International Journal of Civil Engineering

Structural Engineering

Model based damage detection of concrete bridge deck using Aadaptive neuro-fuzzy inference system

A. Tarighat*

Received: February 2013, Accepted: May 2013

Abstract

Damage detection of concrete bridge decks by measurement and monitoring variables related to vibration signatures such as acceleration signals is one of the main tasks of any Bridge Health Monitoring System (BHMS). Generally damage puts some detectable/discoverable signs in the parameters of bridge vibration behavior. Most of the existing methods of damage detection cannot be easily used in real-time diagnosis systems due to the need for some further calculations. These calculations are essential to find frequencies and mode shapes of bridge. In this paper an Adaptive Neuro-Fuzzy Inference System (ANFIS) is used to detect the possible damage location in a concrete bridge deck modeled by finite element method. A few damage scenarios are simulated for different locations of the deck and accelerations as representatives of response at some specific points are calculated. Center of the deck is excited by an impact load. In the proposed ANFIS damage detection model, sampled (not complete) acceleration signals are used as inputs and the most possible region of the deck including damage is found. There is no need to calculate frequencies and mode shapes of the deck as vibration signatures. Results show that this method can decrease the time and cost of visual inspections and be used as real-time damage detection caution system in practice.

Keywords: *Damage detection, finite element method, adaptive neuro-fuzzy inference system, simulated damage scenarios.*

1. Introduction

Although in design codes we are forced to consider some parameters or factors affecting structural behavior such as deformations and stresses, there are more parameters that we cannot consider them in routine designs; as an example stiffness changes considering material deterioration. Consequently there is a level of risk for lack of safety and probable local or global failure of structure. On the other hand structural aging, environmental impacts, and material deteriorations affect the reliability and service life of structures. In order to distinguish the current condition of structures such as bridges engineers inspect, monitor and test them at scheduled and occasional time intervals. Currently health and performance of structures are mainly described by subjective measures which are not identical to different inspectors. In addition, defects, deterioration and damage of the concrete bridge deck are not discovered until it is possible to visually observe the signs they exhibit at which time these would have taken their toll on health. These shortcomings have direct influences on the decision making for maintaining and repairing of structures. Moreover, even experienced engineers may not be able to diagnose the causative mechanisms of damage or deterioration correctly. The degree of global health of a bridge as a structural system including the performance criteria corresponding to the limit-states is needed for effective decision making. Periodic inspections are essential to monitor and measure deterioration rates of a structure under normal operational situations. Also occasional inspections are obligatory whenever environmental attacks or extreme events, such as strong earthquakes or hurricanes are occurred. To quantify the performance of a structure it is required to have a system to monitor and evaluate the integrity of civil structures while in service [1].

Bridges are structures which can experience several types of deteriorations and damages during their service lives. There are many reasons for monitoring the current condition of a bridge structure from health point of view. For example any damage in some parts of a bridge has direct effect on its load bearing capacity especially its vibration characteristics. In other words damage can change the overall behavior of the bridge under loads which cause the bridge to vibrate. Based on this fact any method for damage detection which is capable of showing the location and severity of damage can be

* *Corresponding Author: tarighat@srttu.edu*
Shahid Rajaee Teacher Training University, Lavizan, Tehran, Iran

considered useful for bridge maintenance and repair departments [2].

Monitoring during service provides information on structural behavior under predicted loads, and also registers the effects of unpredicted overloadings. Data obtained by monitoring are useful for damage detection, evaluation of safety and determination of the residual capacity of structures. Early damage detection is particularly important because it leads to make appropriate decisions on time. If the damage is not detected, it continues to propagate and the required structural performance levels might not be guaranteed. Late detection of damage results in higher refurbishment costs or, in some cases, the structure has to be closed and dismantled. In seismic areas the importance of monitoring is more crucial. Based on these facts a structural health monitoring system with an embedded module of damage detection is necessary to monitor structures especially bridges. Among the attractive methods for damage detection problems, artificial intelligence proposes some applicable solutions.

2. Artificial intelligence for damage detection of structures

As a branch of artificial intelligence soft computing is the opposite of hard computing which is traditionally used for many centuries. Soft computing was introduced by Zadeh in the early 1990's [3]. Hard computing approaches model and precisely analyze only relatively simple systems [4]. More complex systems often remain intractable to conventional mathematical and analytical methods. It should be pointed out that simplicity and complexity of systems are relative, and many conventional mathematical models have been both challenging and very productive. But there are some attractive and equally important points that should be considered in solutions. There is a remarkable point that considering the above mentioned solution approaches is not easy and straightforward by traditional mathematical methods [4]. Contrary to hard computing, soft computing deals with imprecision, uncertainty, partial truth, and approximation to achieve tractability, robustness and low solution cost [5]. Components of soft computing are mainly Artificial Neural Networks (ANN) and Fuzzy Logic (FL) [6]. These components or techniques are intended to be complement of each other. Another difference between hard and soft computing is that unlike hard computing schemes, which strive for exactness and full truth, soft computing techniques exploit the given tolerance of imprecision, partial truth, and uncertainty for a particular problem [6]. A more common contrast comes from the observation that inductive reasoning plays a larger role in soft computing than in hard computing.

Model updating approach is usually used in Bridge Health Monitoring Systems. Model updating refers to the methodology that determines the most plausible structural model for an instrumented structural system given its measured response and, possibly, its excitation [7]. This approach is based on a finite element (parametric) structural model. It means that there is some information about the nature of the model [8-9]. Health monitoring techniques may rely on nonparametric system identification approaches, in which a priori information about the nature of the model is not needed [10]. Nonparametric models can be used to detect damage, although it is more difficult to use them for localization of damage. Among the nonparametric identification approaches that have been receiving growing attention are Artificial Neural Networks [11, 12]. ANNs do not require information concerning the phenomenological nature of the system being investigated, and they also have fault tolerance, which makes them a robust means for representing model-unknown systems encountered in the real world. They also do not require any prior knowledge of the system to be identified. They can treat both linear and nonlinear systems with the same formulation [13]. A number of investigators have evaluated the suitability and capability of this network for damage detection purpose [14-18]. ANNs are trained to recognize the vibration response characteristics of healthy and damaged structures in which the properties of individual members are adjusted to reflect varying levels of damage [11, 12, 19-28]. The effectiveness of neural network methods is determined by the completeness of original data library and the reliability of algorithms. The neural network method may be effective for the online monitoring of large structures, such as cable-stayed and suspension bridges.

As the second component of soft computing methods, fuzzy logic is increasingly used for damage detection [29]. Fuzzy logic systems can simulate human decision-making very well. Fuzzy logic is applied as an approach to classify structural damage using vibration data and fuzzy clustering [23, 30]. It is also applicable for damage detection using natural frequencies in the structures with uncertainties in structural properties as well as measurement noise [31].

Third component of soft computing is a systematic hybrid of the two previous components [32-33]. The most famous and versatile method is Adaptive Neuro-Fuzzy Inference System (ANFIS) [34]. Adaptive neuro-fuzzy inference system, which is a method of modeling based on some available data, discards the use of mathematical analytical models. Adaptive neuro-fuzzy inference system is well-suited for complex processes with many different inputs and output. In most cases such problems are highly nonlinear and there is no simple relationship among inputs and outputs. ANFIS can be considered as fuzzy inference method for data modeling. The neuro-adaptive learning method works similarly to that of neural networks. Neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to learn information about a data set. This method is suited for a system for which a collection of input/output data is available and this collection is supposed to be used for modeling the interrelation between input and output (I/O) data. The great advantage of ANFIS is that there is no need to have a predetermined model function or format relating I/O data to each other. In ordinary fuzzy inference method it is required to select membership functions based on the available I/O data. In most cases it is too difficult to find out the best membership functions only by looking at data. ANFIS has the capability of using available I/O data to find the best membership functions. The parameters associated with the membership functions changes through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector. This gradient vector provides a measure of how well the fuzzy inference system is modeling the I/O data for a given set of parameters. When the gradient vector is obtained, any of several optimization routines can be applied in order to adjust the parameters to reduce some error measure. This error measure is usually defined by the sum of the squared difference between actual and desired outputs. ANFIS uses either back propagation or a combination of least squares estimation and back propagation for membership function parameter estimation [35].

1.1. ANFIS Architecture

ANFIS is a multilayer feed-forward network which uses neural network learning algorithms and fuzzy reasoning to map inputs into an output. It is a fuzzy inference system (FIS) implemented in the framework of adaptive neural networks.

In order to explain ANFIS a fuzzy inference system with two inputs x and y and one output z is considered [13]. In a first-order Sugeno fuzzy model with two fuzzy if-then rules we have:

Rule 1: *If x is A1 and y is* B_1, *then* $f_1=p_1x+q_1y+r_1$

Rule 2: *If x is A2 and y is* B_2, *then* $f_2=p_2x+q_2y+r_2$

Figure 1 shows the reasoning procedure for the considered Sugeno model. Figure 2 depicts the ANFIS architecture. As it is shown nodes of the same layer have similar functions. The output of the *ith* node in layer *l* is as $O_{l,i}$.

Brief description of the different layers is given herein:

1.Layer 1: Every node *i* in this layer is an adaptive node with a node function:

$$O_{l,i}=\mu_{Ai}(x), \qquad for\ i=1,\ 2,\ or$$
$$O_{l,i}=\mu_{Bi-2}(y), \qquad for\ i=3,\ 4$$

where *x* (or *y*) is the input to node *i* and *Ai* (or B_{i-2}) is an attribute associated with this node. In other words, $O_{l,i}$ is the membership grade of a fuzzy set *A* (= A_1, A_2, B_1 *or* B_2) and it specifies the degree to which the given input *x* (or *y*) satisfies the quantifier *A*. Here the membership function for *A* can be any appropriate parameterized membership function such as the generalized bell function:

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

where {*ai, bi, ci*} is the premise parameters set. Changing the values of these parameters leads to change of the bell-shaped function. Therefore various forms of membership functions for fuzzy set *A* are possible.

2. Layer 2: Every node in this layer is a fixed node labeled Prod, whose output is the product of all the incoming signals:

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

Each node output represents the firing strength of a rule. In general, any other T-norm operators that perform fuzzy AND can be used as the node function in this layer.

3. Layer 3: Every node in this layer is a fixed node labeled Norm. The ith node calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths:

$$O_{3,i}=\overline{w}_i=\frac{w_i}{w_1+w_2} \qquad i=1,2 \tag{3}$$

Outputs of this layer are called normalized firing strengths.

4. Layer 4: Every node i in this layer is an adaptive node with a node function

$$O_{4,i}=\overline{w}_i f_i=\overline{w}_i\,(p_ix+q_iy+r_i) \tag{4}$$

where $\overline{w}_i$ is a normalized firing strength from layer 3 and {p_i, q_i, r_i} is the parameter set of this node. Parameters in this layer are referred to as consequent parameters.

5. Layer 5: The only node of this layer is a fixed node labeled Sum, which computes the overall output as the summation of all incoming signals:

$$overall\,output=O_{5,1}=\sum_i\overline{w}_i f_i=\frac{\sum_i w_i f_i}{\sum_i w_i} \tag{5}$$

It can be observed that the ANFIS architecture has two adaptive layers: Layers 1 and 4. Layer 1 has modifiable parameters {a_i,b_i, c_i} and {a_j,b_j, c_j} related to the input MFs. Layer 4 has modifiable parameters {p_{ij},q_{ij}, r_{ij}} pertaining to the first-order polynomial. The task of the learning algorithm for this ANFIS architecture is to tune all the modifiable

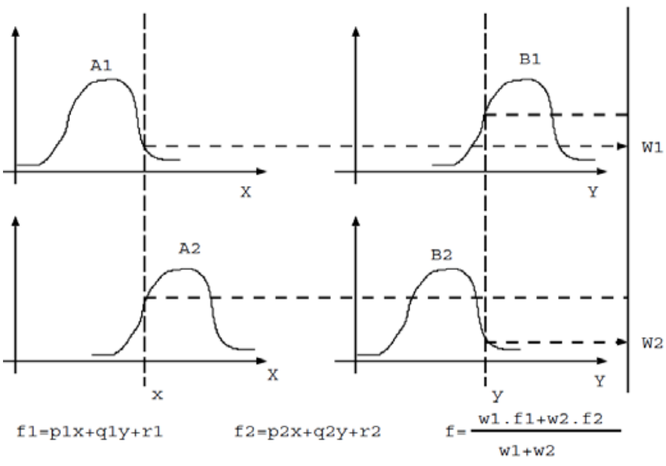


Fig. 1 A two-input first-order Sugeno fuzzy model with two rules

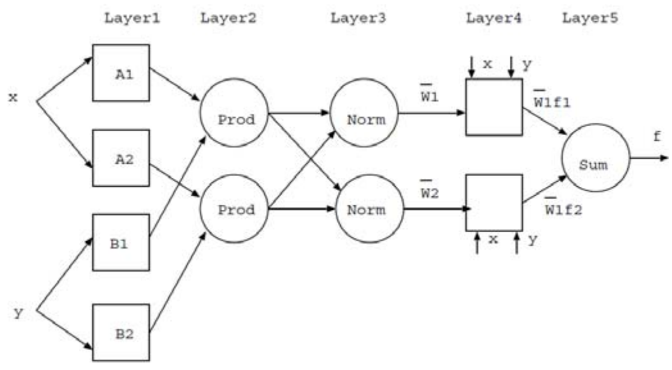


Fig. 2 Equivalent ANFIS architecture

parameters to make the ANFIS output match the training data [35]. Learning or adjusting these modifiable parameters is a two-step process, which is known as the hybrid learning algorithm [36]. In the forward pass of the hybrid learning algorithm, the premise parameters are hold fixed, node outputs go forward until Layer 4 and the consequent parameters are identified by the least squares method. In the backward pass, the consequent parameters are held fixed, the error signals propagate backward and the premise parameters are updated by the gradient descent method. The detailed algorithm and mathematical background of the hybrid learning algorithm can be found in [35-36].

The basic learning rule of ANFIS is the back propagation gradient descent, which calculates error signals (defined as the derivative of the squared error with respect to each node's output) recursively from the output layer backward to the input nodes. This learning rule is exactly the same as the back-propagation learning rule used in the common feed-forward neural networks. From the ANFIS architecture shown in Figure 1, it is observed that given the values of premise parameters, the overall output *f* can be expressed as a linear combination of the consequent parameters. On the basis of this observation, a hybrid-learning rule is employed here, which combines the gradient descent and the least-squares method to find a feasible set of antecedent and consequent parameters. The details of the hybrid rule are given in [13], where it is also claimed to be significantly faster than the classical back-propagation method.

There are two passes in the hybrid-learning procedure for ANFIS. In the forward pass of the hybrid-learning algorithm, functional signals go forward till layer 4 and the consequent parameters are identified by the least-squares estimate. In the backward pass, the error rates propagate backward and the premise parameters are updated by the gradient descent. When the values of the premise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters

$$\begin{aligned} f &= \frac{w_1}{w_1+w_2} f_1 + \frac{w_2}{w_1+w_2} f_2 \\ &= \overline{w}_1 (p_1 x + q_1 y + r_1) + \overline{w}_2 (p_2 x + q_2 y + r_2) \\ &= (\overline{w}_1 x) p_1 + (\overline{w}_1 y) q_1 + (\overline{w}_1) r_1 + (\overline{w}_2 x) p_2 + (\overline{w}_2 y) q_2 + (\overline{w}_2) r_2 \end{aligned} \tag{6}$$

which is linear in the consequent parameters p_1, q_1, r_1, p_2, q_2, and r_2 [35, 37-39]. A flowchart of hybrid learning procedure for ANFIS is shown schematically in Figure 3.

3. ANFIS Modeling damage detection system for concrete bridge deck

The main purpose of this paper is to introduce an easy-to-use and reliable model for damage detection of a typical concrete bridge deck. Among many different methods for damage detection an adaptive neuro-fuzzy inference system is used in modeling. This model uses the numerical values from the virtual vibration tests obtained by finite element analysis of the bridge deck with different damage scenarios. All the above mentioned characteristics of ANFIS modeling method concerning uncertainties in damage detection of a structure show this method can be used in practice to find damaged regions.

The practical method of structural damage detection is based on the results of vibration test/simulation data. The attractiveness of dynamic responses is due to this fact that we are able to detect and locate damage by them. Damage detection is based on the premise that damage in the structure will cause changes in vibration data [41]. There has been a large volume of research, extending over many decades, devoted to vibration-based methods for damage identification in structures [42]. The idea is that changes in the mechanical properties of a structure, especially loss of stiffness caused by cracking and other damage, result in measurable changes to the vibration responses. Global vibration-based methods are therefore still attractive for detecting damage where a priori information is lacking. Moreover, considerable theoretical and experimental progress has been made in the detection and location of damage by dynamic methods [43-46]. Dynamic responses are directly related to global behavior of structure and they can provide rapid inspection of large structural systems. Dynamic methods are based on the variations in parameters in different domains/parts of structure under investigation. These methods are called spatial-domain methods [47]. Spatial-domain methods use changes of mass, damping, and stiffness values to detect and locate damage. In time domain method, system parameters are determined from the observational data sampled in time.

Model independent methods can detect the existence of damage without much computational efforts, but they are not accurate in locating damage [48]. On the other hand, model-referenced methods are generally more accurate in locating damage and require fewer sensors than model-independent techniques, but they require appropriate structural models and significant computational efforts [49-50]. Neural networks and

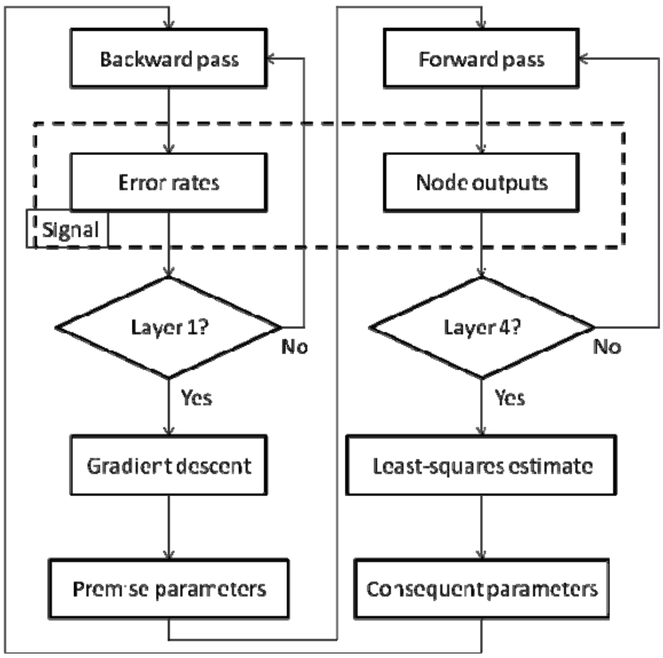


Fig. 3 Hybrid learning procedure of ANFIS [18]

adaptive neuro-fuzzy inference system are recently considered as good model-referenced methods for damage detection systems. They are trained to recognize the vibration response characteristics of healthy and damaged structures in which the properties of individual members are adjusted to reflect varying levels of damage [24-26, 15-18, 27-28, 32-33]. Usually a finite-element model is used to develop failure patterns or damage scenarios that are used to train a model-referenced method so that it can later detect damage in the reference structure [21, 50].

Here in this paper some damage scenarios are introduced to the finite element model. Figure 4 shows the finite element mesh which is used for concrete bridge deck. The dimensions of the concrete bridge deck are 6000*10000 mm. Its thickness is 200 mm. Dimensions of each finite element is 500*500 mm. This deck is simply supported at six points (three points at left edge and three points at right edge). The 4-noded plate element is employed for the finite element model of concrete bridge deck. Concrete modulus of elasticity (E) and the Poisson's ratio (ν) used in numerical model are 21,000 MPa and 0.2, respectively. The value of impact load for exciting deck at its center is 5,000 N. Figure 5 illustrates nine different damage scenarios which are used for simulations. Each scenario is modeled by decreasing stiffness of the elements in the damaged zone. Assigning smaller thickness for elements results in decreased stiffness for them.

In real vibration tests accelerometers are used as sensors. Here in simulations the sampled accelerations of nine specific joints (A1 to A9 in Figure 6) of the finite element model are considered as the results of virtual accelerometers. Sampled accelerations mean that only some points of the obtained/calculated signals are used for modeling ANFIS not all of them. It is intentionally done to show that this method of modeling is capable of showing damaged area relatively well despite the lack of complete data. These incomplete sampled accelerations are used to train the ANFIS model for damage detection based on the different damage scenarios.

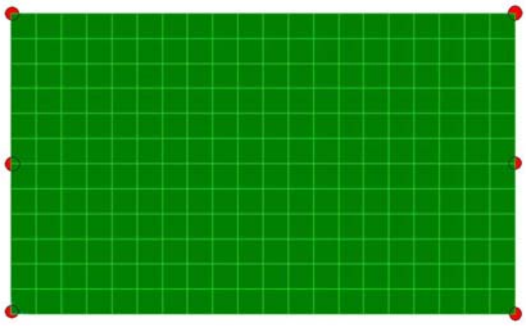


Fig. 4 The finite-element mesh of concrete bridge deck (simply supported at circle points)

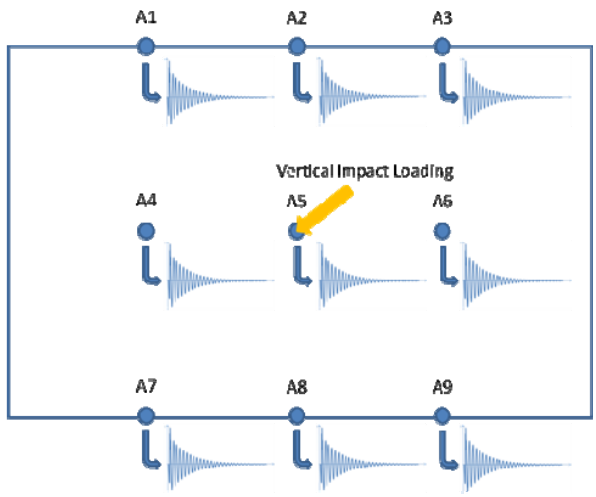


Fig. 6 Layout of virtual accelerometer locations and response signals (nine accelerations at Ai points) from impact load at A5 (deck center)

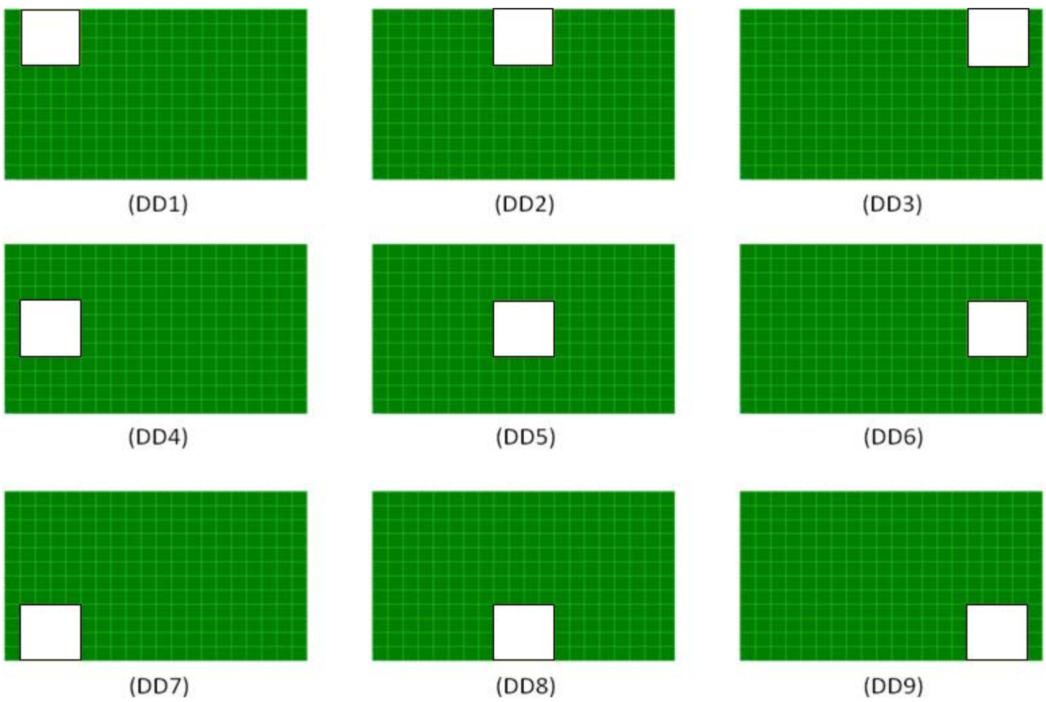


Fig. 5 Nine scenarios for training the damaged detection system (Damaged areas are in white)

Accelerations of the selected points of the deck which are shown in Figure 6 are obtained by linear time history analysis. Table 1 includes the virtual accelerometer coordinates considered on the deck.

Nine different damage scenarios are accounted for the stiffness reduction of finite elements of the model at locations where damage (cracks, voids and …) are considered on the deck. Stiffness reduction is done by considering the smaller thickness (180 mm) of the concrete deck. Table 2 contains the center coordinates and dimensions of each damaged zone. Finally nine different and independent training datasets of accelerations corresponding to the nine damage scenarios are produced by numerical simulations.

The obtained datasets contain acceleration responses of nine virtual accelerometers (A1 to A9) as ANFIS inputs. Time duration of the acceleration responses is 10 seconds recorded at 0.01 second intervals. The total number of each dataset is 1000. Among this number of recorded data only 11 data records from 1 to 2 seconds at 0.1 second intervals are used to train the ANFIS model. This selected sampled acceleration is only 1.1 percent of each complete obtained dataset. Other records of nine virtual accelerometers are used to check the ability of damage detecting of the proposed ANFIS model. Both the training and testing datasets cover all levels and types of damage scenarios.

The outputs of the model are coordinates of the damaged zone centers. Although ANFIS has many advantages there is a disadvantage which limits the modeling features. It can be used only for one output [36]. Here in this phase it is required to predict x and y coordinates of the damaged zones. In order to overcome this problem two ANFIS models are trained for prediction of x and y separately. The both ANFIS-X and ANFIS-Y are built using triangular membership functions. Figure 7 shows the proposed damage detection system.

Table 1 Virtual accelerometer coordinates considered on the deck

Virtual accelerometer designation	Virtual accelerometer coordinates	
	x (mm)	y (mm)
A1	2500	6000
A2	5000	6000
A3	7500	6000
A4	2500	3000
A5	5000	3000
A6	7500	3000
A7	2500	0
A8	5000	0
A9	7500	0

* Origin of the coordinate system is at the lower left corner of the deck.

Table 2 Center coordinates of each damaged zones

Damage zone designation	Center of damaged zone		Dimension of damaged zone	
	x (mm)	y (mm)	x direction (mm)	y direction (mm)
DD1	1500	5000	2000	2000
DD2	5000	5000	2000	2000
DD3	8500	5000	2000	2000
DD4	1500	3000	2000	2000
DD5	5000	3000	2000	2000
DD6	8500	3000	2000	2000
DD7	1500	1000	2000	2000
DD8	5000	1000	2000	2000
DD9	8500	1000	2000	2000

* Origin of the coordinate system is at the lower left corner of the deck.

3. Discussion of Results

The trained ANFIS-X and ANFIS-Y are validated by the testing datasets. It means that the datasets which are not used for training of the two ANFIS models are considered as the nine input accelerations at A1 to A9 points for checking the capability and power of damage detection of concrete bridge deck. Figures 8 to 16 show the results of damage detection for

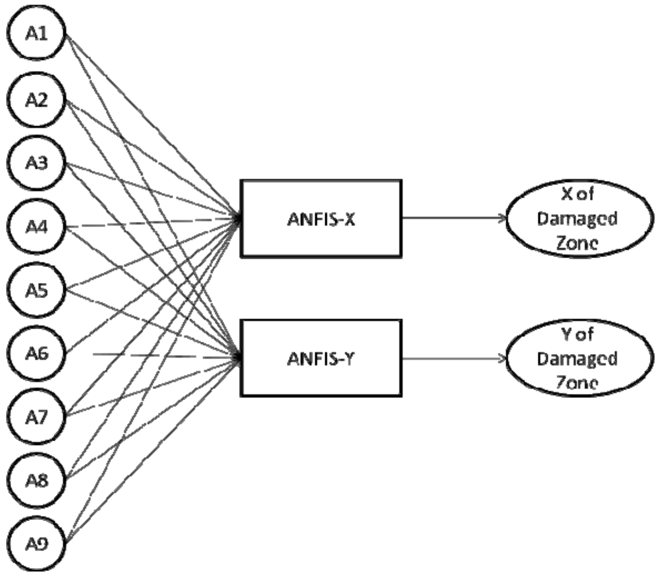


Fig. 7 The proposed damage detection system

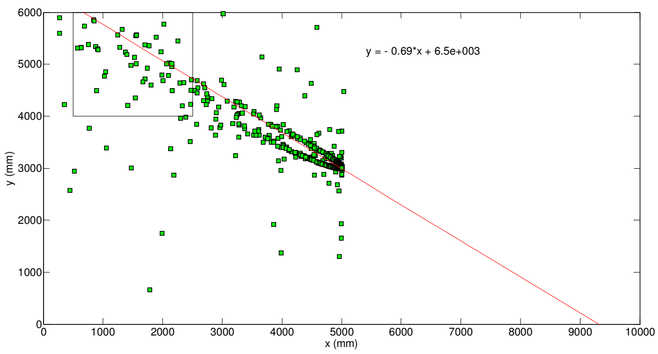


Fig. 8 Results of ANFIS damage detection model (damaged points) for damage scenario No. 1 (DD1)

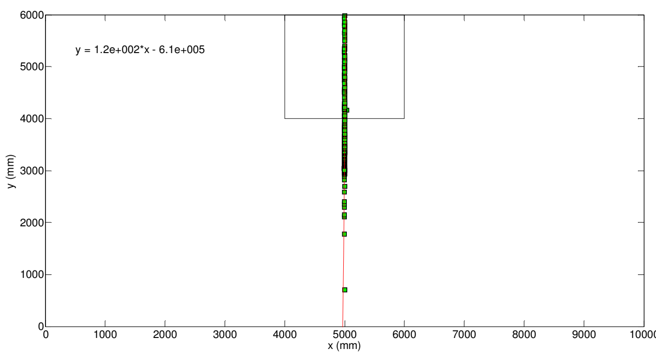


Fig. 9 Results of ANFIS damage detection model (damaged points) for damage scenario No. 2 (DD2)

nine damage scenarios by the proposed system.

Above figures contain some information from calculated results. The scattered result points show at worst the one-fourth area of the deck which contains the damaged region introduced in the considered scenarios. Therefore the proposed ANFIS model can be used for decreasing the time and effort of inspectors to find the damaged area in practice. There are some distinct findings from the obtained results.

Results do not show exactly the center of the damaged zones. Predicted center points of damage zone are scattered around the damaged zone but are almost close to them. It can be detected the line in which the center of damage is situated or greater zone than the damaged area (approximately ¼ of deck). With more attention it becomes obvious that if the

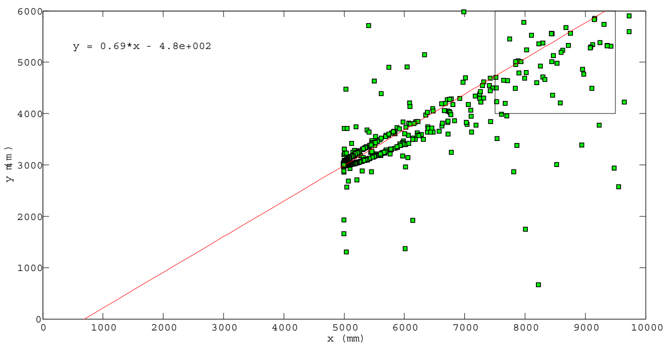


Fig. 10 Results of ANFIS damage detection model (damaged points) for damage scenario No. 3 (DD3)

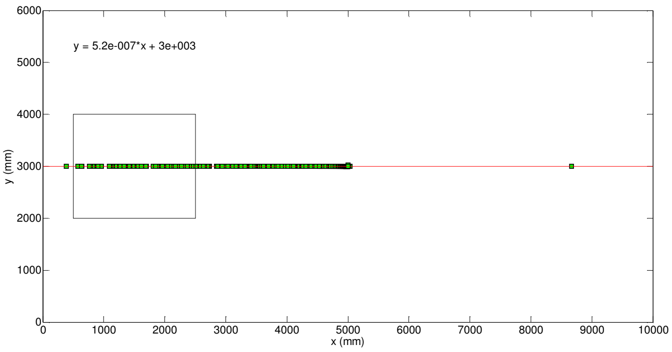


Fig. 11 Results of ANFIS damage detection model for (damaged points) damage scenario No. 4 (DD4)

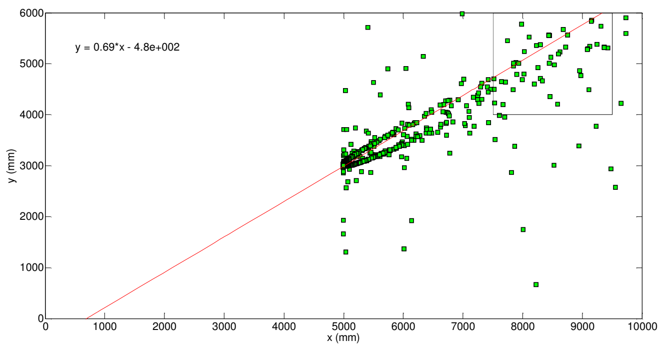


Fig. 14 Results of ANFIS damage detection model for (damaged points) damage scenario No. 7 (DD7)

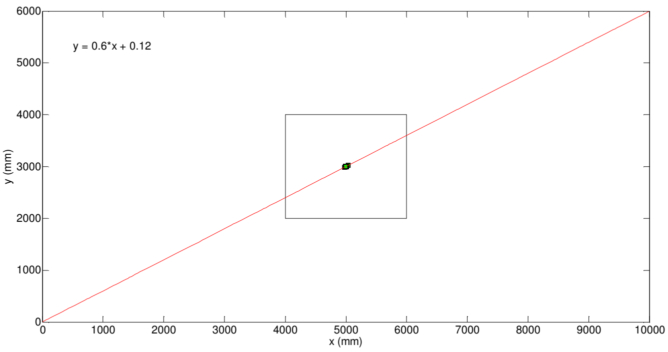


Fig. 12 Results of ANFIS damage detection model for (damaged points) damage scenario No. 5 (DD5)

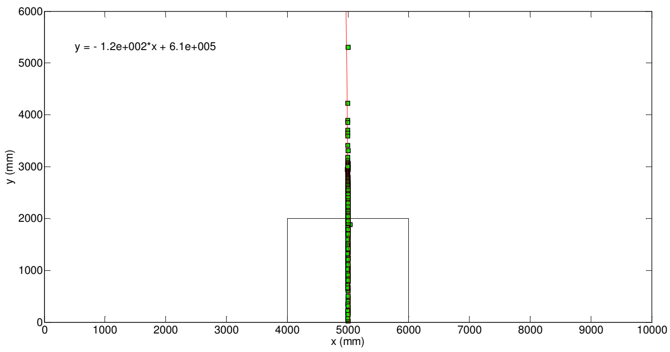


Fig. 15 Results of ANFIS damage detection model for (damaged points) damage scenario No. 8 (DD8)

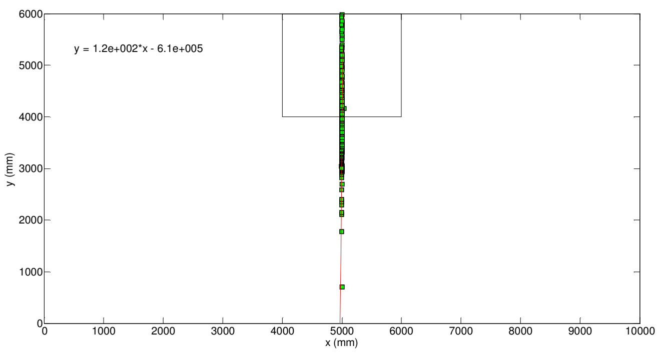


Fig. 13 Results of ANFIS damage detection model for (damaged points) damage scenario No. 6 (DD6)

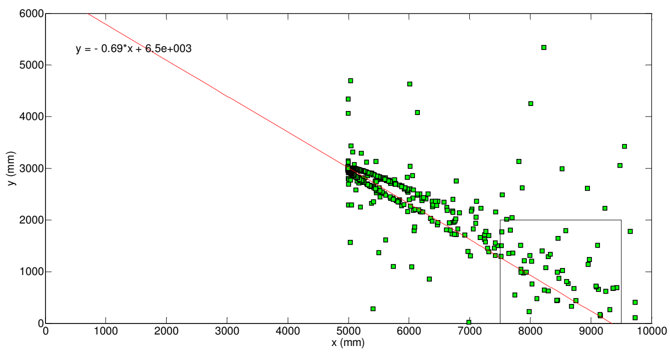


Fig. 16 Results of ANFIS damage detection model for (damaged points) damage scenario No. 9 (DD9)

damaged zone is on the symmetrical axis of the deck these scattered points come across it. There are no scattered points anymore. In other cases which the damaged zones are not on the symmetrical axes, scattered points show the overall direction and possible region of the damaged zone approximately. As a systematic approach it is recommendable to use these scattered points to calculate the best line which passes through them by the regression analysis. This line is very close to the center of the damaged zone and also shows its possible location in sub-deck regions.

Another finding is that there are many points around the center of the deck because it is the most flexible part of the deck and can be easily excited by the impact load. There is only one case that all predicted points are congested at the center. This case is corresponding to the damage at the center. If damaged zone is not at the center, there is a stretch of the predicted points to that damaged zone. This means that deck center is not the damaged zone but since it can be easily excited there are many points around it.

Based on the above mentioned findings it is possible to provide some simple rules for damage detection procedure by the proposed model:

1. At first ANFIS model is used for finding the predicted points of damaged deck. Inputs of the ANFIS are accelerations at points A1 to A9.

2. If predicted points are close to each other and at the center of the deck it is obvious that damaged zone is at the center of the deck.

3. Otherwise by the regression analysis the obtained line shows that the center of the damaged zone is very close to this line and is in the direction from deck center to the scattered points.

Table 3 shows the distance of the damaged zone center from the regression line in each scenario. The results summarized in Table 3 show that deviation of the real center of damaged zone from the predicted point on the regression line is very small and this line passes through the damaged zone as well. Findings show that the proposed model can be used in diagnosis of pre-introduced damaged zones very well. It may be notified that the biggest advantage of this model is that there is no need to know about the undamaged concrete bridge deck and calculate frequencies and mode shapes changes to find damage location. Some of the existing models need this calculation [43]. There is not any obligation to compare the damaged deck with the undamaged deck to gain information about the damaged zone or its location.

In order to verify the proposed model and the recommended three steps of diagnosis of damaged zone a few other damage scenarios which are not used in ANFIS training stage are considered for testing. Six typical different damage scenarios are defined. These new damage scenarios are different from the damage scenarios used for training of ANFIS model not only for damage locations but also for their areas. Figure 17 depicts these scenarios. Table 4 contains the information related to them.

Following simulated vibration tests by linear time history analysis, the damage detection system is used to find out if these new scenarios which are not the same as the training scenarios are detectable. Figures 18 to 23 show the simulation results on the deck for different new scenarios. Keeping in

Table 3 Distance of the damaged zone centers of different scenarios from the corresponding regression lines

Damage zone designation	Regression line	Center of damaged zone X (mm)	Center of damaged zone Y (mm)	Distance of the center of damaged zone from regression line (mm)
DD1	y=-0.69x+6500	1500	5000	382.73
DD2	y=120x-610000	5000	5000	125
DD3	y=0.69x-480	8500	5000	316.89
DD4	y=0.00000052x+3000	1500	3000	0.00078
DD5	y=0.6x+0.12	5000	3000	0.1029
DD6	y=0.0000017x+3000	8500	3000	0.0145
DD7	y=0.69x-460	1500	1000	349.81
DD8	y=-120x+610000	5000	1000	75
DD9	y=-0.69x+6500	8500	1000	300.42

Table 4 Center coordinates of testing damaged zones

Damage zone designation	Center of damaged zone x (mm)	Center of damaged zone y (mm)	Dimension of damaged zone x direction (mm)	Dimension of damaged zone y direction (mm)
DDa	2750	3750	2500	2500
DDb	8250	4250	500	500
DDc	6500	1000	1000	1000
DDd	3750	1750	5500	3500
DDe	3000	5750	3000	500
DDf	9750	4500	500	2000

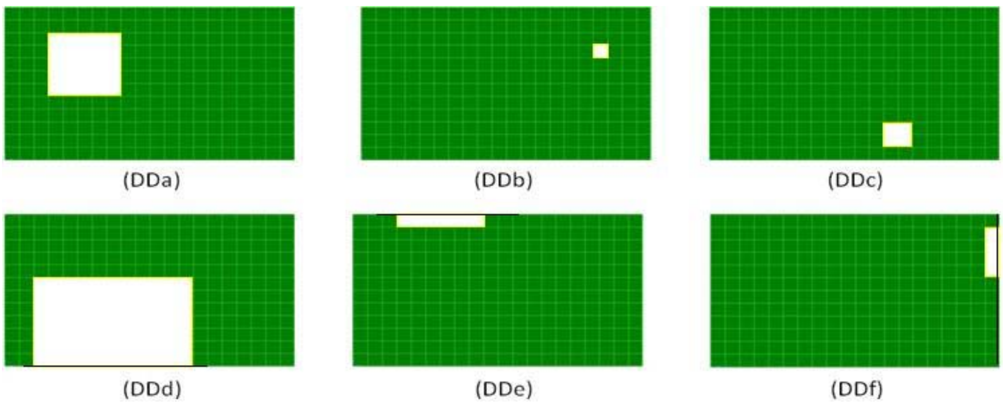


Fig 17 Six scenarios for testing/verifying the damaged detection system

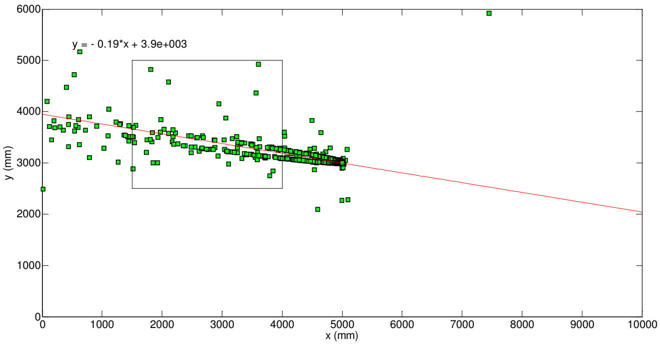


Fig. 18 Results of ANFIS damage detection model for (damaged points) damage scenario DDa

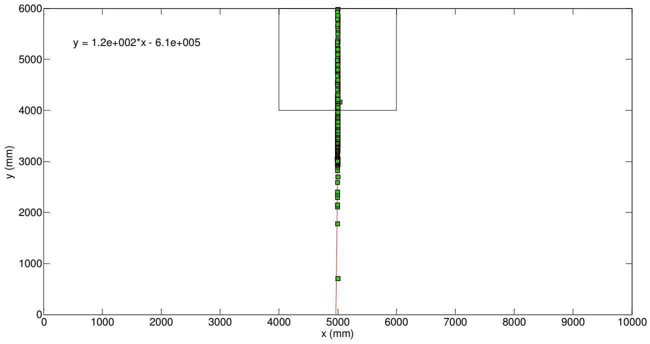
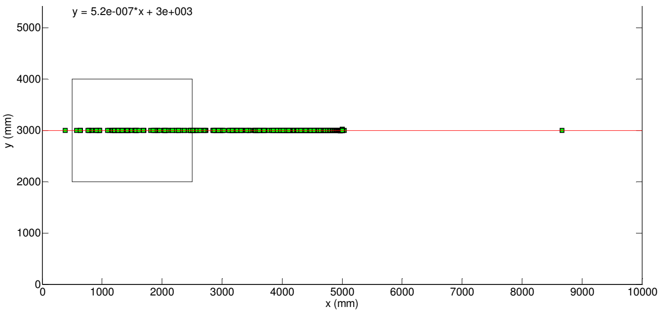


Fig. 21 Results of ANFIS damage detection model for (damaged points) damage scenario DDd



11. Results of ANFIS damage detection model for (damaged points) damage scenario N

Fig. 19 Results of ANFIS damage detection model for (damaged points) damage scenario DDb

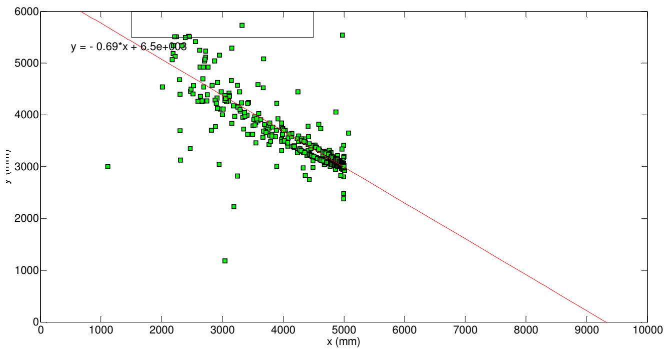


Fig. 22 Results of ANFIS damage detection model for (damaged points) damage scenario DDe

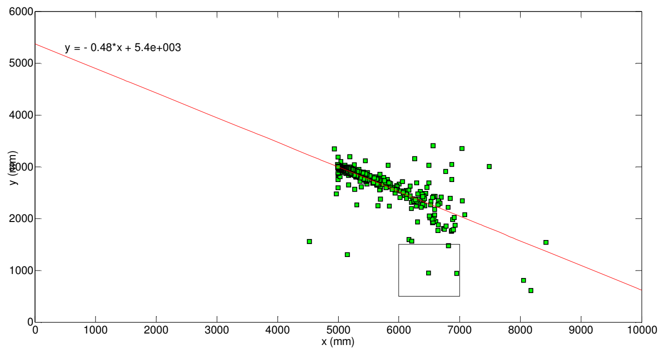
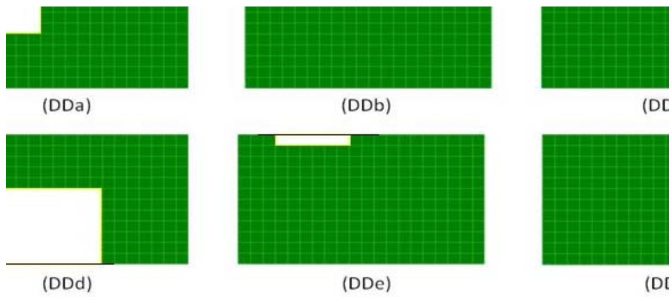


Fig. 20 Results of ANFIS damage detection model for (damaged points) damage scenario DDc



7. Six scenarios for testing/verifying the damaged detection system

Fig. 23 Results of ANFIS damage detection model for (damaged points) damage scenario DDf

mind that these new scenarios are not used in training ANFIS model, the proposed method shows relatively well the ¼-deck region including defined damaged zone. Regression lines of the result points bypass the center of this zone. These findings show the power of the proposed system in finding the ¼-region of the deck containing damaged zone.

Good detections by ANFIS system suggest that by a number of very simple training scenarios system has learned to discover other scenarios as well. This is the most advantageous capability of the proposed ANFIS system. In other words it can generalize its ability for damage detection for different cases. Table 5 shows the distance of the damaged zone center from the line of regression for each scenario. It shows that deviation of the real center of damaged zone from the regression line is pretty small except for DDc and this line passes through some of the damaged zones, too. It can be used to help bridge inspectors to focus on some specific parts of the bridge looking for damaged areas. Another advantage of this model is that it is very simple to use: only a few results of the accelerometers are needed to be used as inputs. System output is the center of the damaged zone without any comparison with benchmark structural model. Based on the above findings and discussion it is decided to enhance the capability of this model by introducing more damage scenarios with more damaged zones at a time. This will be the next step for the development of the system

Table 5 Distance of the damaged zone centers of six new different scenarios from the corresponding regression lines

Damage zone designation	Regression line	Center of damaged zone		Distance of the center of damaged zone from regression line (mm)
		x (mm)	y (mm)	
DDa	y=-0.19x+3900	3750	2750	429.81
DDb	y=0.32x+1400	8250	4250	200
DDc	y=-0.48x+5400	6500	1000	1154
DDd	y=0.7x-580	3750	1750	241.67
DDe	y=-0.69x+6500	3000	5750	1086.5
DDf	y=0.7x-460	9750	4500	1527.9

in the near future.

As mentioned earlier the main benefit of the proposed ANFIS system is the avoidance of building an analytical concrete bridge deck model. Therefore, time and resources are saved and there is a moderate independence from the bridge experts, too. A great advantage of the ANFIS is that it does not face a problem when dealing with noisy or sparse data [51]. In the case that there is a need for systems modifications or for the additions of new functionalities, or for changes on the type and on the number of inputs, then the ANFIS is capable to treat any other inputs with the minimum adaptations on the networks topology and on the formulation. This means that the proposed ANFIS system is flexible enough to be adapted to new conditions. Therefore it may be possible to use more and less accelerometers with minimum effort of changing the ANFIS system.

Dealing with variation in the observations, especially when damage detection is related to the inspectors' experience, is very important and time consuming [52]. The statistical averaging by calculation of the regression line aims to provide predictions that exhibit increased confidence and reliability. This is mainly the reason to carry out regression analysis to find the best line showing the possible damaged zone location.

Below, the advantages of the proposed system are mentioned, by focusing on two key factors that address the system itself; namely the prediction accuracy, and the timely systems response.

The first key factor to evaluate is the systems prediction accuracy. By considering all the data used for damage scenarios, the average prediction is practically be used in many cases. It is important to mention that the average performance of the proposed ANFIS system has a value with indicative and not absolute importance, because it depends on generated data by simulation not some selected data. The acceptable degree of the prediction accuracy would guarantee the correct diagnostic decisions, during the bridge damage detection process.

The second system factor to be discussed is the time duration for the system response. After verification and finalizing the ANFIS system it provides reasonably accurate results in a very short time. It is a main characteristic of any ANFIS model [35]. Therefore, the damage detection system is reliable and responds reasonably fast to incorporate into some practical applications of bridge management systems (BMS). Especially it is inferable that the proposed model can be implemented in real-time or online systems of damage detection modules for Bridge Health Monitoring Systems.

4. Conclusions

As an important functionality of Bridge Health Monitoring System damage detection is a challenging task of maintenance and repair departments. Therefore, damage detection system can be a good tool for reducing cost and time. In this paper an adaptive neuro-fuzzy inference system is developed for damage detection of the concrete bridge deck. The damage detection system is proposed for a simulated concrete bridge deck which is excited by an impact load at its center. The proposed ANFIS model learns the if–then rules between sampled simulated accelerations at some predefined points on the deck and center of the damaged zone. It learns and memorizes the patterns between them for generalization and prediction goals.

Based on the simulations by finite element analyses following main conclusions are made.

1. The proposed system does not require an analytical model of the concrete bridge deck because the trained ANFIS creates a model-referenced system for damage detection.
2. In the proposed ANFIS damage detection model, sampled (not complete) acceleration signals are used as inputs but the most possible region of the deck including damage is found.
3. There is no need to calculate frequencies and mode shapes of the deck as vibration signatures compared to some of the existing damage detection methods.
4. Compared to the alternate methods, proposed ANFIS system exhibits significant advantages; to decrease the time and effort of bridge inspectors to find damaged area by looking for it in sub-deck regions. It does not show the damaged area exactly but can show sub-deck areas which include damaged zone.
5. The proposed system can almost detect damaged areas which are different from the scenarios used for its training. This suggests that it has the capability to generalize its power of damage detection.
6. The response of the proposed method is so fast that it can be integrated in real time damage detection modules of Bridge Health Monitoring Systems.
7. The proposed system can serve as an expert to help bridge inspectors looking for damage in special areas of the deck in a short time.

References

[1] [1] Wang, T. T. and Zong, Z.: 2002, FINAL REPORT: IMPROVEMENT OF EVALUATION METHOD FOR EXISTING HIGHWAY BRIDGES, Department of Civil & Environmental Engineering, Florida International University.

[2] Haritos, N.: 2000, Dynamic testing techniques for structural identification of bridge superstructures, Proceedings of the International Conference on Advances in Structural Dynamics, The Hong Kong Polytechnic University, Hong Kong, 1013-1020.
[3] Zadeh, L. A.: 1994, Fuzzy Logic, Neural Networks, and Soft Computing, Communications of the ACM, 37 (3), 77-84.
[4] Sun, et al.: 2004, Neuro Fuzzy systems-Soft Computing, Pearson Education.
[5] Zadeh, L. A.: 1994, Soft computing and fuzzy logic. IEEE Software, Nov.: 48-58.
[6] Kirankumar, T. M. and Jayaram, M. A.: 2008, Natural Computing in Spatial Information Systems, Proceedings of 2nd National Conference on Challenges & Opportunities in Information Technology (COIT-2008), RIMT-IET, Mandi Gobindgarh. March 29, 262-266.
[7] Ching, J., Muto, M. and Beck, J. L.: 2006, Structural Model Updating and Health Monitoring with Incomplete Modal Data Using Gibbs Sampler, Computer-Aided Civil and Infrastructure Engineering 21, 242–257.
[8] Moens, D. and Hanss, M.: 2011, Non-probabilistic finite element analysis for parametric uncertainty treatment in applied mechanics: Recent advances Review Article, Finite Elements in Analysis and Design, Volume 47, Issue 1, 4-16.
[9] Wan, B., Rizos, D. C., Petrou, M. F. and Harries, K. A.: 2005, Computer simulations and parametric studies of GFRP bridge deck systems Original Research Article, Composite Structures, Volume 69, Issue 1, 103-115.
[10] Oh, S., Kim, J. and Sastry, S.: 2004, A sampling-based approach to nonparametric dynamic system identification and estimation American Control Conference, Dept. of Electr. Eng. & Comput. Sci., California Univ., Berkeley, CA, USA , Volume: 1, 873-879.
[11] Ou, J. P., Li, H. and Duan, Z. D.: 2006, Structural Health Monitoring and Intelligent Infrastructure, Proceedings of the second international conference, China.
[12] Wu, Z. S. and Abe. M.: 2003, Structural Health Monitoring and Intelligent Infrastructure, Proceedings of the First international conference, Japan.
[13] Taskaya, T. and Casey, M. C.: 2005, A comparative study of autoregressive neural network hybrids. Neural Networks, 18, 781–789.
[14] Mourad, S. A., Sadek, A. W. and Batisha, A. F.: 2001, Structural Health Monitoring of Offshore Structures, Proceedings of the Sixth International Conference on the Application of Artificial Intelligence to Civil and Structural Engineering, Civil-Comp Press, Stirlingshire, UK, Paper 16.
[15] Bakhary, N., Hao, H. and Deeks, A. J.: 2007, Damage detection using artificial neural network with consideration of uncertainties, Engineering Structures, Volume 29, Issue 11, 2806–2815.
[16] Mehrjoo, M., Khaji, N., Moharrami, H. and Bahreininejad, A.: 2008, Damage detection of truss bridge joints using Artificial Neural Networks, Expert Systems with Applications, Volume 35, Issue 3, 1122–1131.
[17] Elshafey. A. A., Haddara, M. R., Marzouk, H.: 2010, Damage detection in offshore structures using neural networks, Marine Structures, Volume 23, Issue 1, 131–145.
[18] Vallabhaneni, V. and Maity, D.: 2011, Application of Radial Basis Neural Network on Damage Assessment of Structures, The Proceedings of the Twelfth East Asia-Pacific Conference on Structural Engineering and Construction — EASEC12, Procedia Engineering, 3104–3110.
[19] Xu, B., Wu, Z., Chen, G. and Yokoyama K.: 2004, Direct identification of structural parameters from dynamic responses with neural networks, Engineering Applications of Artificial Intelligence, 17, 931–943.
[20] Lee, J. J., Lee, J. W., Yi, J. H., Yun, C.B. and Jung, H.Y.: 2005, Neural networks-based damage detection for bridges considering errors in baseline finite element models, Journal of Sound and Vibration, 280, 555–578.
[21] Yeung, W. T. and Smith, J. W.: 2005, Damage detection in bridges using neural networks for pattern recognition of vibration signatures, Engineering Structures, 27, 685–698.
[22] Yuen, K. V. and Lam, H. F.: 2006, On the complexity of artificial neural networks for smart structures monitoring, Engineering Structures, 28, 977–984.
[23] Adams, R. D., Cawley, P., Pye C. J. and Stone B. J.: 1978, A vibration technique for nondestructively assessing the integrity of structures, Journal of Mechanical Engineering Science, 20, 93-100.
[24] Gahboussi, J., Garrett, J. H. and Wu, X.: 1991, Knowledge-based modeling of material behavior with neural networks, Journal of Engrg. Mech., ASCE, 117 (1), 132-153.
[25] Wu. X., Gahboussi, J. and Garrett J. H.: 1992, Use of neural networks in detection of structural damage, Computer and Structures, 42 (4), 649-659.
[26] Szewezyk, P. and Hajela P.: 1994, Damage detection in structures based on feature-sensitive neural networks, Journal of Comp. In Civ. Engrg., ASCE, 8 (2), 163- 178.
[27] Jiang, S. F., Fu, C. and Zhang, C.: 2011, A hybrid data-fusion system using modal data and probabilistic neural network for damage detection, Advances in Engineering Software, Volume 42, Issue 6, 368–374.
[28] Shu, J., Zhang, Z., Gonzalez, I. and Karoumi, R.: 2013, The application of a damage detection method using Artificial Neural Network and train-induced vibrations on a simplified railway bridge model, , Engineering Structures, Volume 52, 408–421.
[29] Posenato, D., Lanata, F., Inaudi, D. and Smith, I. F. C.: 2008, Model-free data interpretation for continuous monitoring of complex structures, Advanced Engineering Informatics Volume 22, Issue 1, 135-144.
[30] Biswas. M., Pandey. A. K. and Samman, M. M.: 1990, Diagnostic experimental spectral/modal analysis of a highway bridge, The Int'l Journal of Analytical and Experimental Modal analysis, 5 (1), 33-42.
[31] Chandrashekhar, M. and Ganguli. R.: 2009, Uncertainty handling in structural damage detection using fuzzy logic and probabilistic simulation, Mechanical Systems and Signal Processing, (23), 384– 404.
[32] Korbicz, J. and Kowal. M.: 2007, Neuro-fuzzy networks and their application to fault detection of dynamical systems, Engineering Applications of Artificial Intelligence, Soft Computing Applications, Volume 20, Issue 5, 609–617.
[33] Jiang. S. F., Zhang, C. M. and Zhang, S.: 2011, Two-stage structural damage detection using fuzzy neural networks and data fusion techniques, Expert Systems with Applications, Volume 38, Issue 1, 511–519.
[34] Zerikat, M. and Chekroun, S.: 2008, High performance speed tracking of IM using an adaptive fuzzy NN control, Int. Jr. Sciences & Techniques of Auto. Contr. & Computer Engg., IJ-STA Special Issue, CEM, 516-531.
[35] Jang, J. S. R., Sun, C. T. and Mizutani, E.: 1997, Neuro-Fuzzy and Soft Computing A Computational Approach to Learning and Machine Intelligence, Prentice Hall, USA.
[36] Wang, Y. M. and Elhag. T. M. S.: 2008, An adaptive neuro-fuzzy inference system for bridge risk assessment, Expert Systems with Applications, 34, 3099–3106.
[37] Kandel, A. and Langholz, G.: 1993, Fuzzy Control Systems, CRC Press.
[38] Li. H., Chen, C. L. P. and Huang, H. P.: 2001, Fuzzy Neural Intelligent Systems: Mathematical Foundation and the Applications in Engineering, CRC Press.
[39] Sivanandam, S. N., Sumathi, S. and Deepa, S. N.: 2007, Introduction to Fuzzy Logic using MATLAB, Springer-Verlag, Berlin Heidelberg.
[40] Aydin, A. C., Tortum, A. and Yavuz, M.: 2006, Prediction of concrete elastic modulus using adaptive neuro-fuzzy inference system, Civil Engineering and Environmental Systems, 23 (4), 295–309.
[41] Nair, K. K. and Kiremidjian, A. S.: 2007, Time Series Based Structural Damage Detection Algorithm Using Gaussian

Mixtures Modeling, Journal of Dynamic Systems, Measurement, and Control, Vol. 129, 285-293.
[42] Sari, M. S. and Butcher, Eric A.: 2011, Three Dimensional Vibration Analysis of Rectangular Plates With Undamaged and Damaged Boundaries by the Spectral Collocation Method, Paper No. DETC2011-48049, ASME 2011 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference Volume 1: 23rd Biennial Conference on Mechanical Vibration and Noise, Parts A and B Washington, DC, USA, 37-45.
[43] Kim, J-T., Ryu, Y-S., Cho, H-M. and Stubbs, N.: 2003, Damage identification in beam-type structures: frequency based method vs mode-shape-based method, Engineering Structures 25, 57-67.
[44] Messina, A.: 2004, Detecting damage in beams through digital differentiator filters and continuous wavelet transforms, Journal of Sound and Vibration 272, 385-412.
[45] Kokot, S. and Zembaty, Z.: 2008, Damage reconstruction of 3d frames using genetic algorithms with Levenberg-Marquardt local search, Soil Dynamics & Earthquake Engineering 29, 311-323.
[46] Rucka, M. and Wilde, K.: 2006, Application of continuous wavelet transform in vibration based damage detection method for beam and plates, Journal of Sound and Vibration 297, 536-550.
[47] Ramanamurthy, E. V. V. and Chandrasekaran, K.: 2011, VIBRATION ANALYSIS ON A COMPOSITE BEAM TO IDENTIFY DAMAGE AND DAMAGE SEVERITY USING FINITE ELEMENT METHOD, International Journal of Engineering Science and Technology (IJEST), Vol. 3, No. 7, 5865-5888.
[48] Friwell, M. I., Penny, J. E. T., and Wilson, D. A. L.: 1994, Using vibration data and statistical measures to locate damage in structures, Int. J. Anal. and Experimental Modal Analysis, Vol. 9, No. 4, 239-254.
[49] Kaouk, M. and Zimmerman, D. C.: 1994, Structural damage assessment using a generalized minimum rank perturbation theory, AIAA Journal, 32(4), 836-842.
[50] Elkordy, M. F., Chang, K. C. and Lee, G. C.: 1993, Neural networks trained by analytically simulated damage states, Journal of Comp. in Civ. Engrg., ASCE, Vol. 7, No. 2, 130-145.
[51] Jang, J. S. R.: 1993, ANFIS, Adaptive-Network-based Fuzzy Inference Systems, IEEE Transactions on Systems, Man and Cybernetics, 23 (3), 665-685.
[52] Padilla, M. J. A. and Sanchez, M. F. J.: 2004, An adaptive fuzzy expert system to evaluate human visual performance, Fuzzy Sets and Systems, 142, 321–334.