INTERNATIONAL JOURNAL OF OPTIMIZATION IN CIVIL ENGINEERING
Int. J. Optim. Civil Eng., 2014; 4(4):451-472

STRUCTURAL DAMAGE DETECTION BY MODEL UPDATING METHOD BASED ON CASCADE FEED-FORWARD NEURAL NETWORK AS AN EFFICIENT APPROXIMATION MECHANISM

H. Fathnejat[1], P. Torkzadeh[2], E. Salajegheh[2*,†] and R. Ghiasi[2]
[1]*Department of Civil Engineering, Graduate University of Advanced Technology, Kerman, Iran*
[2]*Department of Civil Engineering, Faculty of Engineering, Shahid Bahonar University of Kerman, Kerman, Iran*

ABSTRACT

Vibration based techniques of structural damage detection using model updating method, are computationally expensive for large-scale structures. In this study, after locating precisely the eventual damage of a structure using modal strain energy based index (MSEBI), To efficiently reduce the computational cost of model updating during the optimization process of damage severity detection, the MSEBI of structural elements is evaluated using properly trained cascade feed-forward neural network (CFNN). In order to achieve an appropriate artificial neural network (ANN) model for MSEBI evaluation, a set of feed-forward artificial neural networks which are more suitable for non-linear approximation, are trained. All of these neural networks are tested and the results demonstrate that the CFNN model with log-sigmoid hidden layer transfer function is the most suitable ANN model among these selected ANNs. Moreover, to increase damage severity detection accuracy, the optimization process of damage severity detection is carried out by particle swarm optimization (PSO) whose cost function is constructed based on MSEBI. To validate the proposed solution method, two structural examples with different number of members are presented. The results indicate that after determining the damage location, the proposed solution method for damage severity detection leads to significant reduction of computational time compared to finite element method. Furthermore, engaging PSO algorithm by efficient approximation mechanism of finite element (FE) model, maintains the acceptable accuracy of damage severity detection.

Received: 20 August 2014; Accepted: 4 November 2014

---

*Corresponding author: Department of Civil Engineering, Faculty of Engineering, Shahid Bahonar University of Kerman, Kerman, Iran
†E-mail address: eysasala@uk.ac.ir (E. Salajegheh)

KEY WORDS: damage detection; approximation mechanism; cascade feed-forward neural network; modal strain energy based index; particle swarm optimization.

1. INTRODUCTION

Nowadays, Vibration based technique as a structural health monitoring (SHM) tool to identify and assess damage is employed for various methods of structural damage detection. SHM exerting vibration measurements are global methods that detect damage parameters based on the principle that disruption of the structural performance due to damage in a structure changes its vibration parameters, namely, natural frequencies, mode shapes and damping characteristics [1].

In recent years, various types of algorithms based on Artificial Intelligence (AI) techniques for damage detection have been applied. The methods are broadly divided into five categories as follows: (1) neural network techniques [2], (2) support vector machine techniques [3], (3) fuzzy inference techniques [4], (4) genetic algorithm (GA) techniques [5], (5) hybrid techniques [6].

The artificial neural network (ANN) model is robust and fault tolerant [7]. ANN can also effectively deal with qualitative, uncertain, and incomplete information, making it highly promising for detecting structural damage. The feasibility of applying these networks to detect structural damage has received considerable attention. ANN based methodology has been used in two broad domain of structural damage detection procedure: (1) As a promising technique in the domain of inverse damage detection problem to ascertain the damage parameters (location and severity) [2]. (2) As an appropriate approximation mechanism of finite element (FE) model, in the domain of model based damage detection problems which has been typically used for composite beams damage detection [8].

Detection of damage severity is effectively the solution to the inverse problem [9]. However, it may be necessary in many cases to solve the forward problem to generate data for the solution to the inverse problem. Generation of data is usually computationally expensive and ANN models are created to reduce the computational expense. Simulation of (ANN) model as an efficient approximation mechanism (EAM) of finite element (FE) model as a response of updating damaged structure which is 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. The trained ANN model provides an approximation of the numerical model. In this case, an optimization algorithm has been customized using ANN approximations of numerical model to detect damage severities in structural systems. In this paper to speed up effectively optimization process of damage severity detection in structural systems, a very efficient approximation mechanism of finite element (FE) model of the structure has been introduced and developed by using cascade feed forward type of artificial neural networks (CFNNs). In this proposed method a CFNN has been trained by a training dataset whose inputs are damage severities of failure scenarios and outputs are corresponding modal strain energy based indexes (MSEBIs). Using ANN model in process of damage severity detection done by optimization algorithm accelerates this process besides of maintaining the acceptable detection accuracy.

In this study, after detecting the exact location of damage occurrence using MSEBI indicator, to detect the damage severity in structural systems, the particle swarm optimization (PSO) algorithm engaged by CFNN model with log-sigmoid hidden layer transfer function has been applied. Results of damage severity detection obtained from proposed solution procedure are compared with those obtained from PSO engaged by FE model in terms of computational time and accuracy. Moreover, in order to improve detection accuracy of damage severity, an objective function based on MSEBI has been proposed. This proposed cost function representing the errors between measured or actual MSEBIs and those predicted by trained ANN models or FE models, has been minimized by PSO. To achieve an appropriate ANN model as an EAM of FE model, some types of feed-forward artificial neural networks which are more suitable for non-linear approximation, are selected [10]. This set of selected ANNs includes back propagation neural network (BPNN) with log-sigmoid transfer function for hidden layer, BPNN with hyperbolic tangent sigmoid transfer function, cascade feed-forward neural network (CFNN) with radial basis transfer function, CFNN with log-sigmoid transfer function and radial basis function neural network (RBFNN) with wavelet packet transfer function (WRBF) [11]. Appropriate ANN model is distinguished among these networks based on its best performance on specific testing datasets. In order to generate failure scenarios which are training and testing datasets to span the design space, completely, latin hypercube sampling (LHS) method has been applied. A 200-bar double-layer grid and a 216-bar dome truss are studied to demonstrate the efficiency of proposed solution procedure.

The present paper is organized as follows:

In Section 2, we describe the CFNN design structure. MSEBI indicator and proposed objective function based on MSEBI are represented in Sections 3 and 4, respectively. Description of PSO algorithm is brought in section 5. Procedure of achieving an appropriate neural network is expressed in Section 6. Solution procedure of damage detection and LHS method are described in section 7. Examples are studied in Section 8 and conclusions are presented in Section 9.

2. CASCADE FEED-FORWARD NEURAL NETWORKS

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 [12]. The additional connections in cascade feed-forward neural network (CFNN) improve the speed at which the network learns the desired relationship [13]. 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[14]. Fig. 1 shows the general structure of cascade feed-forward neural network.

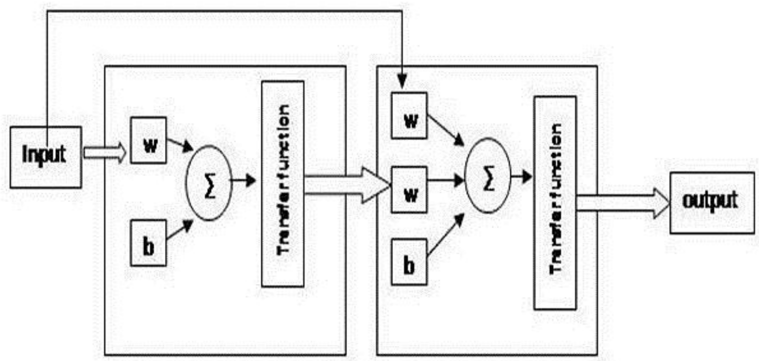

Figure 1. Cascade feed-forward neural network general structure

3. MODAL STRAIN ENERGY BASED INDEX (MSEBI)

In this study, an objective function has been constructed using efficient index based on the modal strain energy (MSE) to accurately detect the damage severity of the suspected elements of a damaged structure. The modal analysis uses the overall mass and stiffness of a structure to find its natural frequencies and mode shapes. It has the mathematical form of [15]:

$$(K - \omega_i^2 M)\varphi_i = 0, \quad i = 1, \dots, ndf \tag{1}$$

where K and M are the stiffness and mass matrices of the structure, respectively; ω_i and φ_i are the ith circular frequency and mode shape vector of the structure, respectively. Also, ndf is the total degrees of freedom of the structure. The mode shapes are usually normalized with respect to the mass matrix and therefore the relations $\varphi_i^T M \varphi_i = 1$ and $\varphi_i^T K \varphi_i = \omega_i^2$ can be established.

Since the mode shape vectors are equivalent to nodal displacements of a vibrating structure, therefore in each element of the structure has the strain energy been stored. The strain energy of a structure due to mode shape vector are usually referred to as modal strain energy (MSE) and can be considered as a valuable parameter for damage identification. The modal strain energy of eth element in ith mode of the structure can be expressed as:

$$mse_i^e = \frac{1}{2}\varphi_i^e K^e \varphi_i^e, \ i = 1, \dots, ndf, \ e = 1, \dots, nte \tag{2}$$

where K^e is the stiffness matrix of eth element of the structure and φ_i^e is the vector of corresponding nodal displacements of element e in ith mode. The total modal strain energy of ith mode of the structure can also be determined by summation of MSE of all elements nte, given by

$$mse_i^e = \frac{1}{2}\varphi_i^e K^e \varphi_i^e, i = 1, \ldots, ndf, e = 1, \ldots, nte \tag{3}$$

For computational purpose, it is better to normalize the MSE of elements with respect to the total MSE of the structure:

$$nmse_i^e = \frac{mse_i^e}{mse_i} \tag{4}$$

where $nmse_i^e$ is the normalized MSE of eth element in ith mode of the structure. The mean of Eq. (4) for the first nm modes can now be selected as an efficient parameter as

$$mnmse^e = \frac{\sum_{i=1}^{nm} nmse_i^e}{nm}, \quad e = 1, \ldots, nte \tag{5}$$

In general, when damage occurs in a structural element, it can be simulated by decreasing one of the stiffness parameters of the element such as the elasticity modulus (E) cross sectional area (A), moment of inertia (I) and so on. Therefore, the damage occurrence is led to increasing the MSE and consequently the efficient parameter $mnmse^e$. As a result, in this study, by determining the efficient parameter $mnmse^e$ for each element of healthy and damaged structures denoted here as $(mnmse^e)^h$and $(mnmse^e)^d$respectively, an efficient indicator for estimating the presence and severity of the damage in the element can be defined. This indicator termed here as modal strain energy based index ($MSEBI$) and can be determined as

$$MSEBI^e = \frac{(mnmse^e)^d - (mnmse^e)^h}{(mnmse^e)^h}, \quad e = 1, \ldots, nte \tag{6}$$

It should be noted that, as the damage locations are unknown for the damaged structure with respect to real data applications, therefore for this case the element stiffness matrix of the healthy structure is used for estimating the parameter $(mnmse^e)^h$. According to the Eq. (6), for a healthy element the index will be equal to zero ($MSEBI^e = 0$) and for a damaged element the index will be greater than zero ($MSEBI^e > 0$) [16].

4. THE PROPOSED OBJECTIVE FUNCTION FORMULATION OF THE OPTIMIZATION PROBLEM BASED ON MSEBI

In this section, an objective function to detect damage severity based on modal strain energy based index has been presented. A root squared error between measured $MSEBIs$ ($MSEBI_M$) and $MSEBI$ predicted by trained ANN models or FE models as an objective function in order to determine the damage severities of suspected elements can be expressed as:

$$RSEMSEBI = \sqrt{\sum_{e=1}^{nte}(MSEBI^e - MSEBI_M^e)^2} \qquad e = 1, \dots, nte \tag{7}$$

where, $RSEMSEBI$ is root square error of modal strain energy based index and e is the number of structure elements.

5. PARTICLE SWARM OPTIMIZATION

In this paper a particle swarm optimization (PSO) is applied to determine the damage severity. PSO finds a set of reduced damage variables X_r minimizing the RSEMSEBI as:

$$\begin{array}{ll} \text{Find} & X_r^T = \{x_{r1}, x_{r2}, \dots, x_{rm}\} \\ \text{Minimize} & w(X_r) = RSEMSEBI(X_r) \\ & x_{ri} \in R^d \quad , \quad i = 1, \dots, m \end{array} \tag{8}$$

where R^d is a given set of discrete values and damage severities $x_{ri} (i = 1, \dots, m)$ can take values only from this set. Also, w is an objective function that should be minimized.

The PSO has been inspired by the social behavior of animals such as fish schooling, insect swarming and bird flocking [17]. It involves a number of particles, which are initialized randomly in the search space of an objective function. These particles are referred to as swarm. Each particle of the swarm represents a potential solution of the optimization problem. The particles fly through the search space and their positions are updated based on the best positions of individual particles in each iteration. The fitness values of particles are obtained to determine, which position in the search space is the best. In kth iteration, the swarm is updated using the following equations:

$$V_i^{k+1} = \rho^k V_i^k + c_1 r_1 (P_i^k - X_i^k) + c_2 r_2 (P_g^k - X_i^k) \tag{9}$$
$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{10}$$

where Xi and Vi represent the current position and velocity vectors of the ith particle, respectively; P_i is the best previous position of the ith particle and P_g is the best global position among all the particles in the swarm; r_1 and r_2 are two uniform random sequences generated from interval [0,1]; c_1 and c_2 are the cognitive and social scaling parameters, respectively and ρ^k is the inertia weight used to discount the previous velocity of particle preserved. The inertia weight ρ^k may be defined to vary linearly from a maximum value ρ^{max} to a minimum value ρ^{min}.Velocity vector Vi is limited to a lower bound V^l and an upper bound V^u[6].

6. PROCEDURE OF ACHIEVING AN APPROPRIATE NEURAL NETWORK

It is reported that ANNs with two hidden layers are sufficient for S type (Eqs. (12) and (13)) (Sigmoid and Hyperbolic tangent functions). However, for a small ANN, we can't be sure that an ANN with two hidden layers is better than one with only one hidden layer [19]. Therefore one hidden layer is chosen.

Primary studies show that the pure line activation function (Eq. (11)) for output layer is more advantageous than the S type activation function (Eqs. (12) and (13)). In this study some types of feed-forward artificial neural networks which are more suitable for non-linear approximation, are selected [10]. This set of selected ANNs includes back propagation neural network (BPNN) with log-sigmoid transfer function for hidden layer, BPNN with hyperbolic tangent sigmoid transfer function, cascade feed-forward neural network (CFNN) with radial basis transfer function, CFNN with log-sigmoid transfer function and radial basis function neural network (RBFNN) with wavelet packet transfer function (WRBF) [11]. Network architecture of all the selected ANNs are the same, includes a layer of inputs, a layer of output neurons, and one hidden layers of neurons. ANN inputs are damage severities of failure scenarios and outputs are MSEBIs. 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 [20]. In order to distinguish an appropriate ANN Among these networks, at first, 500 damage scenarios as training and testing datasets are empirically generated using LHS method for training and testing the set of selected ANNs. Then, a suitable network is selected based on the root mean square error (RMSE) of testing datasets.

$$O_j = Purelin(V_j) = V_j \tag{11}$$

$$O_j = \mathrm{Logsig}(V_j) = 1 \,/\, (1 + e^{-(V_j)}) \tag{12}$$

$$O_j = Tansig(V_j) = (1 - e^{-2(V_j)}) \,/\, (1 + e^{-2(V_j)}) \tag{13}$$

7. PROCEDURE OF DAMAGE DETECTION

The step by step procedure of damage detection is summarized as follows:

Step 1: computing the MSEBI for all the structural elements to determine suspected elements; the elements whose MSEBI values are greater than zero.

Step 2: generating failure scenarios with the damage severity range between 0.1 and 0.5

with the pace of 0.1, when the number of suspected elements is determined.

Step 3: developing a finite element (FE) model which computes the mode shapes of the structure and finally the MSEBI for each element 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: engaging directly the ANN model by the optimizer to evaluate the objective function to be minimized to determine the damage severities of suspected elements.

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 described by McKay in 1979 [18].

In order to get real simulations by CFNN, and also to decrease required training data sets, to determine the number of necessary training and testing data sets for development of ANN model, specific convergence criteria is selected.

8. NUMERICAL RESULTS AND DISCUSSIONS

8.1 Example 1: 200-bar double-layer grid

A 200-bar and $20m \times 20m$ double-layer grid with a height of 1.6 m is considered as the first example. The top, bottom and diagonal layers of the double-layer grid are shown in Fig. 2. The structure is supported on the corner nodes of the bottom layer. The material properties of elements include Young's modulus of $E = 2.1\times10^2\,Gpa$ and mass density of $\rho=7850\,kg/m^3$. The cross sectional areas of elements in diagonal, bottom and top layers are $A_d = 10\ cm^2$, $A_b = 12\ cm^2$ and $A_t = 18\ cm^2$, respectively. Table 4 represents two damage scenarios having damage severities, expressed in ratios of elasticity modulus reduction, ranging from 10% to 50%.

Table 1: Damage scenarios

Scenario	Damaged element ID	Damage severity	Scenario	Damaged element ID	Damage severity
A	7	0.1	B	4	0.5
	21	0.2		19	0.25
	39	0.3		24	0.3
	42	0.3		38	0.15
	54	0.1		50	0.4
	73	0.4		68	0.45
	91	0.4		82	0.2
	102	0.5		101	0.5
	166	0.3		142	0.1
	178	0.5		191	0.5

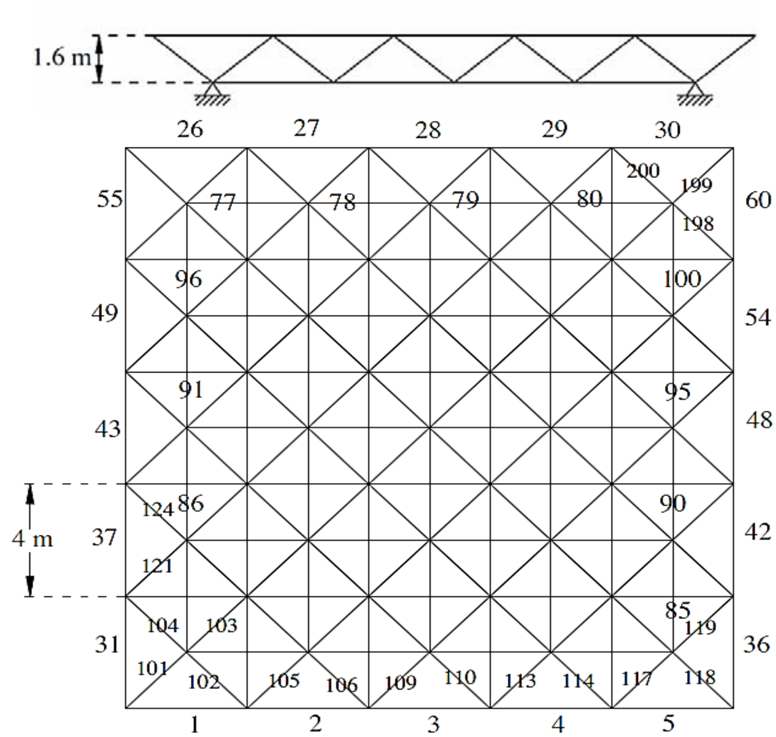

Figure 2. Double-layer grid with 200 elements

8.1.1 Finding the damage location using MSEBI

In the first stage of identifying the induced damage, the modal strain energies of different elements of the double-layer grid for both healthy and damaged structures are determined at first and then, the indicator MSEBI is evaluated via the Eq. (6). Figs. 3 and 4 show the value of MSEBI versus element number for scenarios A and B, respectively.

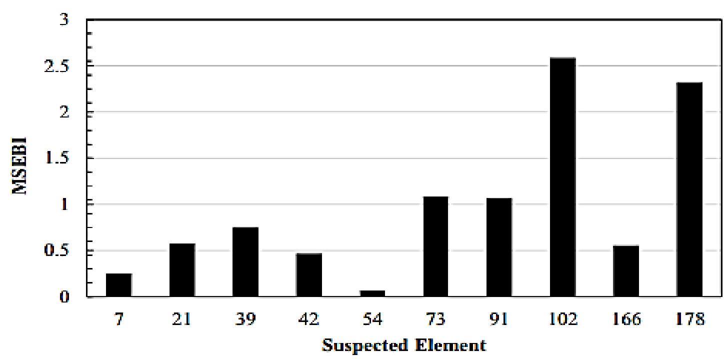

Figure 3. Suspected damage elements in double-layer grid (Scenario A)

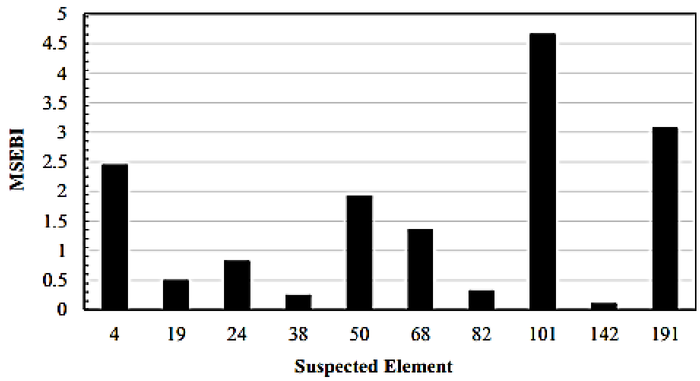

Figure 4. Suspected damage elements in double-layer grid (Scenario B)

It can be seen from Figs. 3 and 4 that for the damages considered, the MSEBI of suspected elements in the both scenarios are detected as nonzero values, while other elements' MSEBIs are zero.

8.1.2 Determining the damage severity using PSO engaged by FE model vs. PSO engaged by ANN model

At this stage the reduced damage detection problem having fewer damage variables instead of 200 original ones can be solved via the optimization algorithm. In this section, the new procedure for solving the damage severity problem has been proposed. This procedure contains the PSO algorithm which has been engaged by an appropriate ANN model as an updating model in optimization process of damage severity detection. The PSO is employed to find a set of damage severity variables minimizing the RSEMSEBI of Eq. (7). The PSO algorithm with the specifications listed in Table 2 is applied to solve the problem.

Table 2: The specifications of the PSO algorithm

Parameter	Description	Value
npop	The number of particles	50
niter	The maximum number of iterations	200
C1	Cognitive parameter	2.0
C2	Social parameter	2.0
ρ_{min}	Minimum of inertia weight	0.4
ρ_{max}	Maximum of inertia weight	0.9

8.1.2.1 Determining the damage severity using PSO engaged by FE model

In this panel, an inverse problem of damage severity detection has been solved by PSO which has been engaged by direct finite element updating model. Figs. 5 and 6 show the results of damage severity detection of suspected elements obtained by this solution procedure.

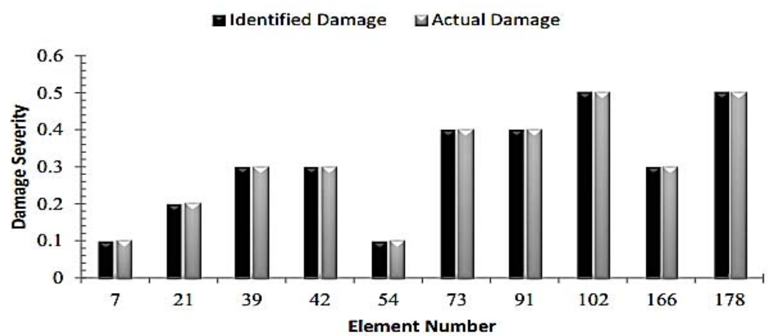

Figure 5. Damage severity of elements in double-layer grid (Scenario A)

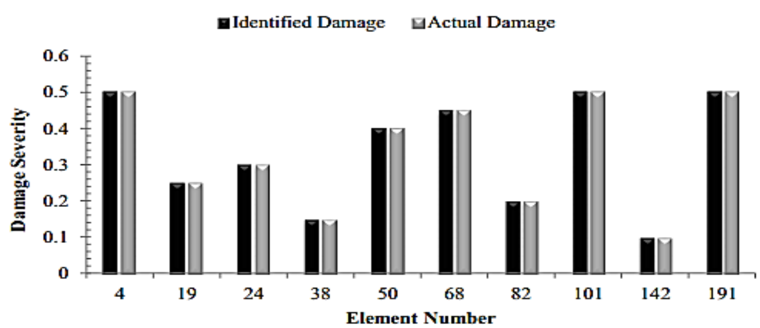

Figure 6. Damage severity of elements in double-layer grid (Scenario B)

Figs. 5 and 6 show that the proposed cost function based on MSEBI for PSO algorithm determine the damage severities with a high accuracy. But to achieve such an outcome was time consuming process that takes about 3,900 seconds. In order to reduce this time, an effective solution method which has been presented in this study is used and fully explained in the next section. (*core ™ i5 2.67 GHz CPU*)

8.1.2.2 Determining the damage severity using PSO engaged by an appropriate ANN model (CFNN model with log-sigmoid transfer function)

8.1.2.2.1 Distinguishing an appropriate ANN model as an efficient approximation mechanism of FE model

In this panel, damage severities have been determined using PSO engaged by distinguished appropriate ANN model. ANN inputs are damage severities of failure scenarios (in this example 10 damaged elements) and outputs are MSEBIs. After testing the networks for different number of MSEBIs as the number of output matrix features based on error of damage severity detection accuracy, the 50 is selected as an optimum number of output layer neurons. Number of training and testing datasets is equal to 500 as mentioned in section 6.

Table 3 shows the root mean square error (RMSE) of testing datasets for set of selective ANNs for each damage scenario. As it comes from this table, it can be seen that the CFNN with log-sigmoid transfer function has the lowest RMSE, so this ANN is chosen as an EAM of finite element (FE) model.

Table 3: The RMSE of testing datasets

	CFNN with RBF transfer func.	**CFNN with log-sigmoid transfer func.**	**BPNN with log-sigmoid transfer func.**	**BPNN with tan-sigmoid transfer func.**	**WRBFNN**
Scenario A	0.0016	0.0015	0.0017	0.0017	0.0421
Scenario B	0.0018	0.0014	0.0019	0.0020	0.0401

8.1.2.2.2 Adjusting the properties of the selected ANN (CFNN model with log-sigmoid transfer function)

In this example, number of input features (neurons) is equal to number of suspected elements (10), number of output features (neurons) is equal to 50 as outlined in the above sections and number of hidden neurons is 20 for CFNN. Given that the total number of damage scenarios per 10 marked suspected elements for this 200-bar double-layer grid with the damage severity range between 0.1 and 0.5 with the pace of 0.1 is equal to 5^{10} (Eq. (14)), determining the sufficient number of training and testing datasets is necessary. In order to determine the effect of number of datasets on final prediction of CFNN, the root mean square error of testing datasets for different number of training and testing datasets has been calculated and results are illustrated in Fig. 7.

$$All\ Possible\ Damage\ Scenarios = s^{d} \tag{14}$$

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

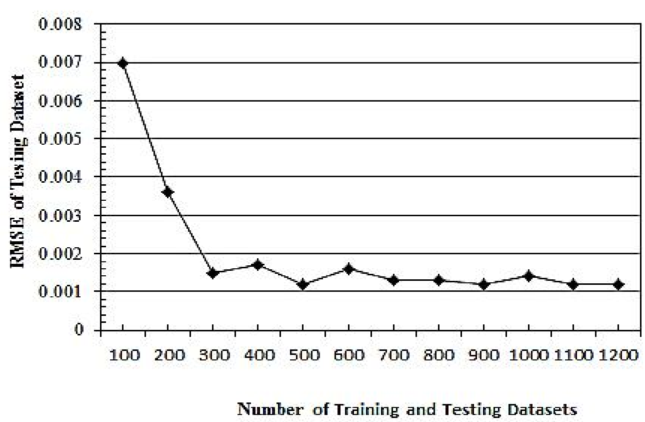

Figure 7. RMSE of testing datasets as a function of the number of training and testing datasets

Fig. 7 shows that if the number of datasets is greater than 300, the RMSE of testing datasets is settled down approximately to a straight line; so some points which are larger than 300 may have a small advantage for training the CFNN. But the other hand, CFNN training with a larger number of training datasets takes a more time.

8.1.2.2.3 Results of damage severity detection using PSO engaged by CFNN model

Figs. 8 and 9 show the results of damage severity detection using PSO engaged by CFNN model with log-sigmoid transfer function and adjusted properties.

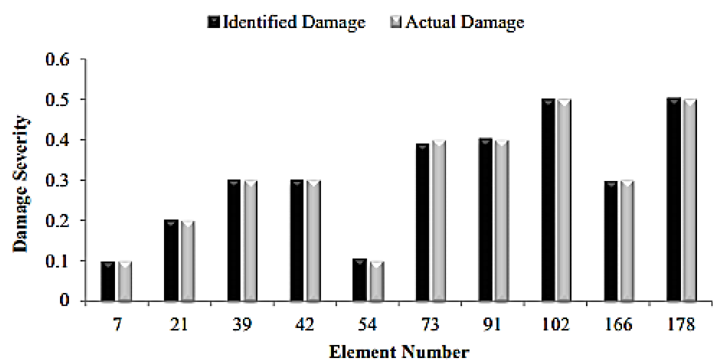

Figure 8. Damage severity of elements in double-layer grid (Scenario A)

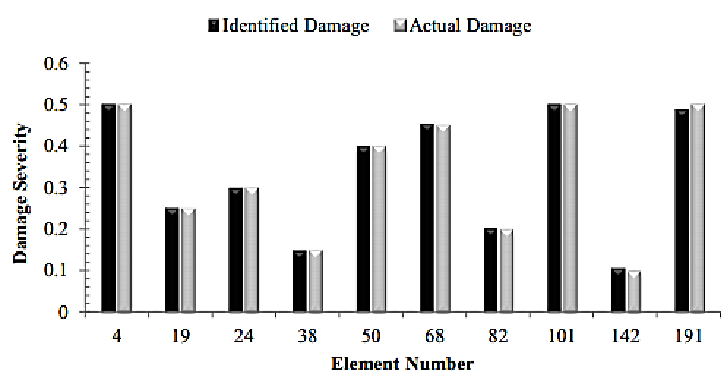

Figure 9. Damage severity of elements in double-layer grid (Scenario B)

Figs. 8 and 9 show the damage severities of suspected elements for both A and B damage scenarios. As the results show the damage severities are detected with acceptable accuracy. For scenario A, the maximum error (Eq. (15)) of damage severity detection is equal to 6.51 percent for damaged element number 54 and the minimum error is equal to 5.02E-5 percent for damaged element number 42. For scenario B, the maximum error of damage severity detection is equal to 6.68 percent for damaged element number 142 and the minimum error is equal to 9.67E-4 percent for damaged element number 50. This detection accuracy besides of considerable reduction of computational cost, can effectively lead to efficient damage detection solution method for large-scale structures. Finally, in order to illustrate the desirable performance of proposed method, comprehensive comparison is given in the next section.

$$Error = \frac{Identified\ severity - Actual\ severity}{Actual\ Severity} \times 100 \tag{15}$$

8.1.3 Comparison between two solution procedures of damage severity detection in terms of computational speed and accuracy

In this section, the proposed method of using appropriate ANN model instead of FE model as an updating model in optimization process of damage severity detection has been analyzed and compared. In all of the solution procedures, PSO specifications are the same. Table 5 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 PSO implementation time are considered together. (*core ™ i5 2.67 GHz CPU*)

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

	Damage severity detection process time (sec)	**RMSE of determined damage severity**
FE model	3829	5.12e-07
CFNN with RBF transfer function Model	606	0.0454
CFNN with log-sigmoid transfer function model	410	0.0129
BPNN with log-sigmoid transfer function model	330	0.0139
BPNN with tan-sigmoid transfer function model	367	0.0375
WRBFNN model	159	0.0493

Firstly, it can be concluded from Table 4 that the idea of using an ANN model as an EAM 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-twelfth 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.

Secondly, it can be observed from Table 4 that the PSO engaged by WRBF neural network has the least computational time, but this solution procedure compared to others is the least accurate. Thus, this ANN model is not appropriate approximation mechanism for FE model.

Finally, among these ANN models, CFNN with log-sigmoid hidden layer transfer function have generally the best performance with regard to both time and accuracy parameters.

In Fig. 10 the convergence history of PSO cost function (RSEMSEBI) value for different models which has been engaged by PSO algorithm versus the maximum number of iterations (200) has been illustrated.

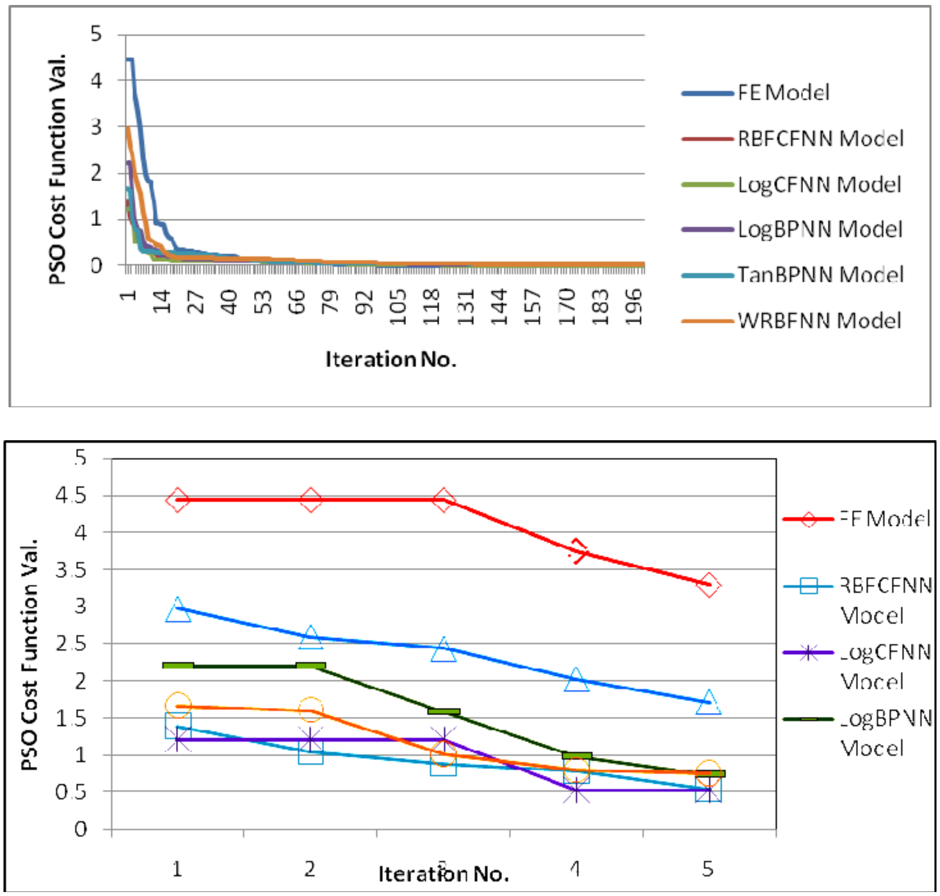

Figure 10. The convergence history of PSO in double-layer grid

As the Fig. 10 illustrates, the CFNN model with log-sigmoid transfer function has the least cost function value for the first iteration of PSO, it leads to increase the speed of PSO convergence. Direct FE model as model updating has the most cost function value for the first iteration and for this model, PSO has the least speed of convergence.

Furthermore, using ANN model as an efficient approximation mechanism of FE model in the optimization process leads to just 300 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 PSO cost function computation based on Eq. (15).

$$\mathit{Maximum\ Number\ of\ PSO\ Cost\ Func.Computation} = npop \times niter \tag{15}$$

where $npop$ is swarm population whose value is 50 and $niter$ is maximum number of PSO iteration whose value is 200. As can be considered, using this new solution procedure contributes to a substantial reduction in the number of FE structural analysis which shows itself in damage severity detection of large-scale structures.

8.2 Example 2: A 216-bar diamatic dome

A 216-bar diamatic dome with the diameter and height of 33m and 10m is considered as the second example. The cross sectional areas of all elements are 50 cm^2. The mass density and Young's modulus are assumed to be $\rho = 7850\ \mathrm{kg/m^3}$ and $E = 2.1 \times 10^2\ \mathrm{Gpa}$. Fig. 11 represents an overview of this structure. In order to study the effect of different number of suspected elements on proposed solution procedure, two different damage scenarios as shown in Table 5 are assumed in this example.

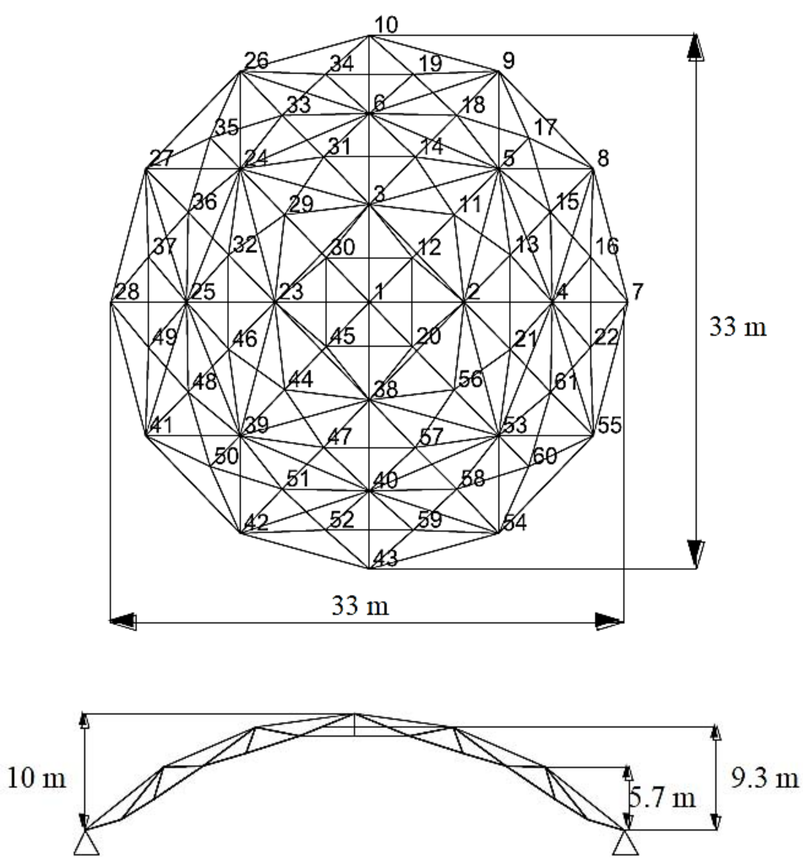

Figure 11. 216-bar diamatic dome

Table 5: Damage scenarios

Scenario	Damaged element ID	Damage severity	Scenario	Damaged element ID	Damage severity
A	5	0.32	B	3	0.15
	52	0.14		29	0.25
	83	0.15		44	0.3
	114	0.26		78	0.35
	149	0.35		82	0.43
	200	0.45		92	0.4
				143	0.45
				153	0.5
				175	0.2
				196	0.5
				211	0.3
				215	0.4

8.2.1 Finding the damage location using MSEBI

Since it is difficult to obtain all mode shapes of structures, due to sensor noise or a limited number of sensors, MSEBI indicator is extracted based on first five mode shapes of the structure which has been used in both examples [21]. Results show that despite this issue, suspected elements have been identified with good accuracy. Figs. 12 and 13 show the value of MSEBI versus element number for scenarios A and B, respectively.

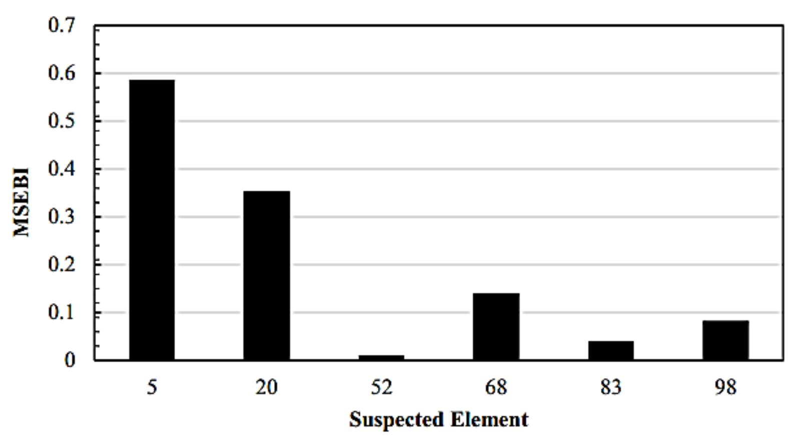

Figure 12. Suspected damage elements in diamatic dome (Scenario A)

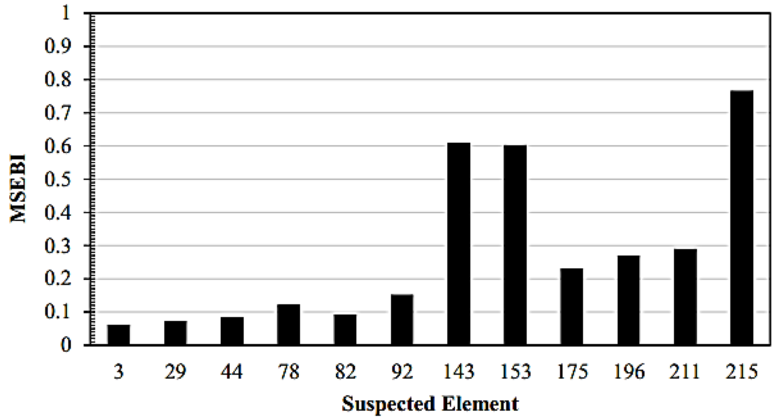

Figure 13. Suspected damage elements in diamatic dome (Scenario B)

8.2.2 Determining the damage severity using PSO engaged by FE model vs. PSO engaged by distinguished appropriate ANN model (CFNN)

For this example, after determining damage severity using PSO engaged by direct FE model for both A and B damage scenarios, these damage variables are determined using PSO engaged by the CFNN model with log-sigmoid hidden layer transfer function and 300 training and testing datasets which has been distinguished as an appropriate ANN approximation mechanism of FE model, previously. Figs. 14 and 15 show the results of damage severity detection of suspected elements in scenarios A and B using PSO engaged by FE model, respectively. Also, Figs. 16 and 17 show the results of damage severity detection of suspected elements using PSO engaged by CFNN model.

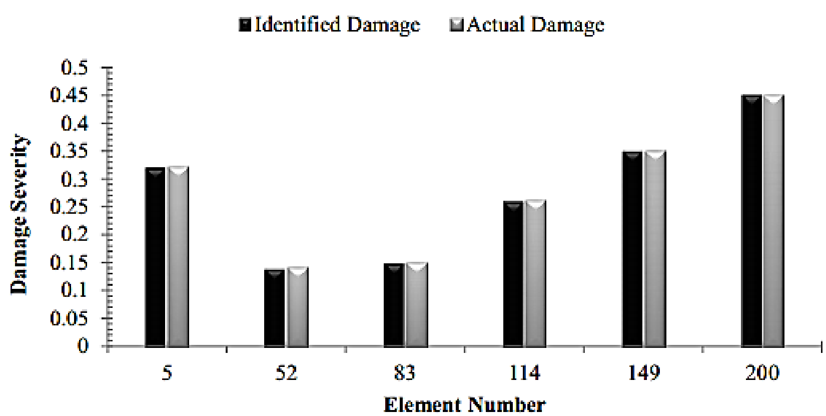

Figure 14. Damage severity of elements using direct FE model in diamatic dome (Scenario A)

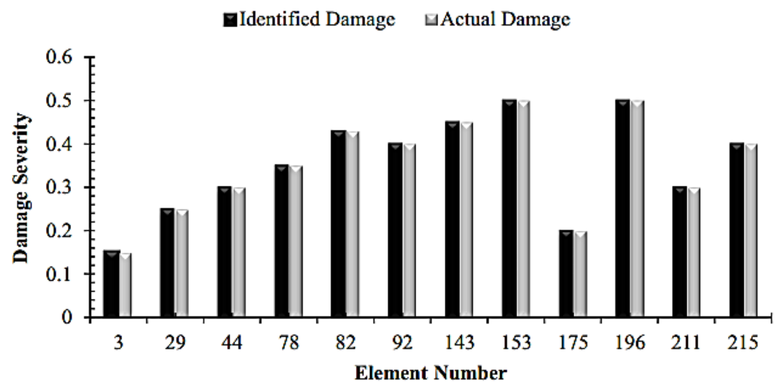

Figure 15. Damage severity of elements using direct FE model in diamatic dome (Scenario B)

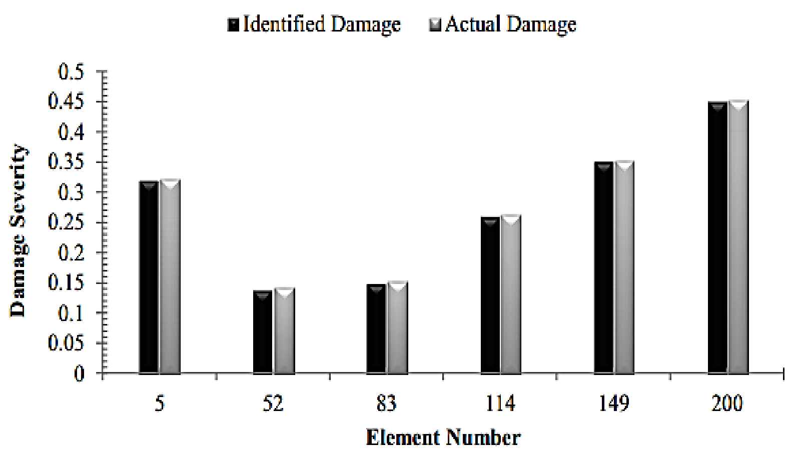

Figure 16. Damage severity of elements using CFNN model in diamatic dome (Scenario A)

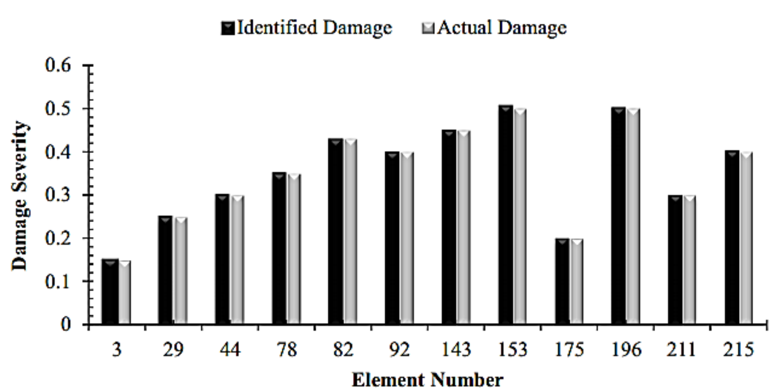

Figure 17. Damage severity of elements using CFNN model in diamatic dome (Scenario B)

In this example, different damage scenarios were studied. 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.

9. CONCLUSION

In this paper, after locating the damage occurrence in the structure using MSEBI indicator, an efficient solution procedure was proposed for damage severity detection in structural systems. Based on this new solution procedure, to reduce effectively computational time of model updating during the process of damage severity detection done by optimization algorithm, the PSO algorithm as an optimizer was engaged by an appropriate ANN model as an EAM of direct FE model. Moreover, to improve the accuracy of damage severity detection a PSO cost function based on MSEBI was minimized. In order to assess the performance of this proposed solution procedure, two space structures were studied as representative of large-scale structures. Based on the numerical results, the following conclusions can be resulted:

1- The computational time of damage severity detection using PSO engaged by ANN model as an EAM of FE model is significantly reduced compared to using direct FE model based PSO (about one-twelfth). 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 large-scale structures.

2- In order to achieve an appropriate ANN model, a set of feed-forward artificial neural networks which are more suitable for non-linear approximation, are trained and tested by testing datasets. Results of ANNs' testing showed that the CFNN with log-sigmoid transfer function has the best performance among other selective neural networks.

3- In order to increase damage severity detection accuracy using PSO, a new objective function based on MSEBI was presented for PSO. The results showed the efficiency of damage severity detection besides contributing to a considerable reduction of computation cost using PSO with MSEBI based objective function engaged by CFNN as an updating model in optimization process.

4- MSEBI indicator which has been applied in both locating damage occurrence and constructing PSO cost function is extracted based on first five mode shapes of the studied structures. The results of location and severity detection show its efficiency in damage detection procedure.

5- In order to get real simulations by CFNN, and also to decrease efficiently required training data sets, to determine the optimum number of training and testing data sets for development of ANN model, CFNN has been trained and tested using different number of datasets. Finally, 300 training and testing datasets were chosen. Using LHS method for data generation and the specific ANN good performance in deal with incomplete datasets concretely leads to detect sufficient number of required training and testing datasets.

REFERENCES

1. Fan W, Qiao P. Vibration-based damage identification methods: a review and comparative study, *Struct Health Monit* 2011; **10**: 83-111.
2. Saadat S, Salichs J, Noori M, Hou Z, Davoodi H, Bar-On I, Suzuki Y, Masuda A. An overview of vibration and seismic applications of NiTi shape memory alloy, *Smart Mater Struct* 2002; **11**: 218.
3. Noori MN, Cao Y, Hou Z, Sharma S. Application of support vector machine for reliability assessment and structural health monitoring, *Int J Eng Under Uncer: Hazards, Assess Mitig* 2010; **2**(3-4): 89-98.
4. Fallahian S, Seyedpoor SM. A two stage method for structural damage inference system and particle swarm optimization, *Asian J Civil Eng* 2010; **11**: 795-808.
5. Naseralavi SS, Salajegheh J, Salajegheh E, Fadaee MJ. An improved genetic algorithm using sensitivity analysis and micro search for damage detection, *Asian J Civil Eng* 2010; **11**: 717-40.
6. Torkzadeh P, Goodarzi Y, Salajegheh E. A two-stage damage detection method for large-scale structures by kinetic and modal strain energies using heuristic particle swarm optimization, *Int J Optim Civil Eng* 2013; **3**: 465-82.
7. Bishop CM. *Pattern Recognition and Machine Learning*, Springer, New York, 2006.
8. Ihesiulor OK, Shankar K, Zhang Z, Ray T. Delamination detection with error and noise polluted natural frequencies using computational intelligence concepts, *Compos Part B: Eng* 2014; **56**: 906-25.
9. Naseralavi SS, Gerist S, Salajegheh E, Salajegheh J. Elaborate structural damage detection using an improved genetic algorithm and modal data, *Int J Struct Stability Dynamics* 2013; **13**(6).
10. Hornik K, Stinchcombe M, White H. Multilayer feedforward networks are universal approximators, *Neural networks* 1989; **2**: 359-66.
11. Gholizadeh S, Salajegheh E, Torkzadeh P. Structural optimization with frequency constraints by genetic algorithm using wavelet radial basis function neural network, *J Sound Vib* 2008; **312**: 316-31.
12. Hedayat A, Davilu H, Barfrosh AA, Sepanloo K. Estimation of research reactor core parameters using cascade feed forward artificial neural networks, *Prog Nucl Energy* 2009; **51**: 709-18.
13. Makas H, Yumusak N, Source AD. A comprehensive study on thyroid diagnosis by neural networks and swarm intelligence, electronics, *Computer and Computation (ICECCO), International Conference* 2013, pp. 180-83.
14. Hagan MT, Demuth HB, Beale MH. *Neural network Design*, Boston, 1996.
15. Paz M. *Structural Dynamics: Theory and Computation*, Springer, 1997.
16. Seyedpoor SM. A two-stage method for structural damage detection using a modal strain energy based index and particle swarm optimization, *Int J NonLinear Mech* 2012; **47**: 1-8.
17. Eberhart RC, Kennedy J. A new optimizer using particle swarm theory, *Proceedings 0f the Sixth International Symposium on Micro Machine and Human Science* 1995, pp. 39-43.
18. Iman RL. *Latin Hypercube Sampling*, Wiley Online Library, 2008.

19. Cybenko G. Approximation by superpositions of a sigmoidal function, *Math Control signals Syst* 1989; **2**: 303-14.
20. Coates A, Ng AY, Lee H. An analysis of single-layer networks in unsupervised feature learning, *International Conference on Artificial Intelligence and Statistics* 2011, pp. 215-23.
21. Zhu S, He W. Progressive damage detection based on multi-scale wavelet finite element model: numerical study, *Comput Struct* 2013; **125**: 177-86.