Chapter 37
Damage Identification Using Experimental Modal Analysis and Adaptive Neuro-Fuzzy Interface System (ANFIS)

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Abstract The adaptive neuro-fuzzy inference system (ANFIS) is a process for mapping from a given input to a single output using the fuzzy logic and neuro-adaptive learning algorithms. Using a given input–output data set, ANFIS constructs a Fuzzy Inference System (FIS) whose fuzzy membership function parameters are adjusted using combination of back propagation algorithm with a least square type of method. The feasibility of ANFIS as strong tool for predicting the severity of damage in a model steel girder bridge is examined in this research. Reduction in the structural stiffness produces changes in the dynamics properties, such as the natural frequencies and mode shapes. In this study, natural frequencies of a structure are applied as effective input parameters to train the ANFIS and the required data are obtained from experimental modal analysis. The performance of ANFIS model was assessed using Mean Square Error (MSE) and coefficient of determination (R^2). The ANFIS model could predict the severity of damage with MSE of 0.0049 and correlation coefficient (R^2) of 0.9976 for traing data sets. The results show the ability of an adaptive neuro-fuzzy inference system to predict the damage severity of the structure with high accuracy.

Keywords Adaptive neuro-fuzzy inference system (ANFIS) • Mean square error (MSE) • Modal analysis • Damage detection

37.1 Introduction

Damage in structural systems is defined as changes to the material and geometric properties, leads to reduction of stiffness 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. Dynamic characteristics have been applied increasingly for damage detection using artificial intelligence (AI) techniques such as, artificial neural networks (ANNs), fuzzy logic (FL) and adaptive neuro-fuzzy interface system (ANFIS).

For example, Mehrjoo et al. [1] focused on reporting damage of joints in two truss bridge structures using natural frequencies and mode shapes as inputs of ANNs. Park et al. [2] proposed a sequential methodology for damage detection in beams using time-modal features and ANNs. 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. [3]. Also many other research efforts were attempting to apply ANNs to identify damage in structural engineering [4–7]. Fuzzy logic systems have been applied to damage identification in structures using modal parameters. For example, structural damage identification using mode shape curvatures and fuzzy logic is investigated by Chandrashekhar and Ganguli [8].

Adaptive Neuro Fuzzy Interface System (ANFIS) is one of the best tradeoff between ANNs and fuzzy systems, providing smoothness due to the fuzzy control interpolation and adaptability due to the ANN backpropagation. 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 [9].

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ANFIS has been shown to be strong in modeling many processes, such as damage detection [10, 11], water engineering [12, 13], Material [14] and Geotechnics [15]. ANFIS is presented by Wang and Elhag [16] for assessment of bridge. ANFIS showed more efficiently in bridge evaluation and perform much better than ANNs and multiple regression analysis. Aso, a neuro-fuzzy system is developed to predict the behavior of steel beam web panels subjected to concentrated loads by Fonseca et al. [11].

The main focus of this research is to investigate the feasibility of using ANFIS trained with natural frequency data to identify the damage in steel bridge girder structure. In this study, the first five natural frequencies of a structure are applied as effective input parameters to train the ANFIS and the required data for the ANNs are obtained from experimental modal analysis. The performance of ANFIS model was assessed using mean square error (MSE) and coefficient of determination (R^2). The ANFIS model could predict the severity of damage with MSE of 0.0049 and correlation coefficient (R^2) of 0.9976. The results show the ability of an adaptive neuro-fuzzy inference system to predict the damage severity of the structure with high accuracy.

37.2 Adaptive Neuro Fuzzy Interface System (ANFIS)

The adaptive neuro-fuzzy inference system (ANFIS) developed by Jang [17] and is the implementation of fuzzy inference system to adaptive networks for developing fuzzy rules with suitable membership functions to have required inputs and outputs [9, 18]. An adaptive network is a feed-forward multi-layer neural network with adaptive nodes in which the outputs are predicated on the parameters of the adaptive nodes and the adjustment of parameters due to error term is specified by the learning rules [9, 12].

Assume that the fuzzy inference system has two inputs x and y and one output z. For a first-order Sugeno fuzzy model [19], has two fuzzy if–then rules as the following:

$$\text{Rule 1: If x is } A_1 \text{ and y is } B_1, \text{ then } f_1 = p_1 x + q_1 y + r_1 \tag{37.1}$$

$$\text{Rule 2: If x is } A_2 \text{and y is } B_2, \text{ then } f_2 = p_2 x + q_2 y + r_2 \tag{37.2}$$

Where pi, qi and r_i (i = 1 or 2) are linear parameters in the then-part (consequent part) of the first-order Sugeno fuzzy model. Architecture of ANFIS consists of five layers, as depicted in Fig. 37.1. A brief explanation of the ANFIS architecture is as follows.

Layer 1: Input nodes. Each node of this layer generates membership grades to which they belong to each of the appropriate fuzzy sets using membership functions.

$$O_{1,i} = \mu A_i(x) \text{ for } i = 1, 2, \text{ or} \tag{37.3}$$

or

$$O_{1,i} = \mu B_{i-2}(y) \text{ for } i = 3, 4 \tag{37.4}$$

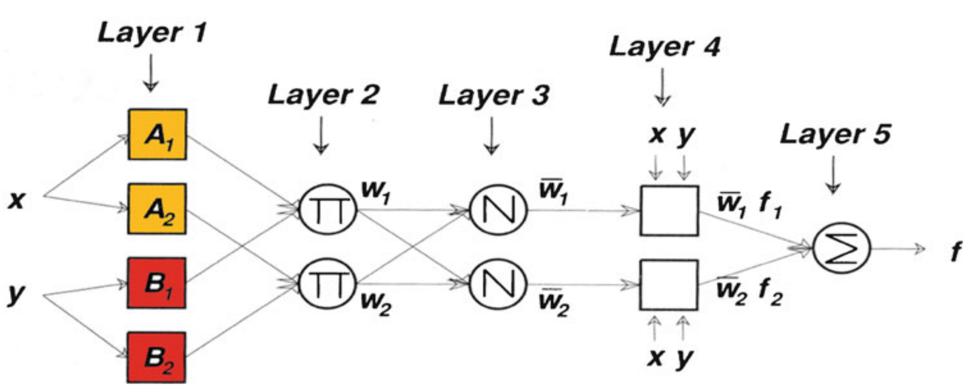

Fig. 37.1 ANFIS architecture for two-input Sugeno fuzzy model

$O_{L,i}$ is the output of the ith node of the layer L. Every node i in this layer is an adaptive node with a node function. In above equations, 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 μBi_{-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 (37.5) and (37.6).

$$\mu_{Ai}(x) = \frac{1}{1 + \left|\frac{x-c_i}{a_i}\right|^{2b_i}} \tag{37.5}$$

$$\mu_{B_{i-2}}(y) = \frac{1}{1 + \left|\frac{y-c_i}{a_i}\right|^{2b_i}} \tag{37.6}$$

Where $\{a_i, b_i, c_i\}$ is the parameter set of the membership functions. Parameters in this layer 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 (37.7) and (37.8).

$$\mu_{A_i}(x) = \exp(-\frac{(c_i - x)^2}{2{\sigma_i}^2} \tag{37.7}$$

$$\mu_{B_{i-2}}(y) = \exp(-\frac{(c_i - y)^2}{2{\sigma_i}^2} \tag{37.8}$$

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 (37.9).

$$\mathrm{O_{2,i}} = \mathrm{w_i} = \mu_{\mathrm{Ai}}(\mathrm{x}) \cdot \mu_{\mathrm{Bi-2}}(\mathrm{y}),\ \mathrm{i} = 1, 2 \tag{37.9}$$

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, $\bar{\omega}_i$is taken as the normalized firing strength, as shown in (37.10)

$$O_{3,i} = \bar{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2} \quad i = 1, 2 \tag{37.10}$$

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 (37.11).

$$O_{4,i} = \bar{\omega}_i f_i = \bar{\omega}_i(p_i x + q_i y + r_i), i = 1, 2 \tag{37.11}$$

Where, $\bar{\omega}_i$ is the normalized firing strength from previous layer. In (37.11) {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 (37.12), the defuzzification process transforms each rule's fuzzy results into a crisp output in fifth layer.

$$\text{Overall Output} = O_{5,1} = \sum_{i=1}^{4} \bar{\omega}_i f_i = \frac{\sum_{i=1}^{4} \omega_i f_i}{\sum_{i=1}^{4} \omega_i} \tag{37.12}$$

37.3 Damage Identification Strategy and Experimental Modal Analysis

In this work it is proposed to apply the first five natural frequencies as inputs of ANFIS for prediction of damage severity. 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 bridge girder in order to achieve the 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 ANFIS. By incorporating the training data, ANFIS technique will be able to give outputs in terms of damage severity using the five first natural frequencies. The test structure as shown in Fig. 37.2 was fabricated from a plate with the dimensions of 1,200 mm length including a 100 mm overhang at both support ends and 210 and 5 mm in width and thickness, respectively. Three stiffeners as shown in Fig. 37.2 were fixed along the length of plate with dimensions of 1,200 mm by 50 mm by 5 mm in 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 7,850 kg/m^3, respectively.

The model steel girder bridge was tested in its undamaged state and under different damaged states to determine the first five natural frequencies. Table 37.1 lists the first five natural frequencies for the undamaged bridge girder.

In the experimental study various damage scenarios were given to the test structure. These scenarios consisted of seven locations with 15 severities for each location. The seven damage locations were at L/13, 2 L/13, 3 L/13, 4 L/13, 5 L/13, 6 L/13 and L/2 of the span length. Only one half of the test structure was used as damage model due to symmetry. Damage was

Fig. 37.2 Test structure

Table 37.1 Frequencies of the first five modes 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

Table 37.2 Cross-section loss of the second moment of area (I) for different damage severity

Damage severity (mm)	I (%)	Damage severity (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

gradually induced by a grinder to cut a slot from the soffit of the middle stiffener of the structure. These damage severities correspond to a cross-section loss of the second moment of area (I) as shown in Table 37.2. For each damaged severity, five peaks were identified which were related to the modal frequencies of the structure.

37.4 Damage Detection Using ANFIS

In this study, 203 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. These samples are randomly divide into two sets with 162 samples for training and 41 samples for testing, respectively.

The task of the training algorithm for ANFIS architecture is to adapt all the adjustable parameters consists of premise parameters and consequent parameters of make the ANFIS output match the training data. Training or adjusting these modifiable parameters is based on the hybrid learning algorithm, which is a combination of least mean square and backpropagation method.

In order to obtain output with higher accuracy, different ANFIS architectures using these data sets with different membership functions (MFs), fuzzy rules and number of MFs were trained and examined to obtain the desired structure of ANFIS. The Gaussian membership functions have been used in this work. In this study, ANFIS was trained using Matlab version (R2007b) and first five natural frequencies are selected as ANFIS inputs and damage severity is considered as ANFIS output.

For each input, different number of Gaussian membership functions are adopted using trial and error method and the maximum number of iterations in the training mode is set to 2,500. After these iterations of training, the MSE became stable in value of 0.0049. After training and testing, the number of MFs was fixed to describe the input and output variables, when the ANFIS model reaches to the acceptable satisfactory level. Figure 37.3 presents architecture of the adaptive neuro-fuzzy inference system to predict damage severity of bridge girder model.

After training step, the ANFIS model can be applied to predict the damage severity of the structure. For evaluating the performance of the trained ANFIS model and to monitor how well the network is training, the test data sets were presented to the network. For this purpose, 41 random data points (20% of all data) were used. The comparison of the predicted damage severity through the ANFIS model with the actual results through experimental for testing dataset are shown in Fig. 37.4. The ANFIS model could predict the severity of damage with MSE of 0.0054 for testing data sets.

The correlation coefficient (R^2) gives more information about the training of network. According to this study the ANFIS results are very close to the experimental results and the correlation coefficient (R^2) value up to 0.9976 and 0.9825 for training and testing data sets, respectively. The results show the ability of an adaptive neuro-fuzzy inference system to predict the damage severity of the structure with high accuracy.

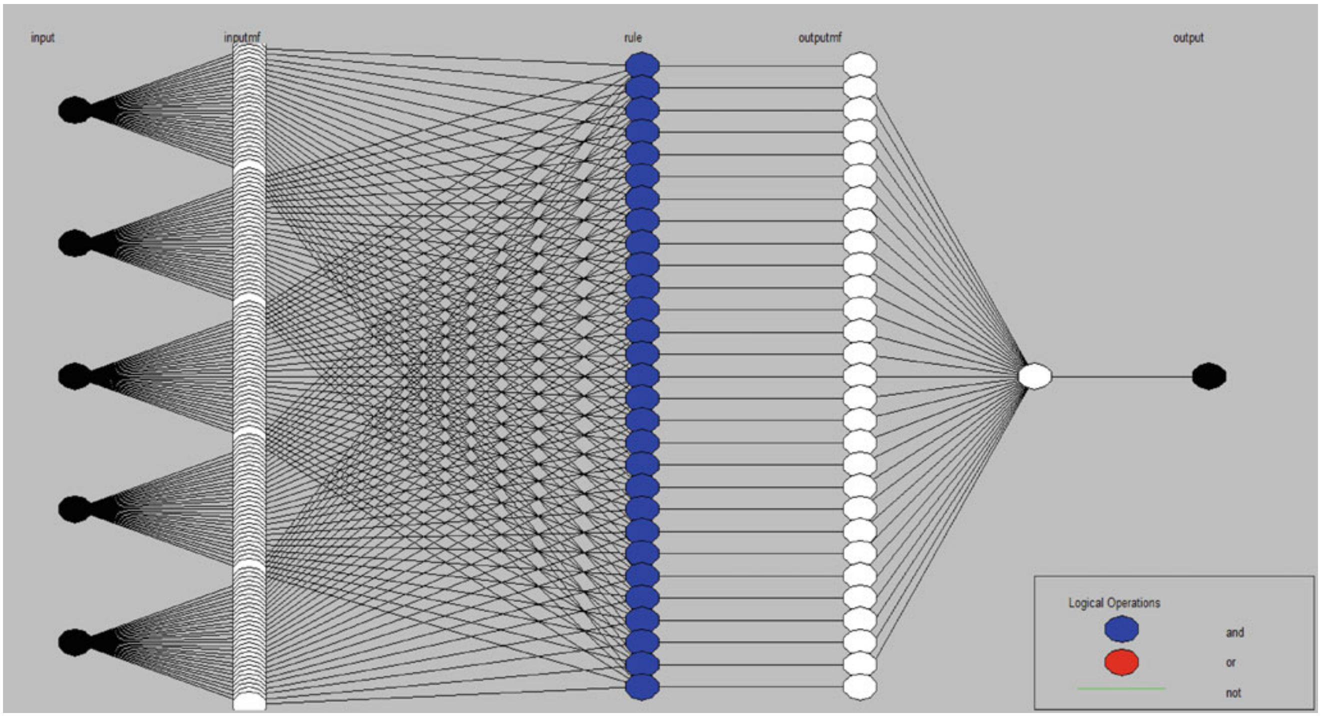

Fig. 37.3 Adaptive neuro-fuzzy structure for damage severity prediction

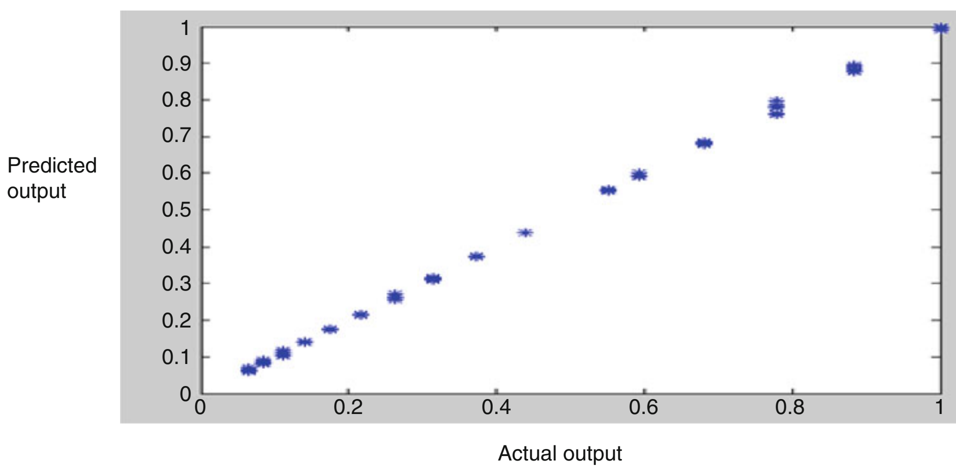

Fig. 37.4 The comparison of the predicted damage severity through the ANFIS model versus experimental results for testing sets

37.5 Conclusion

In this study, adaptive neuro- fuzzy interface system (ANFIS) as an artificial intelligence is used to predict the severity of damage at different locations in a model steel girder bridge. The details of a study on using ANFIS for prediction of damage severity are described. The required data for the ANFIS in the form of natural frequencies are obtained from experimental modal analysis and have been successfully applied as the training and testing samples for the ANFIS. According to results in this study, the hybrid neuro fuzzy model predicted the damage severity of model steel girder bridge with high accuracy.

Correlation coefficient (R^2) value was 0.9976 and 0.9825 for training and testing data sets respectively, which is representing a very good and acceptable correlation. Therefore, it is concluded that an ANFIS trained with just natural frequencies obtained from experimental modal analysis as inputs can very well be applied to evaluate the severity of damage in a structure.

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