Smart Structures and Systems, *Vol. 18, No. 6 (2016) 1233-1250*
DOI: http://dx.doi.org/10.12989/sss.2016.18.6.1233

Damage detection of plate-like structures using intelligent surrogate model

Peyman Torkzadeh[*1], Hamed Fathnejat[2a] and Ramin Ghiasi[1b]

[1]*Department of Civil Engineering, Faculty of Engineering, Shahid Bahonar University of Kerman, Kerman, Iran*
[2]*Department of Civil Engineering, Graduate University of Advanced Technology, Kerman, Iran*

(Received August 5, 2015, Revised April 5, 2016, Accepted April 8, 2016)

Abstract. Cracks in plate-like structures are some of the main reasons for destruction of the entire structure. In this study, a novel two-stage methodology is proposed for damage detection of flexural plates using an optimized artificial neural network. In the first stage, location of damages in plates is investigated using curvature-moment and curvature-moment derivative concepts. After detecting the damaged areas, the equations for damage severity detection are solved via Bat Algorithm (BA). In the second stage, in order to efficiently reduce the computational cost of model updating during the optimization process of damage severity detection, multiple damage location assurance criterion index based on the frequency change vector of structures are evaluated using properly trained cascade feed-forward neural network (CFNN) as a surrogate model. In order to achieve the most generalized neural network as a surrogate model, its structure is optimized using binary version of BA. To validate this proposed solution method, two examples are presented. The results indicate that after determining the damage location based on curvature-moment derivative concept, the proposed solution method for damage severity detection leads to significant reduction of computational time compared with direct finite element method. Furthermore, integrating BA with the efficient approximation mechanism of finite element model, maintains the acceptable accuracy of damage severity detection.

Keywords: damage detection; flexural plate structure; bat algorithm; curvature-moment derivative; optimized cascade feed-forward neural network

1. Introduction

In recent years, significant efforts have been done in the area of vibration-based damage detection methods. These methods are based on the fact that dynamic characteristics, i.e., natural frequencies, mode shapes and modal damping, are directly related to the structure stiffness. Therefore, a change in natural frequencies or a change in mode shapes may indicate a loss of stiffness. Some detailed literature reviews describing the state of the art in the methods for damage detection, localization, and characterization, by examining changes in the dynamic response of a structure can be found in (Hakim and Razak 2014, Fan and Qiao 2011). Many published results

∗Corresponding author, Assistant Professor, E-mail: torkzadeh@uk.ac.ir
[a] M.Sc. Student, E-mail: hamedfathnejat@gmail.com
[b] M.Sc. Student, E-mail: rghiasi.s@gmail.com

http://www.techno-press.org/?journal=sss&subpage=8 ISSN: 1738-1584 (Print), 1738-1991 (Online)

(Ghodrati, Seyed Razaghi *et al*. 2011, Bai, He *et al*. 2012, Xiang, Matsumoto *et al*. 2013, Homaei, Shojaee *et al*. 2014, Dessi and Camerlengo 2014, Ghiasi, Torkzadeh *et al.* 2014) confirm that mode shapes and corresponding mode shape curvatures are highly damage sensitive and can be used for its detection and evaluation. In these works the modulus of the difference in the mode shape data, between the healthy and the damaged structure, is defined as a damage index, and its maximum value typically indicates the location of a certain defect. However, the major drawback of those methods is that they need, as a rule, to know some important data of the healthy structure, which very often cannot be obtained. Previous published results confirm that damage location and size can be assessed by employing exclusively the mode shape curvature data from the damaged structures. Damage index based on mode shape curvatures was successfully applied to identify the location and the size of a defect in a plate structure by Dessi and Camerlengo (2014).

Another promising technique for damage detection of plates was 2-D version of the wavelet transform approach (Hou, Noori *et al*. 2000, Hera, Hou *et al*. 2013). For example, a 2-D discrete wavelet transform (DWT) of the flexural mode shape is uses to detect cracks in plate. The wavelet coefficients of the detail of the first level decomposition were used to determine the location, length and depth of the crack (Loutridis, Douka *et al*. 2005). The biggest disadvantage of the methods based on wavelet transform was to exactly detect the damages at the edges of flexural plate. For this purpose, to overcome this disadvantage in the present study, the method based on curvature-moment relations is applied. Recently, an adaptive-scale damage detection strategy was presented by He and Zhu (2015) based on a wavelet finite element model for thin plate structures.

The use of approximate models known as surrogate models with a much lower computational cost instead of expensive computer analysis codes pervades much of today’s engineering design (Ghiasi, Ghasemi *et al.* 2015). The approximations, or meta-models, are used to replace the actual expensive computer analyses, facilitating multidisciplinary, multi-objective optimization and concept exploration (Huang, Chen *et al.* 2016).

Detection of damage severity is effectively the solution to the inverse problem (Sarvi, Shojaee *et al*. 2014). However, it may be necessary in many cases to solve the forward problem to generate data for the solution of the inverse problem. Generation of data is usually computationally expensive and artificial neural network (ANN) models are created to reduce the computational expense (Gholizadeh 2015). Simulation of ANN model as an efficient surrogate model of finite element (FE) as a response of updating damaged structure employed in the optimization loop through an inverse process to ascertain the damage parameters (damage severity), can replace expensive numerical simulations while enhancing computation efficiency. A new solution procedure based on artificial neural network was proposed to reduce the computational time of model updating during the process of damage severity detection (Fathnejat, Torkzadeh *et al*. 2014).

Hence, a novel two-stage methodology is proposed for the damage detection of flexural plates based on optimized artificial neural network (ANN) and Bat Algorithm (BA). In the first stage, damage location detection of plates is investigated using different damage indices such as curvature-moment and curvature-moment derivative. First, the structure is modeled utilizing OpenSees software (Mazzoni, Mckenna *et al*. 2006) and damages are simulated as thickness reduction of the elements. Then, the data for the fundamental mode shape of the damaged structure is obtained. The damaged areas are appeared as pick points using the damage indices. After detecting the damaged areas, the equations for damage severity detection are solved via Bat optimization algorithm. In the second stage, in order to efficiently reduce the computational cost of model updating during the optimization process of damage severity detection, multiple damage location assurance criterion (MDLAC) index (Nobahari and Seyedpoor 2013) based on the frequency change vector of structures is evaluated using properly optimized cascade feed-forward neural network (OCFNN). To validate this proposed solution method, two examples are presented.

The paper is organized as follows. The brief introduction given in this section is followed by the presentation of the analytical formulation and dynamic analysis for damaged plates given in Section 2. Section 3 then describes Bat algorithm. The brief discussion about CFNN algorithms and proposed optimized CFNN is presented in section 4. Proposed damage detection procedure is described in section 5. Numerical examples are studied in Section 6 and Finally, Section 7 summarizes the conclusions of the work

2. Damage detection algorithm

2.1 Curvature-moment

The idea of the proposed technique is based on the relationship between the mode shape curvature and the flexural stiffness of structures. Any damage induced reduction in the flexural stiffness of a structure subsequently causes an increase in the magnitude of the mode shape curvature. The increase in the magnitude of the curvature is naturally local, thus the mode shape curvature may be considered as an indicator for location of a certain defect. The damage index generalized to the two-dimensional space for the *nth* mode at grid point (*i*, *j*) is expressed as follows (Rucevskis, Sumbatyan *et al*. 2015)

$$DI_{i,j}^{n} = e_1 = \left(\frac{\partial^2 \omega^n}{\partial x^2}\right)_{i,j}^2 + \left(\frac{\partial^2 \omega^n}{\partial y^2}\right)_{i,j}^2 \tag{1}$$

where ω^n is a transverse displacement of a thin structure, n is the mode number, i and j are the numbers of a grid point along coordinates x and y, respectively. Note that we operate with a combination of squares of the second partial derivatives, to evaluate the damage index. In practice, experimentally measured mode shapes are inevitably corrupted by the measurement noise, resulting in local perturbations to the mode shape that may lead to some peaks in the mode shape curvature profiles. These peaks could be mistakenly interpreted as a damage, since they may mask the peaks induced by a real defect and therefore may lead to a false or missed detection of the damage. To overcome this difficulty, the damage index is then defined as an averaged summation of damage indices for all modes normalized with respect to the largest value of each mode

$$DI_{i,j} = \frac{1}{N}\sum_{n=1}^{N}\frac{DI_{i,j}^{n}}{DI_{max}^{n}} \tag{2}$$

2.2 Curvature-moment derivative

The previous proposed combination (moment-curvature) will not properly detect damage location if there is any damaged elements in the corners. Response matrix has also some fluctuations that get damage location mistaken. To overcome the drawbacks mentioned above, a new combination is proposed using e_1 damage indicator. After examining the various cases, the second derivative of e_1 damage indicator is diagnosed as an efficient indicator. The Laplacian matrix e_1 is used to compute this indicator. The finite difference method is used to calculate the derivative. This index is the equation below

$$e_2 = \nabla^2 e_1 \tag{3}$$

where $\nabla^2 e_1$ is the second derivative of e_1. After obtaining e_2 matrix, two and three-dimensional diagram of this matrix is plotted by MATLAB software by Release (2012). Damage is identified with a sudden jump in the three-dimensional diagram.

3. Bat algorithm

In this study, a Bat Algorithm (BA) is employed to determine the damage severity detected properly by the BA binary version has been used for structure optimization of CFNN. The aim is to find a set of reduced damage variables X_r maximizing the *MDLAC* as

$$dF_i = \left(\frac{F_{ui} - F_{di}}{F_{ui}}\right), dF_{Mi} = \left(\frac{F_{ui} - F_{Mi}}{F_{ui}}\right), MDLAC = \frac{\left|dF_{Mi}^T . dF_i\right|^2}{(dF_{Mi}^T . dF_{Mi})(dF_i^T . dF_i)} \tag{4}$$

and

$$\begin{aligned} &Find \quad X_r^T = [x_{r1}, x_{r2}, \dots, x_{rm}] \\ &Minimize\text{:} \quad w(X_r) = -MDLAC(X_r) \\ &x_{ri} \in R^d, i = 1, \dots m \end{aligned} \tag{5}$$

where F_{ui} and F_{di} denote the natural frequency vectors of the undamaged and damaged structure, the subscript M denotes the updating frequency obtained from modal analysis (first five modes for subscript i in this research). R^d is a given set of discrete values and the damage severity $x_{ri}(i=1,\dots,m)$ can take values only from this set. Also, w is an objective function that should be minimized.

BA is a meta-heuristic population based optimization algorithm which was first inspired from the search of bats to find their food (Yang and Gandomi 2012). Bats send some signals to the environment and then listen to its echo which is called echolocation process. BA is mainly constructed by the use of 4 main ideas (Komarasamy and Wahi 2012): 1) the difference between the prey and food is distinguished through the use of echolocation process; 2) Each bat in the position X_i flies with the velocity of V_i producing a especial pulse with the frequency and loudness of f_i and A_i respectively; 3) the loudness of A_i changes in different ways such as reducing from a large value to a low value; and 4) the frequency f_i and rate r_i of each pulse is regulated automatically. Initially, all bats fly randomly in the search space producing random pulses. After each fly, the position of each bat is updated as follows (Gholizadeh and Shahrezaei 2015)

$$\begin{aligned} V_i^{new} &= V_i^{old} + f_i(Gbest - X_i); i = 1, \dots, N_{Bat} \\ X_i^{new} &= X_i^{old} + V_i^{new}; i = 1, \dots, N_{Bat} \\ f_i &= f_i^{\min} + \varphi_1\left(f_i^{\max} - f_i^{\min}\right); i = 1, \dots, N_{Bat} \end{aligned} \tag{6}$$

where $Gbest$ is the best bat from the objective function point of view; N_{Bat} is the number of bats in the population; f_i^{max} / f_i^{min} are the maximum/minimum frequency values of the i^{th} bat and φ_1 is a random value in the range [0,1]. In order to reach a better random walking, another random fly is also simulated. In this regard, a random number β is generated randomly. In each iteration, if the random value β is larger than r_i ,then a new solution around X_i is generated as follows

$$X_i^{new} = X_i^{old} + \varepsilon A_{mean}^{old}; i = 1, \ldots, N_{Bat} \tag{7}$$

where ε is a random value in the range of $[-1,1]$ and A_{mean}^{old} is the mean value of the loudness of all bats. If the random value β is less than r_i then a new position X_i^{new} is generated randomly. The new position is accepted if the bellow equation is satisfied

$$\left[\beta < A_i\right] \& [f\left(X_i\right) < f\left(Gbest\right)] \tag{8}$$

The values of loudness and rate are also updated as follows

$$\begin{aligned} &A_i^{new} = \alpha A_i^{old} \\ &r_i^{Iter+1} = r_i^0[1 - \exp\left(-\gamma \times Iter\right)] \end{aligned} \tag{9}$$

where α and γ are constant values and $Iter$ is the number of the iteration during the optimization process. The detailed flowchart of BA is presented in Fig. 1.

4. Optimized cascade feed-forward neural network (OCFNN)

A common type of feed-forward ANNs is constructed by a layer of inputs, a layer of output neurons, and one or more hidden layers of neurons. Feed-forward ANNs are used typically to parameter prediction and data approximation.

A cascade type of feed-forward ANNs consists of a layer of input, a layer of output neurons, and one or more hidden layers. Similar to a common type of feed-forward ANNs, the first layer has weights coming from the input. But each subsequent layer has weights coming from the input and all previous layers. All layers have biases. The last layer is the network output. Each layer's weights and biases must be initialized. A supervised training method is used to train considered cascade feed-forward ANNs (Hedayat, Davilu *et al*. 2009). The additional connections in cascade feed-forward neural network (CFNN) improve the speed at which the network learns the desired relationship (Makas, Yumusak *et al*. 2013). The Cascade-Correlation architecture has several advantages over existing algorithms: it learns very quickly, the network determines its own size and topology and it retains the structures it has built even if the training set changes (Hagan, Demuth *et al*. 1996). Fig. 2 shows the general structure of cascade feed-forward neural network.

So far, several methods to determine the optimal number of hidden layer neurons has been presented. (Panchal, Ganatra *et al.* 2011) presented a method for analyzing the behavior of MLP network. The number of hidden layer neurons with minimal error is inversely proportional.

Cascade Correlation algorithm begins the training process with minimum number of hidden layer neurons and then during the process of training, adds this number. This algorithm helps to improve the network structure because of preventing the random selection of the type of network structure.

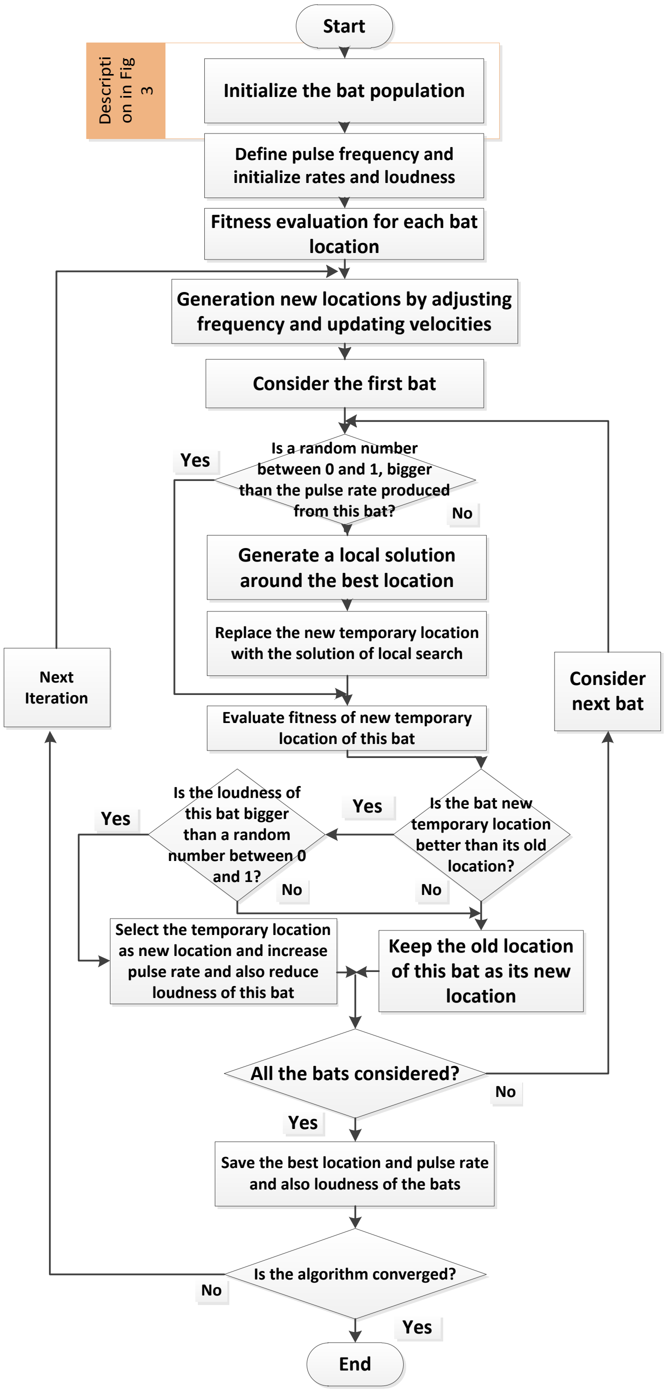

Fig. 1 Bat algorithm flowchart

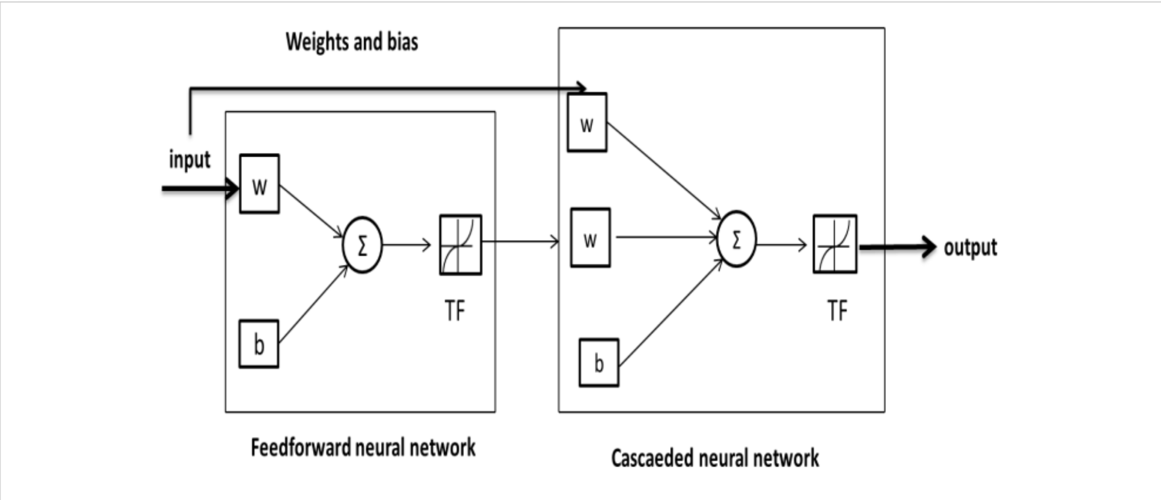

Fig. 2 Cascade feed-forward neural network general structure

In order to improve the performance of CFNN as an efficient surrogate model, an intelligent method to select simultaneously optimized number of hidden layer neurons and type of hidden layer transfer function has been presented. By selecting root mean square error of testing data as an objective function, and number of hidden layer neurons and type of hidden layer transfer function as variables of optimization problem, can achieve optimized structure of CFNN. For this purpose, a set of transfer functions which are suited for hidden layer such as linear, sigmoid, radial basis function and Morlet's basic wavelet are selected (Fathnejat, Torkzadeh *et al.* 2014).

$$Pureline(U_i) = U_i \tag{10}$$

$$Logsig(U_i) = 1/(1+e^{-(U_i)}) \tag{11}$$

$$Tansig(U_i) = (1-e^{-2(U_i)})/(1+e^{-2(U_i)}) \tag{12}$$

$$Radialbasis(U_i) = e^{(-U_i)^2} \tag{13}$$

$$Wavelet(U_i) = \frac{1}{\sqrt{4.5}}\cos(4(U_i/4.5))e^{(-0.5(U_i/4.5)^2)} \tag{14}$$

It is the underlying principle that the number of hidden layer neurons must be two or three times or somewhat bigger than the number of input feature (Ng 2004). Optimizer should select its variables from sets presented in Fig. 3. In this figure, N is indicator of number of input feature.

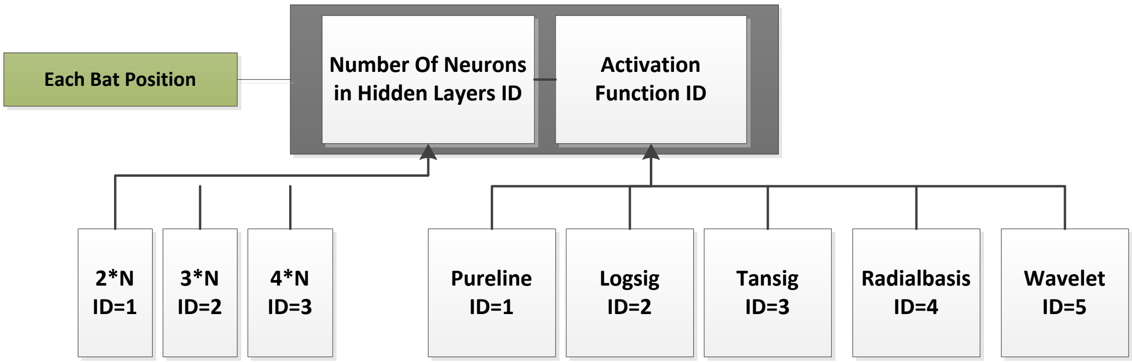

Fig. 3 variables of optimizer

5. Main steps for proposed damage detection method

The main steps for the proposed damage detection method using BA are summarized as follows:

Step 1: Computing the curvature-moment and curvature-moment derivative indices to determine suspected elements.

Step 2: Generating failure scenarios with the damage severity range between 0.05 and 0.35 with the pace of 0.05, when the number of suspected elements is determined. (It is be noted that maximum 35% damage severity percent is hypothetical, although we detect the damages with low rates by structural health monitoring.)

Step 3: Developing FE model which computes the natural frequencies of the structure and finally the MDLAC corresponding to the failure scenarios that have been defined in the previous step.

Step 4: Using the finite element (FE) model of the structure in order to generate training and testing datasets for development of ANN model that is used in the optimization process of damage severity detection.

Step 5: Choosing the best alternatives for number of hidden layer neurons based on number of input variables (damaged elements) and setting mentioned transfer functions as variables of ANN structure in ANN structure optimization problem.

Step 6: Implementing the binary BA to select the optimized number of hidden layer neurons and type of transfer function.

Step 7: Engaging directly the optimized ANN model by the optimizer to evaluate the objective function to be minimized to determine the damage severities of suspected elements. (Applying the surrogate model).

In this study, in order to generate failure scenarios which completely span the design space, Latin Hypercube Sampling (LHS) method has been applied. LHS generates a sample of plausible collections of parameter values from a multidimensional distribution. The LHS was presented by McKay in 1979 (Iman 2008).

6. Numerical results

Two numerical examples are discussed in this section. In example one, point defects, or notches, are considered and damage location and severity detection is performed using proposed solution method. In the second example, the proposed method is extended and employed for detection of linear defects.

6.1 Example 1: Square steel plate 1000 ×1000 mm with 5 mm thickness (point defects)

The flexural steel plate with 41 divisions in the x and y directions modeled utilizing OpenSees software. Damages are simulated as reduction in the thickness of the elements. This reduction is 20 percent for two elements (element number: 1286 and 1287). The spatial coordinates (0.3, 0.4) meter in the manner shown in Fig. 4 is intended.

6.1.1 Finding the damage location using moment curvature

By computing proposed damage indices, three-dimensional representation of damage location is presented in Figs. 5 and 6.

As the Fig. 5 demonstrates the moment-curvature index is identifying mistakenly the corners of the plate as damaged areas.

One of the disadvantages of the methods such as wavelet and wavelet packet transform is that In addition to identifying failure in its original location, the corners of the bending plate are mistakenly identified as damaged areas (Loutridis, Douka *et al*. 2005). The results (Fig. 6) show a high accuracy of curvature-moment derivative method in detecting the damage locations, especially at the corners of the plate.

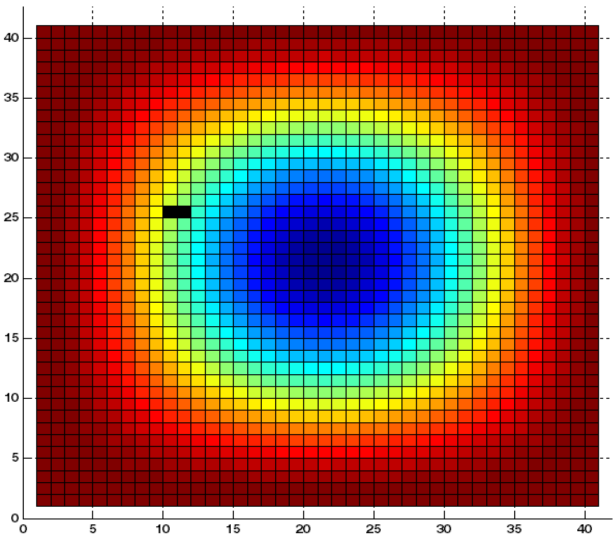

Fig. 4 Damage Location

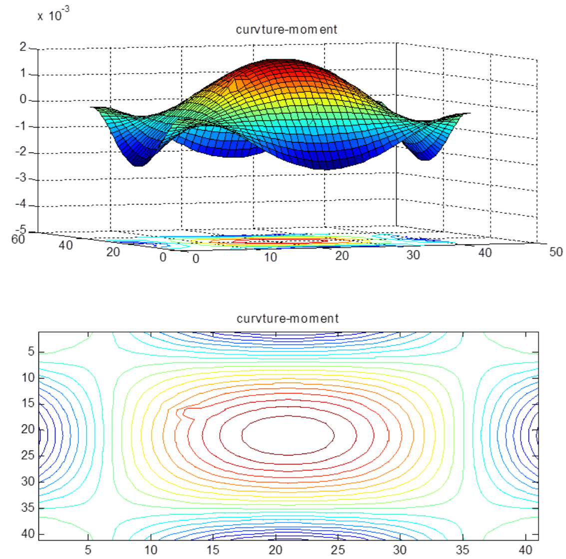

Fig. 5 Two and three-dimensional view of damage location by curvature-moment index

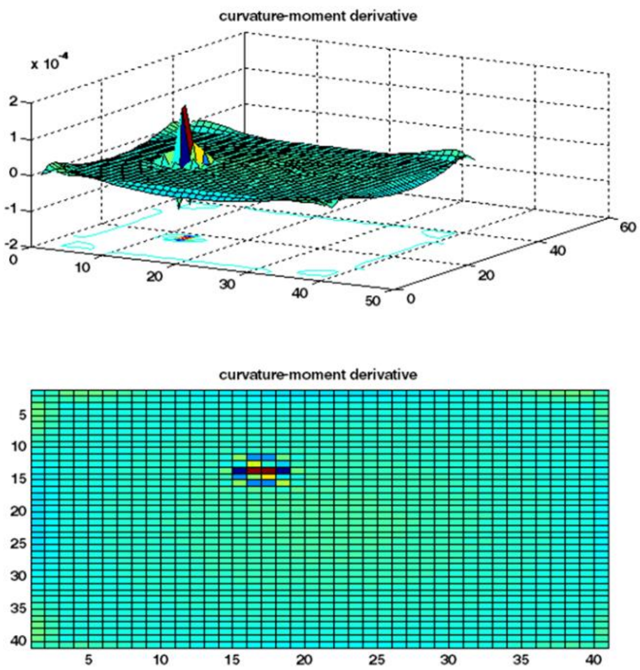

Fig. 6 Two and three-dimensional view of damage location by curvature-moment derivative index

6.1.2 Determining the damage severity

6.1.2.1 Obtaining the optimized structure for CFNN

Optimized CFNN is CFNN with log-sigmoid transfer function and four hidden layer neurons (2*N) (as mentioned in section 3). Table 1 shows the root mean square error (RMSE) of testing datasets for set of selective hidden layer transfer functions for CFNN.

Given that the total number of damage scenarios per two marked suspected elements for this flexural steel plate with the damage severity range between 0.05 and 0.35 with the pace of 0.05 is equal to 8^2 (Eq. (15)). These scenarios are used to train and test the CFNN model. Eighty percent of these scenarios are used as a testing dataset. CFNN inputs are damage severities of failure scenarios and output is MDLAC.

$$All\ Possible\ Damage\ Scenarios = s^d \tag{15}$$

where s is the number of existing damage severities and d is the number of damaged elements.

Based on Table 1 the result of structure optimization for CFNN (log-sigmoid transfer function and four neurons (2*N)) is verified by having the least RMSE.

For validation of the proposed method to design optimally network architecture (type of transfer function and number of neurons), four extra scenarios are considered for this example. The stage of determining suspected elements is done in accordance with the process provided in first stage. According to Table 2 for all damaged scenarios, log sigmoid function is selected as the optimal function. However, the number of hidden layer neurons will change by changing the number of input data features. On the other hand, because of good ability of BA to design quickly optimum network architecture using minimal data, solution procedure proposed in this study can be used at the beginning of each damage detection problem regardless the type of structures.

Table 1 The RMSE of testing datasets for CFNN with the 2*N number of hidden layer neurons

	RBF transfer func.	log-sigmoid transfer func.	Tan-sigmoid transfer func.	Pureline transfer func.	Wavelet transfer func.
RMSE	0.0019	0.0016	0.0020	0.0021	0.0608

Table 2 The RMSE of testing datasets for CFNN using various transfer functions

		Damaged element numbers	CFNN with RBF transfer function	CFNN with log-sigmoid transfer function	BPNN with log-sigmoid transfer function	BPNN with tan-sigmoid transfer function	WRBFNN
RMSE	Scenario A	1286, 1287	0.0016	0.0015	0.0017	0.0017	0.0421
	Scenario B	1286, 1287, 1288,1289	0.0018	0.0014	0.0019	0.0020	0.0401
	Scenario C	20, 21, 22, 23, 24, 25	0.0042	0.0031	0.0039	0.0035	0.0702
	Scenario D	150, 151, 152, 153, 154, 156, 157	0.004	0.0033	0.0038	0.0035	0.071

Table 3 Bat algorithm parameters

Parameter	Description	Value
μ	Population size	50
$f_{\min}$	Minimum frequency	0
$f_{\max}$	Maximum frequency	1
$l_i^0 = l_{\max}$	Initial loudness	1
α	Loudness adaption parameter	0.95
$r_i^0 = r_{\min}$	Initial pulse rate	0.5
γ	Pulse rate adaption parameter	0.98
σ	Standard deviation	2
ρ	Penalty coefficient	1

6.1.2.2 Using BA engaged by FE model vs. BA engaged by Optimized CFNN model to detect damage severity

At this stage the reduced damage detection problem having two damage variables instead of 1681 original ones can be solved via the optimization algorithm. The BA is employed to find a set of damage severity variables minimizing the Eq. (10). The BA algorithm with the specifications listed in Table 3 is applied to solve the problem.

In this section, the new procedure for solving the damage severity detection problem has been proposed. This procedure contains the BA which has been engaged by optimized appropriate ANN model (CFNN model with log-sigmoid transfer function for hidden layer based on results of structure optimization of CFNN). To optimize CFNN structure as mentioned in section 4, the binary version of BA is used. In this example, the number of input features (N) is equal to two (Number of damaged elements). In all of the solution procedures, BA specifications are the same.

Table 4 Comparison the results between two solution methods in terms of computational time and accuracy

Algorithm		Damage severity using optimized CFNN (percent)	Damage severity using direct FE model (percent)	Exact damage severity (percent)
Damaged element number	1286	19.93%	20.05%	20 %
	1287	19.9%	20.02%	20 %
Number of iterations		200	200	
Damage severity detection process time (sec)		782	3912	
Number of FE analyses		300	10000	

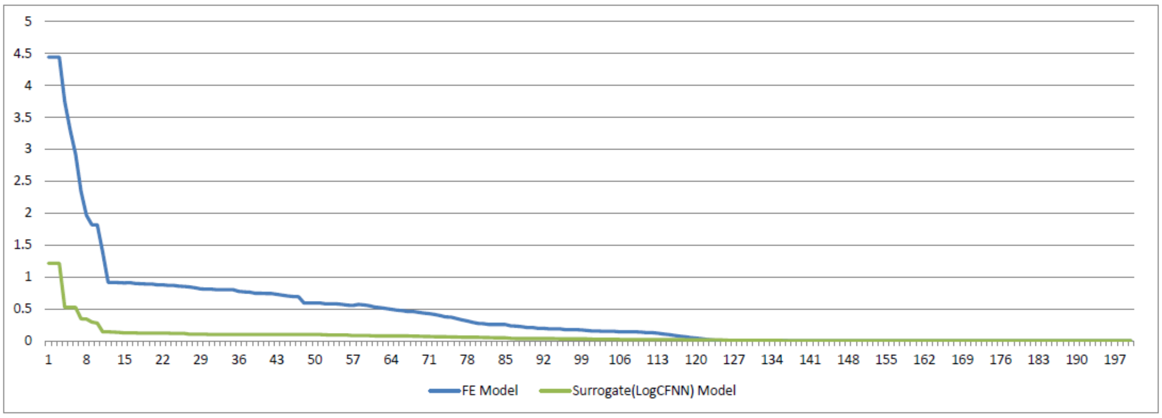

Fig. 7 The convergence history of BA for plate

Table 4 shows the results of comparing between two solution methods in terms of computational speed and accuracy. To compute process time when using an ANN model, data generation time, training and testing time and BA implementation time are considered together (core™ i5 2.67 GHz CPU). The proposed method of using appropriate ANN model instead of direct FE model as an updating model in optimization process of damage severity detection has been analyzed and compared in this section.

It can be concluded from Table 4 that the idea of using an ANN model as a surrogate model of FE model, substantially reduces the computation time of damage severity detection. By this proposed solution method, computation time of proposed procedure is reduced to one-fourth of the former one. Using ANN model in process of damage severity detection done by optimization algorithm accelerates this process besides of maintaining the acceptable detection accuracy.

The convergence history of BA cost function value for different models which has been engaged by BA algorithm versus the maximum number of iterations (200) has been illustrated In Fig. 7.

As the Fig. 7 illustrates, the CFNN model with log-sigmoid transfer function has the least cost function value for the first iteration of BA, it leads to increase the speed of BA convergence. Direct FE model as model updating has the most cost function value for the first iteration and for this model, BA has the least speed of convergence.

6.2 Example 2: Square steel plate 1000 ×1000 mm with 5 mm thickness (line defects)

6.2.1 Finding the damage location using moment curvature

The flexural steel plate with 100 divisions in the x and y directions has been modeled. In order to model a damage with a linear shape as show in Fig. 8, the thickness of elements have reduced by 10 percent.

This example is to demonstrate the ability of each of the two proposed indices to find the damage with linear shape. Figs. 9 and 10 are showing the two and three dimensional view of damage location by curvature-moment and curvature-moment derivative, respectively.

Based on Fig. 9, moment-curvature index does not have the ability to locate linear damage.

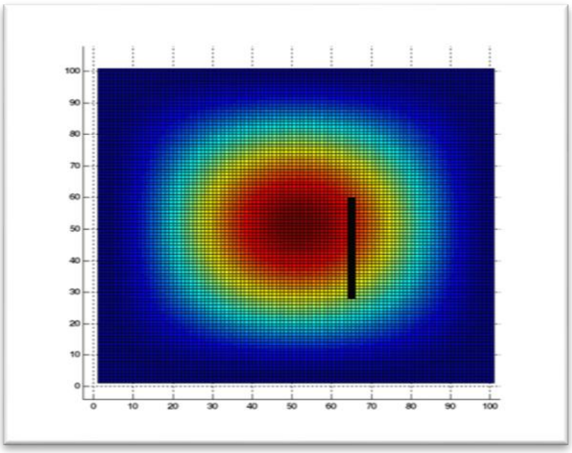

Fig. 8 Damage location

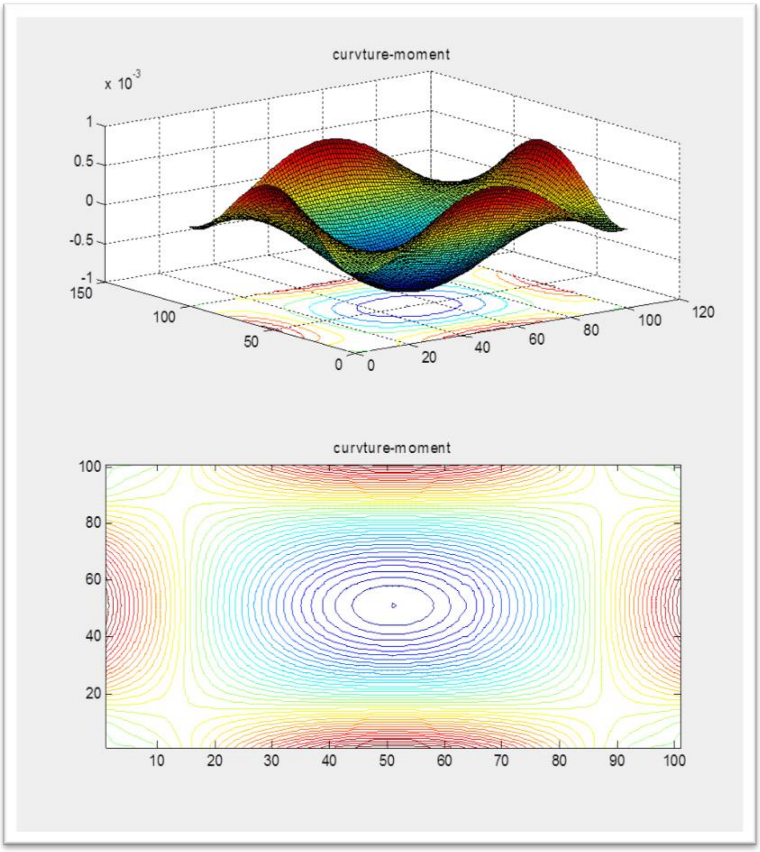

Fig. 9 Two- and three-dimensional view of damage location by curvature-moment index

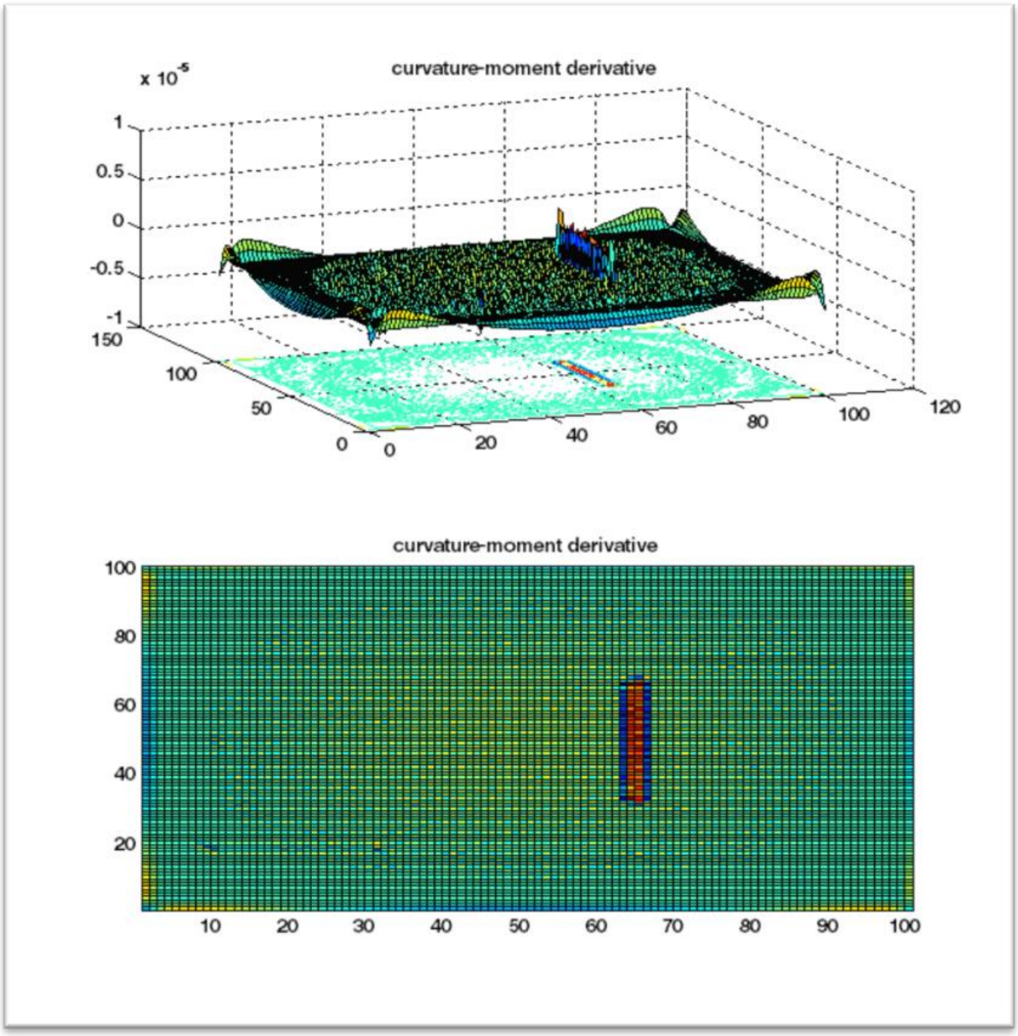

Fig. 10 Two- and three-dimensional view of damage location by curvature-moment derivative index

As the Fig. 10 shows that moment-curvature derivative index has the ability to efficiently find linear damage. In addition, this index does not have moment-curvature's disadvantages such as detecting wrongly presence of damage at corners and presence of large fluctuations.

6.2.2 Determining the damage severity using BA engaged by FE model vs. BA engaged by ANN model

In this example, ANN based surrogate model is used instead of direct FE model as an updating model in optimization process of damage severity detection with more damaged elements. Table 5 shows the results of comparing between two solution methods in terms of computational speed and accuracy.

Table 5 Comparison the results between two solution methods in terms of computational speed and accuracy

Algorithm		Damage severity using CFNN (percent)	Damage severity using direct FE model (percent)	Exact damage severity (percent)
Damaged element number	455	9%	10.04%	10 %
	456	9.24%	10.01%	10 %
	457	9.9%	9.9%	10 %
	458	9.8%	9.85%	10 %
	459	9.2%	10.2%	10 %
	460	8.9%	12%	10 %
	461	10.14%	9.5%	10 %
	462	10.7%	10.02%	10 %
Number of iterations		200	200	
Damage severity detection process time (sec)		801	4021	
Number of FE analyses		300	10000	

Using ANN model as a surrogate model of FE model in the optimization process leads to just 300 (number of scenarios picked by LHS method among the total scenarios based on Eq. (15)) FE structure analyses in order to generate training and testing dataset for ANN model, whereas using direct FE model as an updating model in this process, leads to 10000 FE structure analyses which is equal to maximum number of BA cost function computation based on Eq. (16).

$$Maximum\ Number\ of\ BA\ Cost\ Function\ Computation = npop \times niter \tag{16}$$

where $npop$ is population size of bat algorithm whose value is 50 and $niter$ is maximum number of BA iteration whose value is 200. On the other hand, number of FE analyses is equal to maximum number of BA cost function computation. As can be considered, using this new solution procedure contributes to a substantial reduction in the number of FE structural analysis which shows its priority in damage severity detection of large-scale structures.

According to these results, it is observed that the obtained severities have an acceptable accuracy and thus the proposed solution procedure is not sensitive to the number of suspected elements.

7. Conclusions

In this paper, after locating the damage occurrence in plate-like structures using curvature-moment derivative indicator, an efficient solution procedure has been proposed for damage severity detection. Based on this new solution procedure, to reduce effectively computational time of model updating during the process of damage severity detection, Bat algorithm as an optimizer is engaged by an appropriate ANN model as a surrogate of direct FE model. In order to assess the performance of this proposed solution procedure, point defects or notches, as well as linear defects are considered and two numerical plates model have been studied. Based on the numerical results, the following conclusions can be resulted:

- The results show a high accuracy of curvature-moment derivative method to detect the damage locations, especially at the corners of the plate.
- Curvature-moment derivative index does not have moment-curvature's, wavelet and wavelet packet transform disadvantages such as detecting wrongly presence of damage at corners and presence of large fluctuations.
- The computational time of damage severity detection using BA engaged by ANN model as a surrogate of FE model is significantly reduced compared to using direct FE model based on BA (about one-fourth). Using this new solution procedure contributes to a substantial reduction in the number of FE structural analysis (about One-thirtieth) which is further highlighted in damage severity detection of plate-like structures.
- In order to optimize the CFNN structure, a new method based on BA has been proposed. Results show that CFNN with log-sigmoid transfer function and adequate number of neurons for the hidden layer has the best structure to increase the accuracy of process of replacing the FE model with surrogate model in damage severity detection procedure.

References

Bai, Y., He, S., Nie, W., Gao, J. and Song, X. (2012), “Plane grid structure damage location identification by model curvature”, *Procedia Eng*., **31**, 534-540.

Dessi, D. and Camerlengo, G. (2014), “Damage identification techniques via modal curvature analysis: overview and comparison”, *Mech. Syst. Signal Pr.*, 1-25.

Fan, W. and Qiao, P. (2011), “Vibration-based damage identification methods: A review and comparative”, *Struct. Health Monit.*, **10**(1), 83-111.

Fathnejat, H., Torkzadeh, P., Salajegheh, E. and Ghiasi, R. (2014), “Structural damage detection by model updating method based on cascade feed-forward neural network as an efficient approximation mechanism”, *Int. J. Optim. Civ. Eng.*, **4**(4), 451-472.

Ghiasi, R., Ghasemi, M.R. and Noori, M. (2015), “Comparison of seven artificial intelligence methods for damage detection of structures”, (Eds., Kruis, J., Tsompanakis, Y. and Topping, B.H.V.*), Proceedings of the 15th International Conference on Civil, Structural and Environmental Engineering Computing*, Civil-Comp Press, Stirlingshire, UK, Paper 116.

Ghiasi, R., Torkzadeh, P. and Noori, M. (2014), “Structural damage detection using artificial neural networks and least square support vector machine with particle swarm harmony search algorithm”, *Int. J. Sustain. Mater. Struct. Syst.*, **1**(4), 303-320.

Ghodrati A.G., Seyed Razaghi, S.A. and Bagheri, A. (2011), “Damage detection in plates based on pattern search and genetic algorithms”, *Smart Struct. Syst.*, **7**(2), 117-132.

Gholizadeh, S. (2015), “Performance-based optimum seismic design of steel structures by a modified firefly algorithm and a new neural network”, *Adv. Eng. Software*, **81**, 50-65.

Gholizadeh, S. and Shahrezaei, A.M. (2015), “Optimal placement of steel plate shear walls for steel frames by bat algorithm”,*Struct. Des. Tall Spec. Build.*, **24**(1), 1-18.

Hagan, M.T. Demuth, H.B. and Beale, M.H. (1996), *Neural Network Design*, Boston.

Hakim, S.J.S. and Razak, H.A. (2014), “Modal parameters based structural damage detection using artificial neural networks-a review”, *Smart Struct. Syst.*, **14**(2), 159-189.

He, W.Y. and Zhu, S. (2015), “Adaptive-scale damage detection strategy for plate structures based on wavelet finite element model”, *Struct. Eng. Mech.*, **54**(2), 239-256.

Hedayat, A. Davilu, H. Barfrosh, A.A. and Sepanloo, K. (2009), “Estimation of research reactor core parameters using cascade feed forward artificial neural networks”, *Prog. Nucl. Energ.*, **51**, 709-718.

Hera, A., Hou, Z. and Noori, M. (2013), “Wavelet-based techniques for structural health monitoring”, *Health Assessment of Engineered Structures*, *World Scientific, Ed. Achintya Haldar*, 179-199.

Homaei, F., Shojaee, S. and Ghodrati A.G. (2014), **“**A direct damage detection method using multiple Damage localization index based on mode shapes criterion”, *Struct. Eng. Mech.*, **49**(2), 183-202.
Hou, Z., Noori, M. and Amand, R.S. (2000), “Wavelet-based approach for structural damage detection”, *J. Eng. Mech*. *-ASCE*, **126**(7), 677-683.
Huang, X., Chen, J. and Zhu, H. (2016), “Assessing small failure probabilities by AK–SS: An active learning method combining kriging and subset simulation”, *Struct. Saf.*, **59**, 86-95.
Iman, R. L. (2008), *Latin Hypercube Sampling*, John Wiley & Sons, Ltd.
Komarasamy, G. and Wahi, A. (2012), “An optimized K-means clustering technique using Bat algorithm”, *Eur. J. Sci. Res*., **84**(2), 263-273.
Loutridis, S., Douka, E., Hadjileontiadis, L.J. et al. (2005), “A two-dimensional wavelet transform for detection of cracks in plates”, *Eng. Struct.*, **27**(9), 1327-1338.
Makas, H. Yumusak, N. and Source, AD. (2013), “A comprehensive study on thyroid diagnosis by neural networks and swarm intelligence”, *Electronics, Computer and Computation (ICECCO)*.
Mazzoni, S., Mckenna, F., Michael, H.S. and Gregory, L.F. (2006), “OpenSees command language manual”, *Pacific Earthquake Engineering Research (PEER) Center.*
Ng, A.Y. (2004), “Feature Selection, L 1 vs. L 2 Regularization, and Rotational Invariance”, *Proceedings of The Twenty-First International Conference on Machine learning*, *ACM.*
Nobahari, M. and Seyedpoor, S.M. (2013), “An efficient method for structural damage localization based on the concepts of flexibility matrix and strain energy of a structure”, *Struct. Eng. Mech.*, **46**(2), 231-244.
Panchal, G., Ganatra, A., Kosta, Y. P. and Panchal, D. (2011), “Behavior analysis of multilayer perceptions with multiple hidden neurons and hidden layers”, *Int. J. Comput. Theory Eng.*, **3**(2), 332-337.
Release, M. (2012), *The MathWorks Inc*., Natick, Massachusetts, United States.
Rucevskis, S., Sumbatyan, M.A., Akishin, P. and Chate, A. (2015), “Tikhonov's regularization approach in mode shape curvature analysis applied to damage detection”, *Mech. Res. Commun.*, **65**, 9-16.
Sarvi, F., Shojaee, S. and Torkzadeh, P. (2014), “Damage identification of trusses by finite element model updating using an enhanced Levenberg-Marquardt algorithm”, *Int. J. Optim. Civil Eng.*, **4**(2), 207-231.
Xiang, J., Matsumoto, T., Wang, Y. and Jiang, Z. (2013), “Detect damages in conical shells using curvature mode shape and wavelet finite element method”, *Int. J. Mech. Sci*., **66**, 83-93.
Yang, X.S. and Gandomi, A.H. (2012), “Bat algorithm: a novel approach for global engineering optimization”, *Eng. Comput*., **29**(5), 464-483.

CC