Adaptive Neuro Fuzzy Inference System (ANFIS) and Artificial Neural Networks (ANNs) for structural damage identification

S.J.S. Hakim[a] and H. Abdul Razak[*]

StrucHMRS Group, Department of Civil Engineering, University of Malaya, Kuala Lumpur 50603, Malaysia

Abstract. In this paper, adaptive neuro-fuzzy inference system (ANFIS) and artificial neural networks (ANNs) techniques are developed and applied to identify damage in a model steel girder bridge using dynamic parameters. The required data in the form of natural frequencies are obtained from experimental modal analysis. A comparative study is made using the ANNs and ANFIS techniques and results showed that both ANFIS and ANN present good predictions. However the proposed ANFIS architecture using hybrid learning algorithm was found to perform better than the multilayer feedforward ANN which learns using the backpropagation algorithm. This paper also highlights the concept of ANNs and ANFIS followed by the detail presentation of the experimental modal analysis for natural frequencies extraction.

1. Introduction

Damage in a structure is defined as changes to the geometric and material properties, leads to stiffness reduction and stability which negatively affect the performance of structures. Reduction in the structural stiffness produces changes in the dynamics characteristics, such as the natural frequencies and mode shapes. Damage may be due to operating loads, impact, delamination, fatigue, creep, corrosion and wear, or some other reasons such as earthquakes. Damage detection at an early phase, is very significant to prevent sudden and catastrophic collapse and failures of structural systems. For proper functioning of the structure, damage should be detected, located and repaired if possible. Therefore, in civil engineering, structural health monitoring (SHM) methods have been used to assessment of the condition of structures.

Visual inspections which are the most common methods applied in structural damage detection, are often insufficient for evaluating the condition of structural systems especially when the damage is not observable to see. Therefore, to make sure structural integrity, it is very important to monitor the structural performance when damage is invisible.

In recent decades significant amounts of research have been done on the Artificial Intelligence (AI) techniques such as, Artificial Neural Networks (ANNs), Fuzzy Logic and genetic algorithms

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*Corresponding author, Professor, E-mail: hashim@um.edu.my
[a]Ph.D. Student, E-mail: jamalhakim@siswa.um.edu.my

(GA) to predict and estimate the damage in structures. Artificial intelligence is a soft computing technique for intelligent computing, which parallels the notable capability of the human mind to reason and learn in situations with uncertainty and imprecision (Gao and Ovaska 2001).

ANNs are inspired by human brain and have the ability to learn from their experience in order to improve their performance and to adapt themselves to changes in the environment. ANNs based on dynamic characteristics have been applied increasingly for damage detection owing to their pattern recognition and information processing capabilities. For example, Mehrjoo *et al*. (2008) studied on damage of joints in two truss bridge structures using ANNs. In this study natural frequencies and mode shapes were used as inputs to the neural network for damage detection. Based on the findings, ANN could predict the severity and locate damage of the joints in truss bridges with an error of 1%. The results seem to be quite promising in terms of accuracy.

Lee *et al*. (2005) applied the direct mope shapes and also the ratios or differences of the mode shape components before and after damage as the inputs of ANN for damage identification of simply supported girders bridges. ANN trained using mode shape differences and mode shape ratios could recognize the location of damages with good accuracy. Natural frequencies were applied 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 by combining ANN with genetic algorithm for damage identification. Natural frequency and mode shape were selected as the input parameters to a radial basis neural network to update the finite element model based on experiment modal data was applied by Levin and Lieven (1998). A cantilever beam was used and showed the capability of ANNs for verifying modal updating parameters for the numerical model using experimental modal data. Also many other research efforts attempted to apply ANNs to identify damage in structural engineering (Hakim and Razak 2011, Rosales *et al*. 2009, Ni *et al*. 2006, Lu and Tu 2004, Chang *et al*. 2002).

Over the last decade Zadeh (1965) proposed the fuzzy logic theory to attempt to solve complicated systems in various problems. Fuzzy logic is a soft computing technique which at the same time handles linguistic knowledge and numerical data. Fuzzy systems are defined as rule-based systems that are constructed from a collection of linguistic rules which can represent any system with accuracy, i.e., they work as universal approximators. The fuzzy rule-based system is an IF–THEN rule-based system, given by, IF antecedent, THEN consequent (Cevik 2011, Sivanandam *et al*. 2007). One of the main benefits of fuzzy logic compared with other intelligence methods which deal with inaccurate data is that its fuzzy knowledge base (FKB) is in a rule format, simple to examine and understand. This rule format makes it easy to update and maintain the FKB (Zio and Gola 2009).

Fuzzy logic systems are becoming very popular in different fields such as engineering, pattern classification and recognition, process control, image processing, economics and decision making (Ganguli 2002, Taha and Lucero 2005).

Damage identification in structures using modal parameters based on fuzzy logic techniques have been considered by many researchers. For example, structural damage identification using mode shape curvatures and fuzzy logic was investigated by Chandrashekhar and Ganguli (2011). In this research single and multiply damaged with uncertainties in structural geometric properties were considered. Based on this study, the fuzzy logic systems based on curvature damage factor was suggested as a strong tool for structural damage identification.

Also crack detection in cantilever beam using fuzzy logic technique was done by Parhi and Choudhury (2011). In this work, crack was analyzed using fuzzy logic and finite element analysis.

The input parameters to the fuzzy controller were the first three natural frequencies and output parameters were the relative crack depth and relative crack location. According to this work, fuzzy logic technique can predict the depths and locations very close to the finite element analysis.

ANNs are very good at pattern recognition and can be trained properly from data and generalize highly nonlinear mapping between diverse domains but they are not good at explaining how they reach their decisions and are poor in term of reasoning capabilities. Fuzzy logic systems are based on IF-THEN rules and logical inference the fuzzy logic can explain its reasoning. Fuzzy logic systems, which can reason with imprecise information, are good at explaining their decisions but they cannot automatically obtain the rules they use to make those decisions. However, fuzzy logic systems do not have the learning ability and cannot modify themselves to adjust to a new environment (Zheng *et al.* 2011). These limitations encouraged the researchers to create the intelligent hybrid systems where two or more techniques are combined in a method that overcomes individual techniques and attain higher performance by utilizing capabilities of each individual technique (Lei *et al.* 2007, Liu *et al.* 2002).

Adaptive Neuro Fuzzy Interface System (ANFIS) is one of the greatest tradeoff among ANNs and fuzzy logic systems, offering smoothness due to the fuzzy control interpolation and adaptability due to the ANN backpropagation. ANFIS provide a technique for the fuzzy modeling procedure to achieve information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data (Jang 1993). ANFIS is a class of ANN, which is based on fuzzy interface system and incorporates both ANN and fuzzy logic principles and has benefits of both techniques in a single framework.

Application of ANFIS as a strong tool in modeling of many processes such as damage identification and structural engineering (Mohammadhassani *et al.* 2013a, b, Salajegheh *et al.* 2009, Fonseca *et al.* 2008, Altug *et al.* 1999), water engineering (Samandar 2011, Chang and Chang 2006), material (Karaagac *et al.* 2011) and geotechniques (Jalalifar *et al.* 2011) is investigated. An adaptive neuro-fuzzy system (ANFIS) was presented by Wang and Elhag (2008) for assessment of a bridge. ANFIS was more efficient in the evaluation process and performed much better than ANNs and multiple regression analysis.

The application of ANFIS to predict the behaviour of steel beam web panels subjected to concentrated loads is described by Fonseca *et al.* (2008). In this study the architecture of ANFIS was composed of one neuro-fuzzy classification model to classify the beams based on its pertinence to a specific structural response and one patch load prediction neural network to use the pertinence established by the neuro-fuzzy classification model and finally determine the beam patch load resistance.

Application of ANFIS for design optimization of geometrically space trusses was studied by Salajegheh *et al.* (2009). In this research, ANFIS models were applied to predict the element stresses of the space trusses and nodal displacement. Results of ANFIS were compared with ANN and showed better performance than ANN.

A novel technique for crack identification using ANFIS is proposed by Shim and Suh (2002). In this research, ANFIS was applied to obtain the input-output relation of the structural system. Location and depth of crack was mentioned as inputs of ANFIS and the structural eigenfrequencies was considered as output. This technique is shown on two-dimensional clamped-free beam structures. The crack parameters of the structure were estimated within 3% error. Results were promising and good agreements were achieved between the location and depth of crack compared with reference structure.

The main focus of this research is to investigate the possibility of using ANFIS and ANN trained with only natural frequency data to identify the severity of damage in steel bridge girder structure. The identification capabilities of these models will be compared. The required data in form of natural frequencies are obtained from experimental modal analysis.

2. Methodology

The suggested approach in this study consists of two steps. In the first stage, experimental modal analysis for data acquisition and feature extraction is done and first five natural frequencies of the undamaged and damaged bridge girder model are extracted. In the second step, the obtained data sets including natural frequencies are applied for training and testing of an ANN and ANFIS model to recognize the severity of damage. In the following sections, the main characteristic of the selected soft computing models consists of ANNs and ANFIS are explained. Experimental modal analysis of undamaged and damaged structure is also described.

2.1 Artificial neural networks

ANNs are parallel information processing system based on biological neurons models and as one of the useful computational models applied in almost all branches of science. ANNs can provide significant answers even when the data are incomplete or include errors and can process information extremely rapidly when used to solve actual problems (Hakim 2006, Hagan *et al*. 1996).

ANN is composed of many processing elements namely artificial neurons, which are linked together. The model of an artificial neuron is depicted in Fig. 1. The artificial neuron receives n weighted input signals (w) , which are summed and passed through an activation function (f) to generate an output signal (Hakim 2006).

According to this explanation the output of an artificial neuron can be expressed in Eq. (1) (Hagan *et al*. 1996, Haykim 1999). In Eq. (1), x_j, O, w and w_0 are input, output, weight and bias of artificial neuron, respectively.
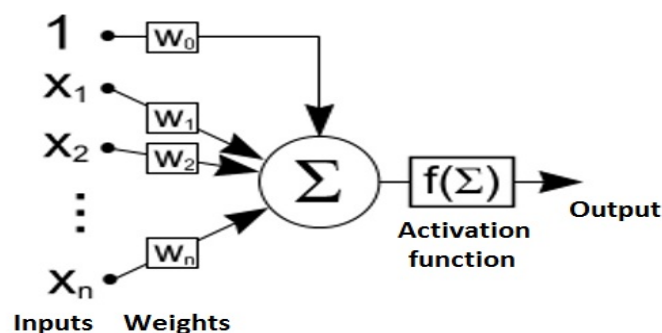
$$O = f(\sum_{j=1}^{N} w_i x_j + w_0)$$ (1)

Fig. 1 Schematic structure of an artificial neuron

A typical architecture of ANN has three layers namely input, hidden and the output layer. In the hidden and output layers of ANN, an extra neuron namely bias with a constant output that is 1 is added to each neuron.

Input signals are received at the input layer, pass through the hidden layer and arrive at the output layer of ANN. These layers can have a diverse number of neurons and activation functions such as sigmoid and linear functions. All neurons are linked to the neurons in the next layer through their connectivity weights (Cheng *et al*. 2007, Hakim *et al*. 2011). Architecture of an ANN with 5 neurons in input layer, 3 neurons in hidden layer and one neuron in output layer is shown in Fig. 2.

An ANN obtains knowledge during the learning process. Learning is the procedure that ANN can adjust the connectivity weights in order to obtain the desired output. The learning modes can be supervised or unsupervised learning.

In supervised learning the training samples need an input vector at the inputs and an output vector at the output layer. However in unsupervised learning, the training samples need only an input vector at the input layer (Hagan *et al*. 1996).

Backpropagation (BP) algorithm in multi-layer feed-forward networks is the most applicable algorithm due to the mathematical design of the learning complex nonlinear relationships. Among different neural networks, Multi-Layer Perceptron (MLP) is most commonly applied in structural damage detection (Haykin 1999, Hakim and Abdul Razak 2011b). BP algorithm has a performance index, which is the least Mean Square Error (MSE) (Lee 2003, Civalek 2004, Noorzaei *et al*. 2007). In MSE algorithm, the error is calculated as the difference between the target output and the network output. The MSE algorithm is a type of supervised training, in which the learning rule is provided with a set of examples of desired network behavior such as:

$\{p_1,t_1\}, \{p_2, t_2\},\ldots\ldots\ldots,\{p_q, t_q\}$

where p_q is an input to the neural network and tq is the corresponding target output. As each input is applied to the network, the network output is compared to the target.

The least Mean Square Error (MSE) algorithm adjusts the weights and biases of the neural network so as to minimize this mean square error. The process of forward and backward propagation continues until the error is reduced to an acceptable level. The equation that describes MSE operation is written as Eq. (2). (Naderpour *et al*. 2010, Noorzaei *et al*. 2008).

$$MSE = \frac{\sum_{i=1}^{n}(t_i - o_i)^2}{n} \tag{2}$$

where
n = number of training pattern , t_i = output of target and o_i = output of network

2.2 Adaptive neuro fuzzy interface system (ANFIS)

The adaptive neuro fuzzy inference system (ANFIS) developed by Jang(1992, 1993 and 1997) is the implementation of fuzzy inference system to adaptive networks for developing fuzzy rules with proper membership functions to have required inputs and outputs. An adaptive network is a feed-forward multi-layer neural network with adaptive nodes in which the outputs are predicted on the parameters of the adaptive nodes and the adjustment of parameters due to error term is specified by the learning rules (Samandar 2011, Jang 1993).

The two ANFIS training types are backpropagation and hybrid. Using a specified input/output data set, ANFIS constructs a Fuzzy Inference System (FIS) whose membership function parameters are adjusted using either a backpropagation algorithm alone or in combination with a least square type of method. This adjustment allows the Fuzzy inference systems to learn from the data they are modeling. Generally training type in adaptive ANFIS is hybrid. Hybrid training is mixed with least mean squares and backpropagation. In the presented study ANFIS uses hybrid method for membership function parameter estimation.

2.2.1 Architecture and algorithm

As represented in Fig. 3, each fuzzy system has three main parts comprising fuzzification, inference and defuzzification. According to this representation, a fuzzy inference system is composed of five functional blocks as follows (Kumar and Taheri 2007);

(i) input parameters to input membership functions.
(ii) input membership function to rules.
(iii) rules to a set of output characteristics.
(iv) output characteristics to output membership functions.
(v) the output membership function to a single-valued output, or a decision associated with the output.

Mamdani and Sugeno are two different types of inference used in fuzzy logic systems. Sugeno method works very well with optimization and adaptive techniques and is well-suited to mathematical analysis. Also this method works well with linear techniques and it has guaranteed continuity of the output surface (Sugeno 1985). According to aforementioned advantages, ANFIS only supports Sugeno method. So, brief explanation of Sugeno method is described.
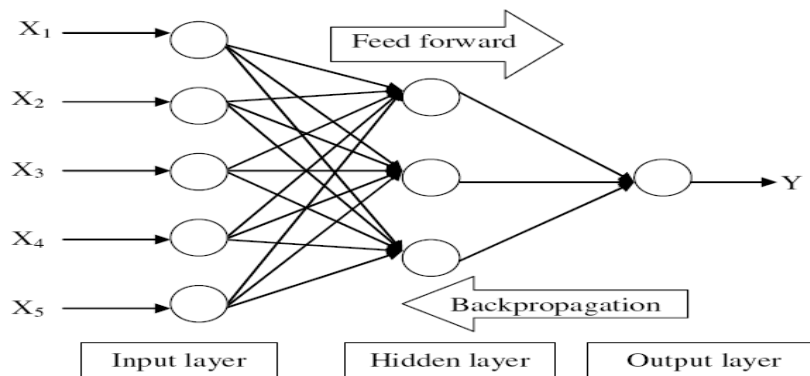

Fig. 2 Architecture of a typical multilayer feedforward neural network
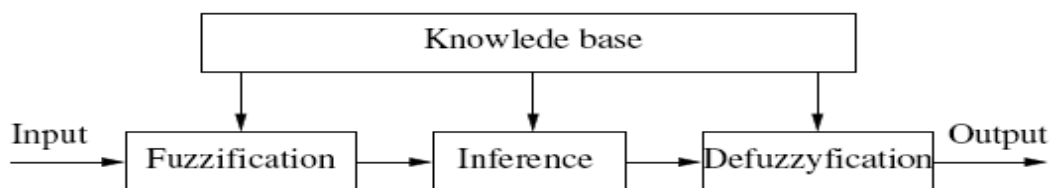

Fig. 3 Fuzzy inference system

Assume that the fuzzy inference system has two inputs x and y and one output z. For a first-order Sugeno fuzzy model (Takagi and Sugeno 1985), it has two fuzzy if–then rules as given in Eq. (3) and Eq. (4).

$$\text{Rule1: If } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } f_1 = p_1x + q_1y + r_1 \tag{3}$$

$$\text{Rule 2: If } x \text{ is } A_2 \text{ and } y \text{ is } B_2, \text{ then } f_2 = p_2x + q_2y + r_2 \tag{4}$$

where p_i, q_i and r_i (i = 1 or 2) are linear parameters in the then-part (consequent part) of the first-order Sugeno fuzzy model.

Fig. 3 shows the reasoning mechanism for Sugeno model. ANFIS model is one of the implementations of a first order Sugeno fuzzy inference system. The corresponding equivalent ANFIS architecture for two-input first-order Sugeno fuzzy model with two rules is shown in Fig. 4.

The architecture of ANFIS consists of five layers, as depicted in Fig. 5. A short explanation of the ANFIS architecture is as follows;

Layer 1: Input nodes. In this layer each node generates membership grades to which they belong to each of the appropriate fuzzy sets using membership functions, as shown in Eq. (5) and Eq. (6).

$$O_{1,i} = \mu A_i(x) \text{ for } i = 1, 2, \text{ or} \tag{5}$$

$$O_{1,i} = \mu B_{i-2}(y) \text{ for } i = 3, 4 \tag{6}$$

$O_{L,i}$ is the output of the i_{th} node of the layer L. Every node i in this layer is an adaptive node with a node function. In Eq. (5) and Eq. (6), x, y are the inputs to node i, and A_i, B_{i-2} are the linguistic labels characterized by appropriate membership functions μA_i and μB_{i-2}, respectively. Therefore, $O_{1,i}$ is the membership grade of a fuzzy set (A_1, A_2, B_1, B_2).

The Gaussian and bell-shaped membership functions are more popular for specifying fuzzy sets. The bell-shaped membership function as typical membership function is given by Eq. (7) and Eq. (8).

$$\mu_{A_i}(x) = \frac{1}{1 + \left| \frac{x - c_i}{a_i} \right|^{2b_i}} \tag{7}$$

$$\mu_{B_{i-2}}(y) = \frac{1}{1 + \left| \frac{y - c_i}{a_i} \right|^{2b_i}} \tag{8}$$

where $\{a_i, b_i, c_i\}$ is the parameter set of the membership functions. These parameters are referred to as premise part of fuzzy if–then rules that changes the shapes of the membership function.

Another fuzzy membership function that is often used to represent fuzzy and linguistic terms is the Gaussian which is given by Eq. (9) and Eq. (10).

$$\mu_{A_i}(x) = \exp(-\frac{(c_i - x)^2}{2\sigma_i^2}) \tag{9}$$

$$\mu_{B_{i-2}}(y) = \exp(-\frac{(c_i - y)^2}{2\sigma_i^2}) \tag{10}$$

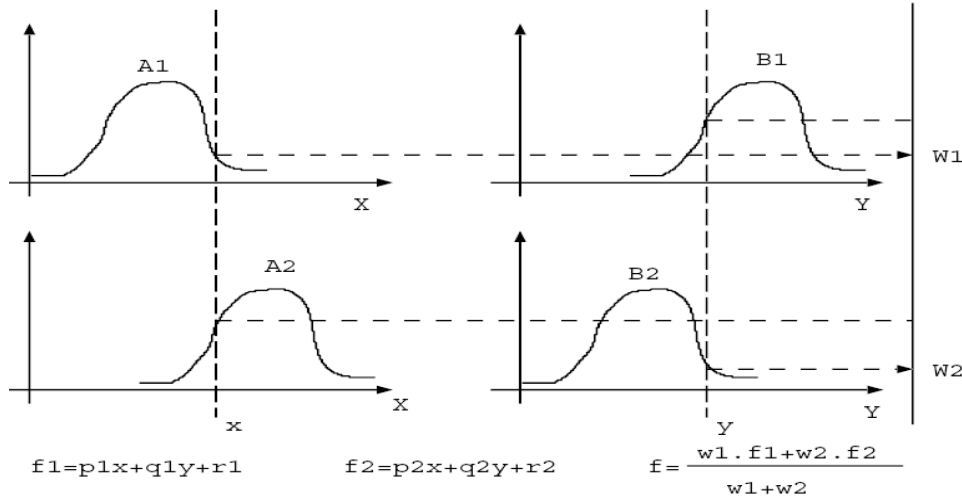$$f1=p1x+q1y+r1 \qquad f2=p2x+q2y+r2 \qquad f=\frac{w1.f1+w2.f2}{w1+w2}$$

Fig. 4 Two-input first-order Sugeno fuzzy model with two rules

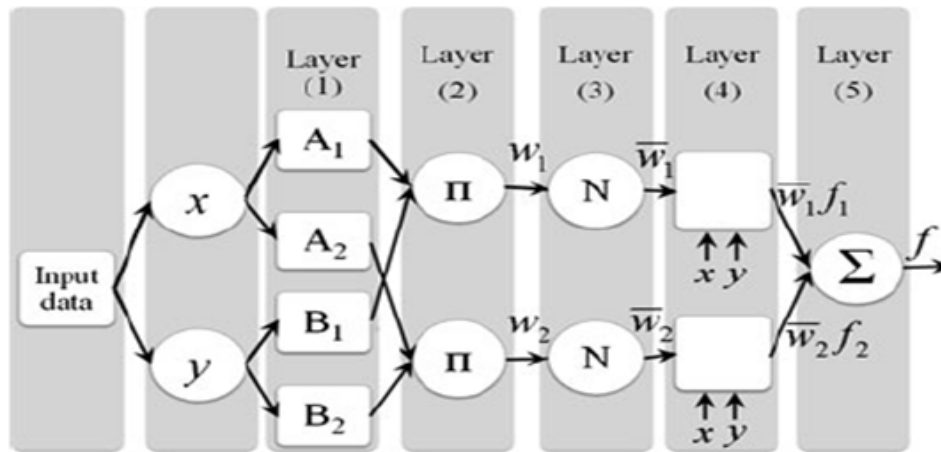Fig. 5 Basic structure of ANFIS for two-input Sugeno fuzzy model

where c_i and σ_i are the centre and width of the ith fuzzy set A_i, respectively.

Layer 2: Rule nodes. Every node in this layer is a fixed node labeled Prod. In this layer, the AND operator is used to obtain one output that represents the result of the antecedent for that rule, i.e., firing strength. Each node represents the fire strength of the rule in this layer.

Firing strength means the degrees to which the antecedent part of a fuzzy rule is satisfied and it shapes the output function for the rule. Hence the outputs $O_{2,i}$ of this layer are the products of all the incoming signal from Layer 1, as shown in Eq. (11).

$$O_{2,i} = w_i = \mu_{Ai}(x) \cdot \mu_{Bi-2}(y), \ i = 1, 2 \tag{11}$$

Layer 3: Average nodes. Every node in this layer is a fixed node labeled Norm. In the third layer, the ith node calculates the ratio of each ith rule's firing strength to the sum of all rules firing

strength. Outputs are called normalized firing strengths. Consequently, $\overline{\omega}_i$ is taken as the normalized firing strength. Eq. (12) shows output of layer 3.

$$O_{3,i} = \overline{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2} , \ i = 1,2 \tag{12}$$

Layer 4: Consequent nodes. Every node i in this layer is an adaptive node .The node function of the fourth layer computes the contribution of each ith rule's toward the total output. Node function in this layer is defined as Eq. (13).

$$O_{4,i} = \overline{\omega}_i f_i = \overline{\omega}_i (p_i x + q_i y + r_i), i = 1,2 \tag{13}$$

where $\overline{\omega}$ is the normalized firing strength from previous layer. In Eq. (13), $\{p_i, q_i, r_i\}$ are the coefficients of this linear combination and are also the parameter set in the consequent part of the Sugeno fuzzy model.

Layer 5: Output nodes. The single node in this layer is a fixed node labeled sum and computes the overall output as the summation of all the incoming signals. As shown in Eq. (14), the defuzzification process transforms each rule's fuzzy results into a crisp output in fifth layer.

$$\text{Overall Output=} O_{5,i} = \sum_{i=1}^{4} \overline{\omega}_i f_i = \frac{\sum_{i=1}^{4} \omega_i f_i}{\sum_{i=1}^{4} \omega_i} \tag{14}$$

ANFIS uses a hybrid learning algorithm namely the gradient descent approach and the least-squares approach to update parameters. The gradient descent approach is applied to adjust premise non-linear parameters ($\{a_i, b_i, c_i\}$) while the least-squares method is applied to identify consequent linear parameters ($\{p_i, q_i, r_i\}$) (Chang and Chang 2006).

In the learning process initially the least mean square approach is applied to recognize the consequent parameters while the antecedent parameters such as membership functions are assumed to be fixed for the current cycle through the training set. Then, the error signals propagate backward. Gradient descent approach is used to update the premise parameters, through minimizing the overall quadratic cost function, while the consequent parameters remain fixed (Jang 1993, Chang and Chang 2006)**.**

3. Results and discussion

3.1 Damage identification strategy and experimental modal analysis

Changes in physical properties of the structure such as mass and stiffness causes a shift in dynamic parameters such as the natural frequency, and mode shape and damping ratio of the structure. Therefore, by measuring these dynamic characteristics we will be able to predict the changes in physical properties resulting from damage. In this work it is proposed to apply the first five natural frequencies as inputs of ANN and ANFIS for prediction of damage severity. Since the natural frequencies of a structure depend on physical properties of the structure, the natural frequencies will change when there is damage.

To identify the natural frequencies as dynamic properties of the bridge girder, experimental

modal analysis with different damage scenarios was performed. In the first stage, modal testing was performed using an undamaged model of a bridge girder in order to obtain the first five modal frequencies. Later, numerous damage scenarios were created by introducing different severity of damage at different locations along the bridge girder. The results of experimental modal analysis will be use as training data for the ANN and ANFIS. By incorporating the training data, the potential of these two artificial intelligence techniques to identify the damage severity using the five first natural frequencies will be investigated.

The test structure as shown in Fig. 6(a) was fabricated from a plate with the dimensions of 1200 mm length including a 100 mm overhang at both support ends and 210 mm and 5mm in width and thickness, respectively. As depicted in Fig. 6(b), three stiffeners are fixed along the length of plate with dimensions of 1200 mm by 50mm by 5mm in length, width and height, respectively. The modulus of elasticity of the steel, the Poisson's ratio and the density were, $2.1 \times 10^{11} \text{kg/m}^2$, 0.2 and 7850 kg/m^3, respectively.

In modal testing, the bridge girder was excited by a shaker at a certain reference point and the responses of the bridge girder were measured by accelerometers. In experimental modal analysis, the converted signals from the shaker and the accelerometers were analyzed and the modal parameters of the bridge girder were determined. The arrangement of the accelerometers is shown in Fig. 7.
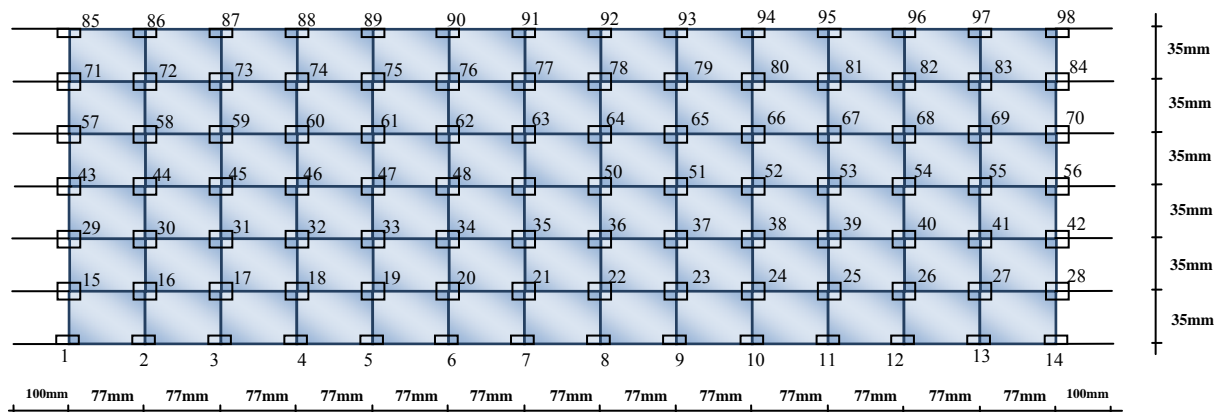

Fig. 6 Test structure

Fig. 7 Accelerometers position

As it is clear from the test grid of specimen for measuring, the test grid model was chosen to have 98 points in seven sets between two supports at both end of the bridge girder. Fourteen accelerometers in each set were used to record the response of specimen. The accelerometers having sensitivity range from 95 mV/g to 100 mV/g.

The time history signals of the shaker and the accelerometers were amplified and the response signals were processed using a multi-channel signal analyzer. This hardware is used to convert the analogue input signal from the transducer into a digital form and contains optional inputs and processing modules.

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 2500 Hz with 6401 FRF data points. So, the frequency resolution of 0.39 Hz per data point is considered in this study. The acquired response time history signals were then converted into frequency spectra domain using the Fourier transforms. 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 are measured and saved using the acquisition software, a modal analyzer software is then used to calculate FRFs (frequency domain data) and execute the modal analysis. FRFs were obtained from the software, and the modal parameter contains natural frequencies and mode shapes were extracted from the FRFs by a curve fitting technique.

In short, from experimental modal analysis, the dynamic properties of the model bridge girder including FRFs, natural frequencies and mode shapes were determined at each undamaged and damaged state.

One of the major problems with the analysis of vibration data and during the process of Fast Fourier Transform (FFT) is that the signal is assumed to be periodic over the sampling interval chosen. In general this will not be true, and leads to a problem known as leakage**.** Leakage is the unwanted distortion caused by artificial truncation of sampled data. A common tool used to overcome the leakage problem is windowing. This function consists of a process of 'weighting' the original time history data to reduce the noise distortion and the effect of leakage. A good window function will produce a Fourier transform that is close to that which would be produced if the signal were sampled for an infinite time. There are a few developed window functions, such as uniform, Hamming, Hanning, force and exponential windows (Avitabile 1998, Maia *et al.* 1997). In this study, the improvement on the Fourier transform using Hanning window was obvious and Hanning window was used for the response signals to ensure that the signals showed enough decay at the end of the sampling period.

The model steel girder bridge was tested 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 extracted first five modes of the undamaged state of the model are shown in Fig. 8.

Table 1 Frequencies of the structure at undamaged state

Natural Frequencies(Hz)				
Mode 1	Mode 2	Mode 3	Mode 4	Mode 5
110.41	177.2	352.5	428.05	701.4

In the experimental study various damage scenarios were given to the test structure. 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. Only one half of the test structure was induced with damage due to symmetry. This was achieved by introducing a slot by grinding from the soffit of the middle stiffener of the structure. These damage severities correspond to a cross-section of loss of the second moment of area (I) as shown in Table 2.
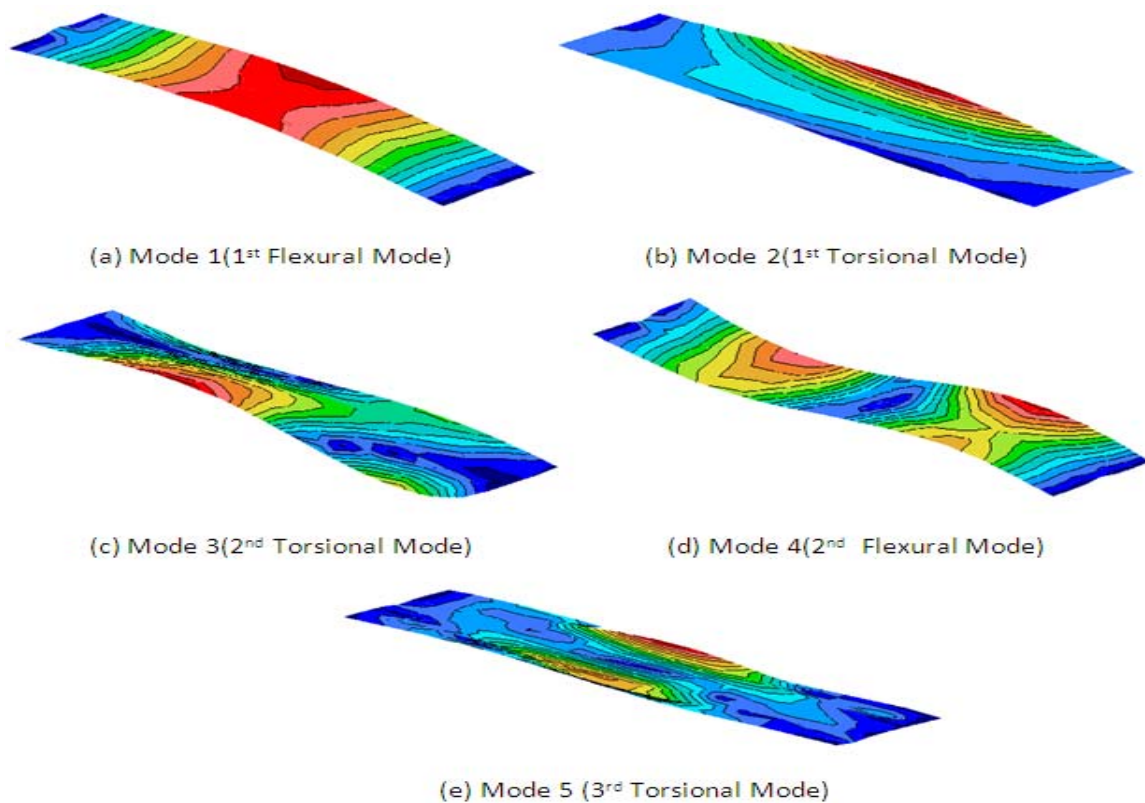

(a) Mode 1(1st Flexural Mode)   (b) Mode 2(1st Torsional Mode)

(c) Mode 3(2nd Torsional Mode)   (d) Mode 4(2nd Flexural Mode)

(e) Mode 5 (3rd Torsional Mode)

Fig. 8 Modes shape for undamaged cases

Table 2 Loss of the second moment of area (I) for different damage severity

Cut slot (mm)	I* (%)	Cut slot (mm)	I* (%)
2	11.50	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	-	-

*I: Cross-section loss of the second moment of area

Table 3 Natural frequencies of the first five modes for damage at 5L/13

Damage Severity (mm)	Mode No.				
	1 (HZ)	2 (HZ)	3 (HZ)	4 (HZ)	5 (HZ)
2	107.31	168.11	342.27	422.31	694.13
4	106.13	167.44	341.29	421.45	695.18
6	106.37	166.62	339.81	421.83	695.56
8	105.72	167.26	335.68	422.93	693.32
10	104.33	165.65	331.75	420.44	691.71
12	104.09	162.32	330.92	418.25	690.88
14	103.51	161.34	330.51	416.55	688.64
16	103.21	160.13	329.52	414.75	689.36
18	102.93	159.14	329.04	413.78	687.34
20	102.62	157.64	330.71	412.54	685.47
22	102.14	155.61	325.94	411.65	683.62
24	101.68	153.12	325.57	409.71	682.41
26	101.07	155.73	324.31	407.73	681.84
28	100.91	154.78	322.55	406.16	680.33
30	100.42	152.38	321.76	405.23	679.29

For each damaged severity, five peaks were identified which were related to the modal frequencies of the structure. Table 3 shows the first five frequencies for a damage case for the test structure and it is apparent that the natural frequencies drop when damage is induced. These results will be used for training ANNs and ANFIS techniques for damage severity.

3.2 Data selection

In this study, 200 different sets of data from undamaged and damaged of scaled down steel girder bridge deck were collected from the experimental modal analysis. These data were gathered for damage severity of the test structure containing the first five natural frequencies. In this research, divisions of the datasets were carried out randomly into training and testing datasets. Out of the 200 datasets, 160 (80%) were used as training datasets, while the remaining data (20%) are used for testing phase (40 data sets). The scattering of input information for the training part have an effect on the precision of a neural network. Therefore, classification of the input information is very important in the training part.

3.3 Damage detection using ANN

In this study, feedforward backpropagation algorithm for ANN training was selected. At first an input vector comprising of the first five natural frequencies 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 error, which will propagate through the network in backward step. The process of training is successfully completed, when the iterative process has converged.

During this process, the mean square error (MSE) will be minimized, and consequently the output of ANN will be closed to the target output. An accurate trained ANN gives successful damage identification when a new sample is given as input. The output parameter of ANN is damage index, representing the severity of damage. This damage index is ratio of cross-section

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Table 4 Damage index values as output of ANN

Cut slot (mm)	Damage Index	Cut slot (mm)	Damage Index
2	0.885	18	0.2622
4	0.779	20	0.216
6	0.6815	22	0.1756
8	0.5927	24	0.1406
10	0.5520	26	0.1106
12	0.439	28	0.0852
14	0.3733	30	0.064
16	0.3145	-	-

loss of the second moment of area for damaged case to undamaged case. The value of damage index based on different damage severity is given in Table 4.

Alyuda Neuro Intelligence software, version 2.2 is used for the purpose of training. Once the network is trained using training data, it is ready for predicting the severity of damage in the test structure. The data sets were normalized between -1 and 1 and fed to the input neurons. The values of damage index corresponding to each set of natural frequencies have been also fed to the network as desired outputs. The training process continues to update and adjust the weights of the ANN until the network can produce satisfactory outputs compared to target values. In this research, the training process was stopped when any of the following conditions were satisfied:

  (i) The maximum number of iterations reached 70000.
  (ii) The mean square error (MSE) of the network for the training set reached 0.004.

The decision on how many hidden layers and neurons should be used in hidden layer is rather arbitrary and there are no rules to find out the number of them and trial and error approach is applied to obtain the optimum numbers. Many architecture networks having different conditions were conducted, trained and tested using available data sets in this work. After trying different networks with one and two hidden layers and taking into consideration the network error, it was decided to have one hidden layer in architecture of ANN in this study. However, in a network with one hidden layer, good convergence has been achieved. According to Saeed *et al.* (2011), if the hidden layers numbers and neurons in the ANN are too small, it may not be able to represent the system adequately. Also, when network is too big, it becomes over trained. With increasing of hidden neurons, training error is reduced, but there are a critical number of hidden neurons existing for minimizing error rate. It can be said that, a network with too many hidden neurons can simply memorize the accurate response to each sample in its training set instead of learning a general solution.

It was shown that the network with 12 neurons in hidden layer has minimum average training error. Also, the correlation of this network is higher than other networks. Therefore, it was shown that the network architecture comprises of five neurons in the input layer corresponding to the five first natural frequencies, one hidden layer with twelve neurons and one neuron in the output layer corresponding to severity of damage in the test structure. This network is selected as the best possible architecture in this study and produced the best predictions for the damage severity of bridge girder. It is important to note that utilizing more than 12 neurons in network makes the computation process complicated and expensive in terms of time. The final architecture for this network is depicted in Fig. 9.

Different combinations of momentum value and learning rate using trial and error have been

executed for this architecture. In this study, ANN has been tested during the training process for different values of learning rates of 0.01, 0.05, 0.1, 0.15, 0.2, 0.25 and 0.3 and for momentum value of 0.55, 0.60, 0.65, 0.70, 0.75 and 0.80. Results showed that constructed ANN with learning rate 0.2 and 0.65 for momentum parameter, yields minimum error. Therefore these values have been found to be most suitable for selected network in this study. In this network Hyperbolic Tangent Sigmoid (tansig) and Log-Sigmoid (logsig) functions were used for hidden and output layer as activation functions, respectively.
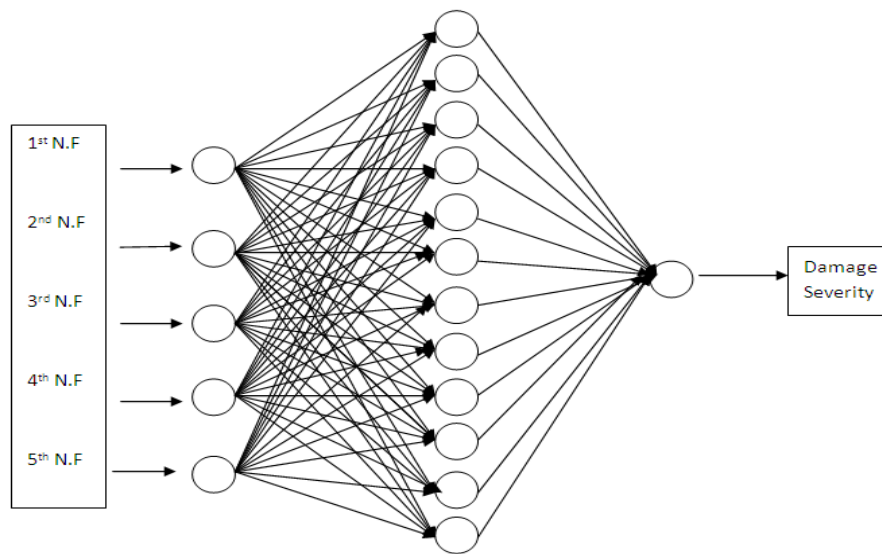

Fig. 9 ANN architecture

The network is then trained for 70,000 iterations until the training error reach minimum and the network is stable. In short, training of this architecture (5-12-1) with value of 0.2 and 0.65 for learning rate and momentum respectively is continued until 70,000 iterations and the average training error reaches to 5.6%. After that, the network was saved and the corresponding connectivity weights were saved. Comparison of predicted damage severity by ANN and actual value from experimental testing (target value) is depicted in Fig. 10.

Calculation of average training error shows that ANN predicted damage severity with average percentage error of 5.6% for training data sets. The correlation coefficient (R^2) gives more information about the training of network, having a value between 0 to 1. If the correlation coefficient is close to 1, it shows how much the learning is successful. This coefficient is calculated by using Eq. (15).

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n} (t_i - o_i)^2}{\sum_{i=1}^{n} o_i^2} \right) \tag{15}$$

As mentioned in Eq. (2) t_i is target value, o_i is predicted output value and n is number of samples. The smaller MSE and larger R^2 mean a better performance. The selected network was capable in providing good correlation between the natural frequency information and extent of damage in terms of damage index for a given set of natural frequencies. This network has minimum MSE i.e., 0.00404 and maximum correlation i.e., 0.973 compared to other networks with different architectures.

After the network was trained, testing of ANN was carried out to avoid over-fitting and examine the accuracy of the selected architecture. After training, the network has learned the samples and when tested with new data, it should be able to identify the severity of damage with an acceptable error. As mentioned previously, the testing phase has been done using 40 numbers of new data sets, which were not used in the training data set. Fig. 11 shows the comparison damage severities predicted by ANN and the experimental results for testing phase.
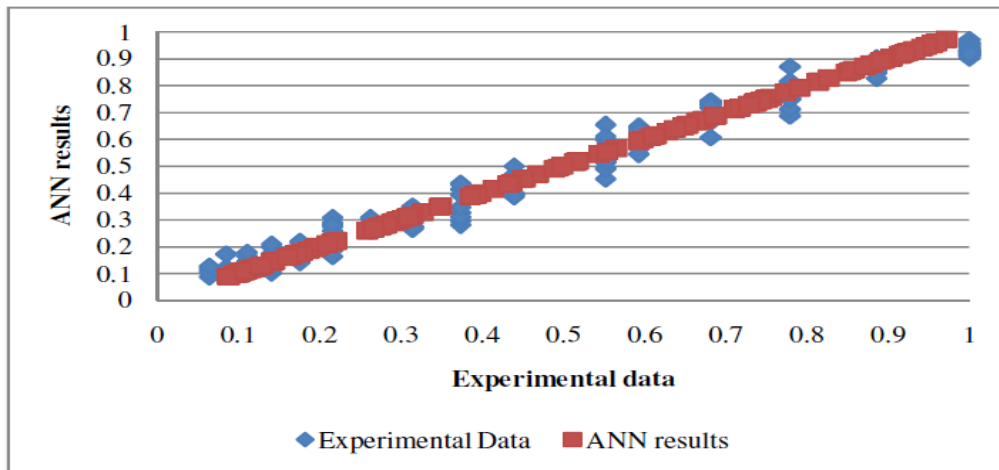

Fig. 10 Comparison of damage severity identified by ANN and experimental for training sets
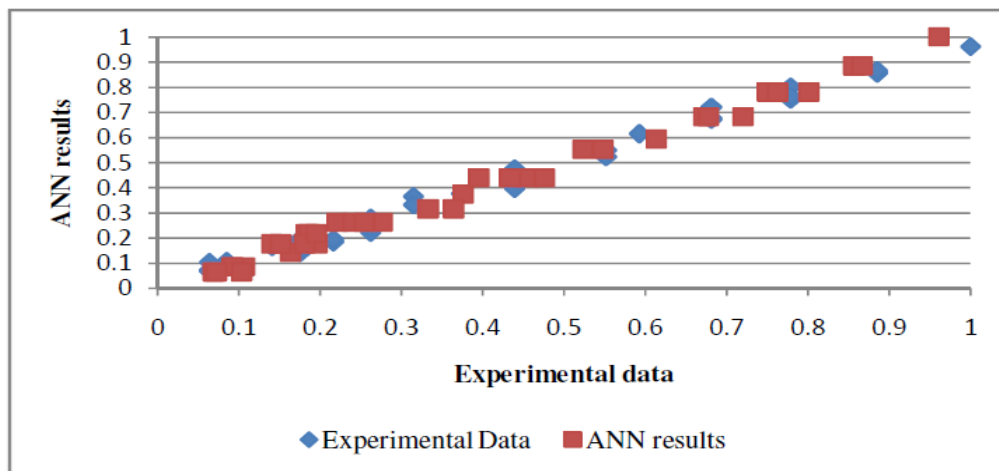

Fig. 11 Comparison of damage severity identified by ANN and experiments for testing sets

From Fig. 11, it can be highlighted that there is a good agreement between the predicted values and that of the experimental data. ANN was successful in predicting the severity of damage with average error of 6.25% for testing sets. MSE for testing process was 0.00482. According to results, the correlation coefficient (R^2) reached to 0.926 for testing data set. The testing results were very close to actual output and demonstrate that the ANN was successful in training the relationship between the input and output data with an acceptable error.

3.4 ANFIS models for determining the damage severity

The task of the training algorithm for ANFIS architecture is to adapt all the adjustable parameters to make the ANFIS output match the training data (Bateni and Jeng 2007). Training is based on the hybrid learning algorithm where premise and consequent parameters are to be updated after each data set is presented into the algorithm. The hybrid learning algorithm is a combination of least mean square and backpropagation method.

The main advantage of the hybrid algorithm is that it converges much quicker since it decreases the search space dimensions of the original backpropagation method applied in ANNs. Hybrid algorithm consists of forward pass and backward pass. In the forward pass the input membership function parameters are hold fixed, the signal moved forward until layer 4 and the output membership function parameters are trained and identified using least mean square method. In the backward pass, the output membership function parameters are held fixed, the error signals will be passed back and the premise parameters (the input membership function parameters) will be adjusted using the gradient decent method. The summary of backward and forward pass for ANFIS is shown in Table 5. According to this table consequent parameters are identified under the condition that the premise parameters are fixed. However, the output can be stated as a linear combination of the consequent parameters.

Table 5 Forward and backward pass for ANFIS

Parameter	Forward pass	Backward pass
Premise parameters	Fixed	Gradient descent
Consequent parameters	Least-squares estimator	Fixed
Signals	Neuron outputs	Error signals

During the training of ANFIS a fuzzy system can learn the features from the data sets and applies these features into the system rules. On the other hand, the parameters of MFs that are premise and consequent parameters are adjusted through the training procedure such that the outputs of ANFIS model match the real values in the training data sets.

In order to build the ANFIS models for determining the severity of damage in the bridge girder model, data sets as mentioned in section 3.2, extracted from experimental modal analysis were applied for training and testing, respectively.

With the purpose of obtaining output with higher precision, different ANFIS architectures using these data sets with different membership functions (MFs), fuzzy rules and number of MFs were trained in this study. The aim of the training procedure is to minimize the training error between the output predicted from ANFIS and the actual target. Training phase permits a fuzzy system to be trained the features from the data sets and utilizes these features into the system rules.

In this study, ANFIS was trained using Matlab version (R2010b) and first five natural frequencies are selected as ANFIS inputs and damage severity is considered as ANFIS output. Types and numbers of MFs for inputs and outputs are changed to improve the performance of ANFIS during training. The bell membership functions are used in this investigation and for each input, different number of them is adopted using trial and error approach. The maximum number of iterations in the training mode is set to 2700. After these iterations of training, the MSE became stable with a value of 0.00389. The comparison of the damage severity predicted by ANFIS model and experiments for training dataset are shown in Fig. 12.
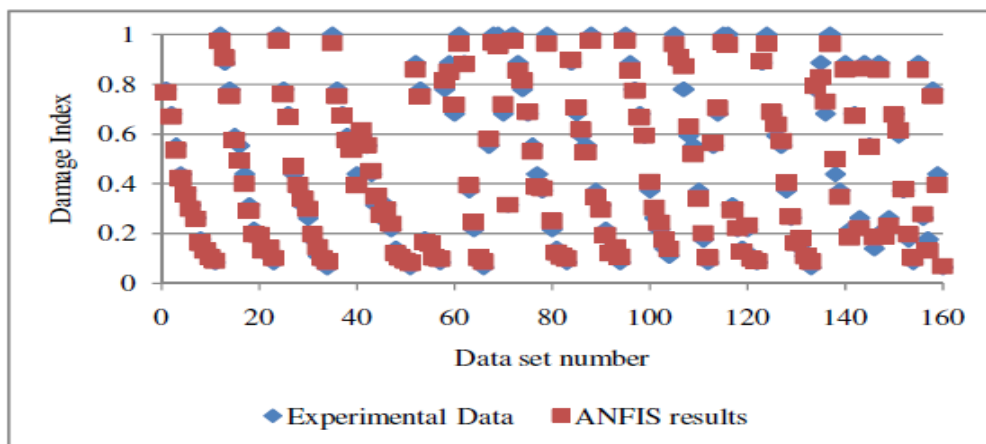

Fig. 12 Comparison of the identified damage severity through the ANFIS model versus experimental results for training sets

The number of MFs for each input was fixed to 29 to describe the input and output variables, when the ANFIS model reaches an acceptable level after training. Fig. 13 presents architecture of the adaptive neuro-fuzzy inference system to predict damage severity of the bridge girder model. According to this architecture there are 29 fuzzy membership functions and 29 rules for layers 2 and 3 were generated, with regards to the five inputs as shown in Fig. 13.

After the training step, the ANFIS model can be applied to identify the damage severity of the structure. For evaluating the performance of the trained ANFIS model and to check how well the network is trained, the test data sets were presented to the network. The comparison of the identified damage severity through the ANFIS model with the actual results through experimental for testing dataset are shown in Fig. 14. The ANFIS model could identify the severity of damage with MSE of 0.00442 for testing data sets.

According to this study the ANFIS results are very close to the experimental results and the correlation coefficient (R^2) values obtained are 0.998 and 0.982 for training and testing data sets, respectively. Results show a highly acceptable coefficient of correlation between the identified and experimental data and imply that the developed ANFIS model can be applied as a very good tool for identification of damage severity in the bridge girder model.

According to the analysis, it can be seen that the reliability of the predictive model is very dependent on a large quantity of data sets and with more sample data, more accurate model can be constructed.
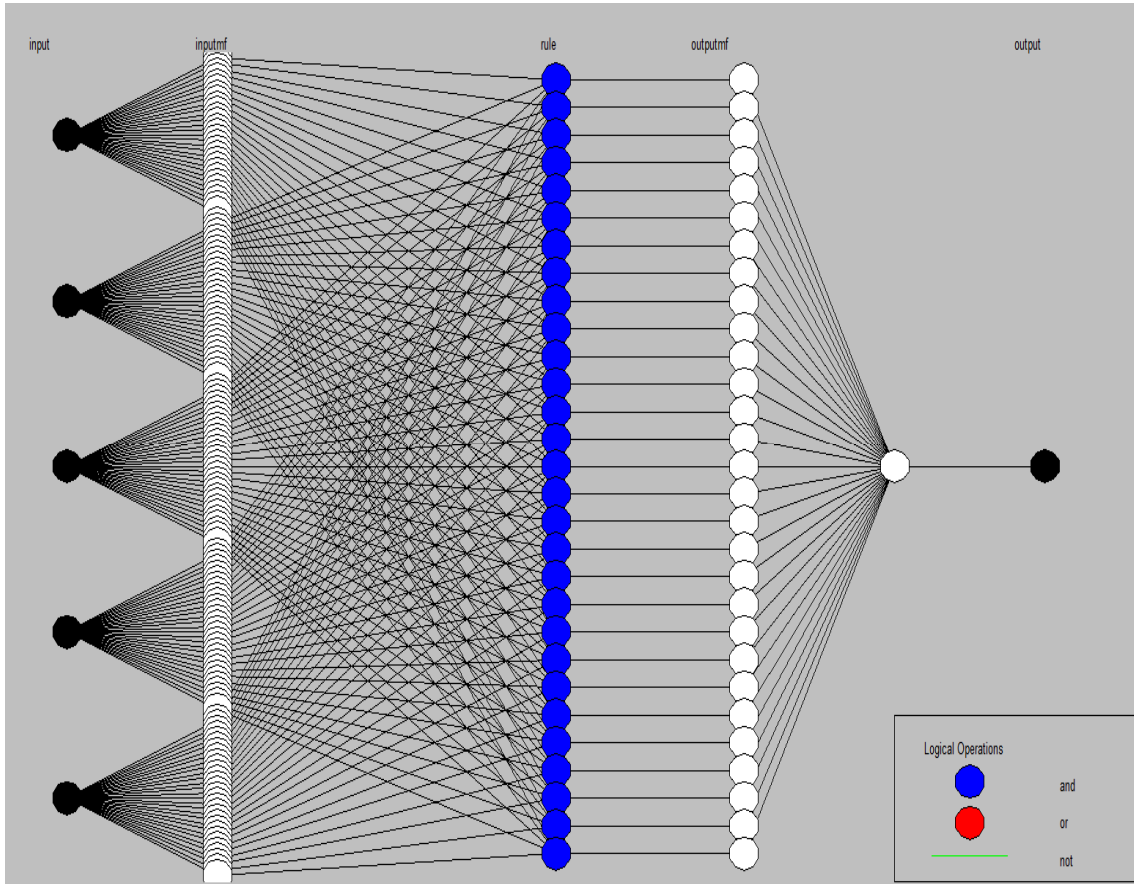
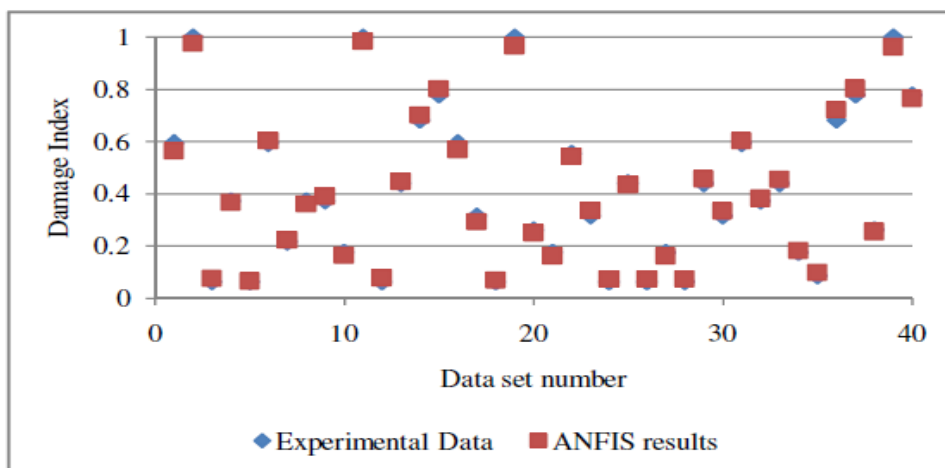Fig. 13 Adaptive neuro-fuzzy structure for damage severity identification

Fig. 14 Comparison of the identified damage severity through the ANFIS model versus experimental results for testing sets

ANFIS determines the relationship between each input variable and surface roughness. Surface roughness represents the mapping between inputs and output and shows the output surface for any output versus two inputs to the system. Using this surface in Matlab environmental can choose any two inputs and any one output for plotting. For illustrating the output surface in this study which there are five inputs and one output, the surface is generated a three-dimensional output surface where any two of the inputs vary, but three of the inputs must be held constant. The surface roughnesses are very useful in cases with two or more inputs and one output. In this study, two input parameters were performed at a time and effects of them on damage severity of the bridge girder are shown in three dimensional surface plots as depicted in Fig. 15. The surface roughness shows the effectiveness of input parameters on severity of damage.

The ANFIS results were compared with ANNs. The aim of this comparison is to demonstrate the effectiveness and the advantages of the methods used and to compare each one. The statistical
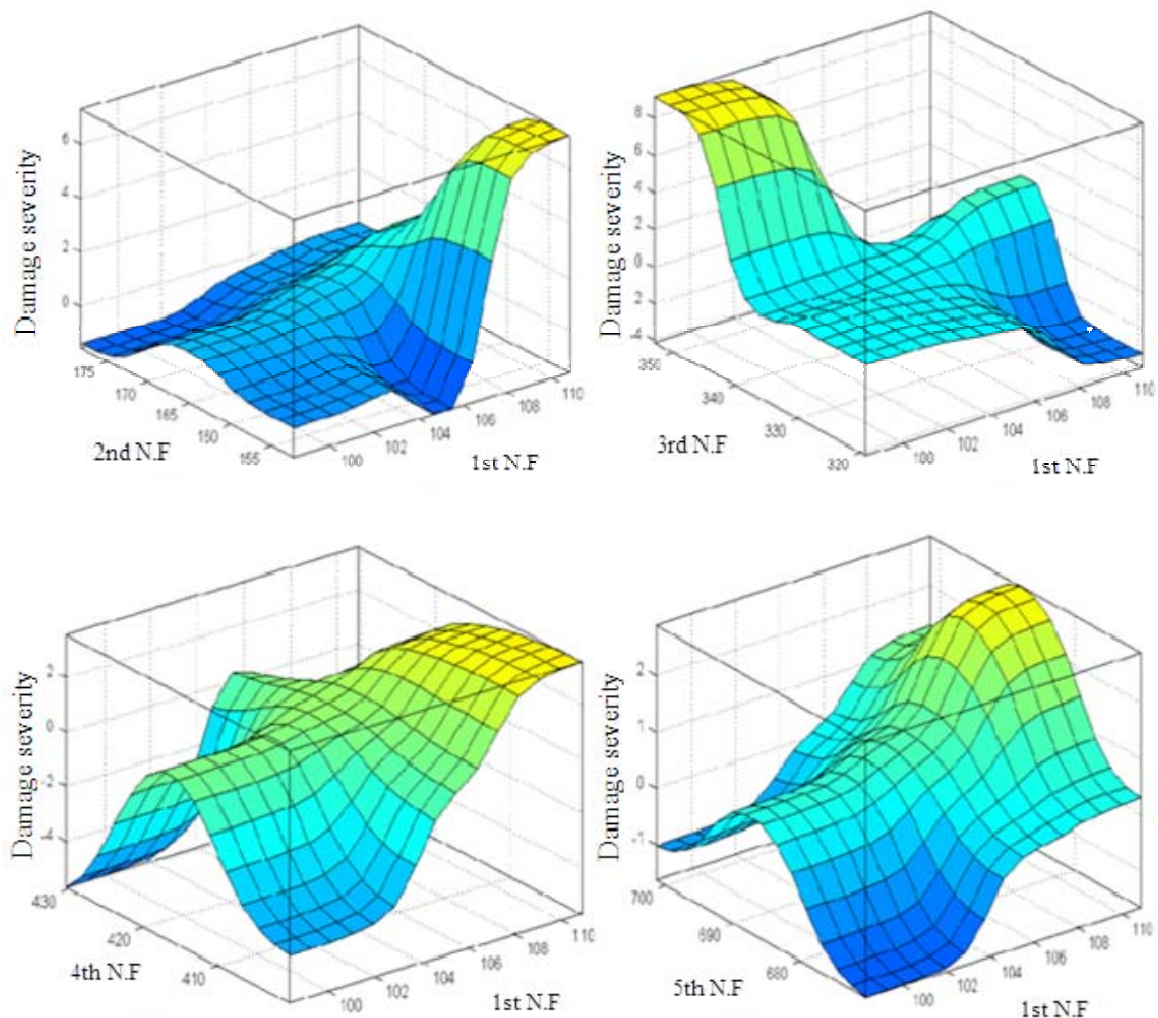

Fig. 15 Impact of variation input parameters on damage severity (output)

Table 6 Statistical parameters in ANFIS and ANN models

Methods	Statistical Parameters			
	MSE(Training)	MSE(Testing)	R^2(Training)	R^2(Testing)
ANN	0.00404	0.00482	0.973	0.926
ANFIS	0.00389	0.00442	0.998	0.982

parameters for design values of the structure under investigation found from training and testing in ANFIS and BPNN are compared in Table 6.

Table 6 shows that the MSE for training and testing phase in ANFIS model is 0.00389 and 0.00442, respectively, while the values for ANN is 0.00404 and 0.00482 for training and testing, respectively. Also, as shown in this table, correlation coefficients obtained are 0.998 and 0.982 for training and testing sets using ANFIS technique, while the values for ANN are 0.973 and 0.926.

All of the statistical values in this table show the ability of an adaptive neuro-fuzzy inference system and demonstrate that the proposed ANFIS achieves a better performance than the BP ANN for predicting damage severity. This can be explained by the fact that ANN is very sensitive to inadequate and noisy data and cannot find precise spatial relationship between the variables when existing data are noisy and inadequate, compared to ANFIS method. Also it can conclude from the Table 6 that the performance of ANFIS with hybrid algorithm is better than that of ANN. This point out that classical backpropagation learning algorithm is not enough and effective for ANFIS and performance can also be increased by using the hybrid learning algorithm. Application of ANFIS shows a very encouraging level of performance for the problem of damage severity in bridge girder an overall improvement compared to the ANN method.

4. Conclusions

This paper presents the application of ANN and ANFIS as two different artificial intelligence techniques for the identification of the damage severity in a model steel girder bridge based on changes in vibration test data. Experimental modal analysis was performed to extract the required data i.e. the natural frequencies of the first five modes for undamaged and damaged structure.

Different architectures of ANNs have been used for damage identification based on changes in natural frequencies. In order to provide improved damage identification, ANFIS models were proposed and implemented. The ANFIS models are compared with BPNN and are proved to have a better performance generality than BPNN. According to results in this study, ANN predicts the damage severity with larger MSE than ANFIS for training and testing data sets. Also the results for ANFIS technique in term of correlation values were much better than ANN for training and testing data sets.

The results showed that the ANFIS has improved the accuracy and offered better damage identification compared to the ANN, thus has the potential to give better performance over the ANN technique. In this study, limited data sets were used for training and testing of ANN and for this reason ANN was not so sensitive compared to ANFIS method. According to this research, ANN can be utilized as an early evaluation and other artificial intelligence technique such as ANFIS can be implemented to identify the severity of damage in a bridge girder with higher accuracy.

Acknowledgements

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