes", *Steel Composite Struct., An Int'l J*., **9**(3), 223-237.

Suh, M.W., Shim, M.B. and Kim, M.Y. (2000), "Crack identification using hybrid neuro-genetic technique", *J. Sound Vib*., **234**(4), 617-635.

Wu, Z.S., Xu, B. and Yokoyama, K (2002), "Decentralized parametric damage based on neural networks", *J. Computer-Aided Civil Infrastruct. Eng*., **17**(3), 175-184.

Xu, B., Wu, Z.S. and Yokoyama, K. (2002), "A localized identification method with neural networks and its application to structural health monitoring", *J. Struct. Eng., JSCE, **48A***, 419-427.

Yau, J.D. (2005), "Damage detection of a cracked column via a neural network approach", *J. Adv. Steel Struct*., **2**, 1749-1754.

Zapico, J.L., Gonzalez, M.P. Worden, K. (2003), "Damage assessment using neural networks", *J. Mech. Sys. Signal Process*., **17**(1), 119-125.

Matlab 7.11 (R2010b), The MathWorks Inc., MA, USA. http://www.tnodiana.com

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