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Truss structure damage identification using residual force vector and genetic algorithm

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Abstract. In this paper, damage detection has been introduced as an optimization problem and a two-step method has been proposed that can detect the location and severity of damage in truss structures precisely and reduce the volume of computations considerably. In the first step, using the residual force vector concept, the suspected damaged members are detected which will result in a reduction in the number of variables and hence a decrease in the search space dimensions. In the second step, the precise location and severity of damage in the members are identified using the genetic algorithm and the results of the first step. Considering the reduced search space, the algorithm can find the optimal points (i.e. the solution for the damage detection problem) with less computation cost. In this step, the Efficient Correlation Based Index (ECBI), that considers the structure's first few frequencies in both damaged and healthy states, is used as the objective function and some examples have been provided to check the efficiency of the proposed method; results have shown that the method is innovatively capable of detecting damage in truss structures.

Keywords: damage detection; residual force vector; genetic algorithm; optimization; modal frequency; mode shape

1. Introduction

Since damage in structures can cause irrecoverable consequences, much researches and efforts have been made to propose different efficient non-destructive detect methods. Among those, the vibration-based techniques, based on the variations of structural vibration properties, have attracted the attention of many researchers (Mesina *et al.* 1998, Fugate *et al.* 2001, Yam *et al.* 2003, Yan *et al.* 2007, Deraemaeker *et al.* 2008, Shih *et al.* 2009, Nicknam and Hosseini 2012). The main idea of the Vibration-Based Damage Detection (VBDD) methods is based on the fact that the damage reduces the structure stiffness and hence causes some changes in its vibration properties. Mathematically, damage detection is an indeterminate, nonlinear problem for which different methods have been proposed.

Optimization search algorithms are the robust tools that are attractive for many researchers for solving engineering problems. (Kang *et al.* 2013a,b, Dizangian and Ghasemi 2015a,b, Ghasemi and Varaee 2016a,b, Camp and Farshchin 2014, Stolpe 2016, Artar 2016, Gholizadeh *et al*. 2017, Nobahari et al. 2017)

For solving a structural damage identification problem, a very widely used method is to convert it to an optimization problem wherein the variables are the extents of damage to the structural members.

Hao and Xia (2002) employed a genetic algorithm with real number encoding to detect the structural damages. They considered three different criteria; the frequency changes, the mode shape changes and their combination in their study. Perera and Torres (2006) used genetic algorithm for structural damage identification. They considered the changes in frequencies and mode shapes of the structure. Sandesh and Shankar (2010) proposed a novel search algorithm, a hybrid of particle swarm optimization method and genetic algorithm. They benefited from this algorithm for multiple damages identification in a thin plate. A hybrid real-coded Genetic Algorithm with damage penalization was implemented by Meruane and Heylen (2011) to identify the structural damage location and severity. Kang *et al.* (2012) combined particle swarm optimization with an artificial immune system to assess the structural damages. They utilized natural frequencies and mode shapes to form the objective function.

Although many researches have revealed the power and capability of optimization search algorithms in detecting damage in structures, they all have a common big problem; they need a massive computational volume to detect the damage, intensifying considerably with an increase in the number of members. Different methods have been proposed to reduce the computation volume; one of which is the two-step technique. In the first step, the undamaged members are eliminated and hence the problem variables are reduced causing a reduction in the dimensions of the search space. In the second step, the optimization algorithm faces a problem with much fewer variables compared with the initial problem; causing relatively a less computational volume. This technique has attracted the attention of many researchers.

Various two-stage methods for damage detections were carried out by researchers, details of which are introduced

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here. A two-stage method was presented by Gue and Li (2009) to determine the location and extent of multiple structural damages by using information fusion technique and genetic algorithm. Yun *et al.* (2009) having utilized subset selection and genetic algorithm, proposed a two-stage structural damage detection. In the first stage they used subset selection to locate multiple damages. In the second stage, the extents of the damaged members were quantified by applying genetic algorithm. Another two-stage damage assessment approach was proposed by Cury *et al.* (2011). The first stage focused on structural damage location determination by means of the strain energy deviation between damaged and undamaged structural vibration modes. In the second stage damage quantification developed through the analysis of measured natural frequencies of damaged structure and its corresponding intact numerical model. Jiang *et al.* (2011) used fuzzy neural networks (FNNs) and data fusion techniques and proposed a two-stage structural damage identification method. Having employed PSO and modal strain energy concept, Seyepoor (2012) proposed a two-stage method for structural multiple damage identification. In the first stage, he introduced a modal strain energy based index to determine the suspected members to damage. In the second stage, by using the results of the first stage, the damage severity was determined using a particle swarm optimization technique. Xiang and Liang (2012) proposed a two-stage method for multiple damage assessment in thin plates. In the first stage they focused on damage location detection by applying the 2-D wavelet transform to the modal shape. The damage extents at the identified locations were then determined in the second stage using a particle swarm optimization (PSO) algorithm.

This paper proposes a different two-stage damage identification method for truss structures. In the first stage, a residual force vector based index (RFVBI) is introduced to determine the most probable damaged members. In the second stage to evaluate the damage severity of the truss members, the damage assessment problem is defined as an optimization problem where the damage severity for the spotted members from the first stage, are the variables for optimization. A genetic algorithm is employed to solve this optimization problem. Finally, three numerical examples are considered to investigate the efficiency and robustness of the proposed method.

2. Damage simulation

The existence of damage in a member reduces its stiffness and can be simulated in the form of a reduction in such parameters as the elasticity modulus, moment of inertia, and cross sectional area. In this paper, the damage is defined as the reduction in the elasticity modulus a

$$x_i = \frac{E - E_i}{E} \tag{1}$$

Where E and E_i are the i^{th} member's moduli of elasticity in correspondingly healthy and damaged states and x_i is the damage variable varying between "zero" and "one"; it is "zero" if the member is fully healthy and "one" if it is completely damaged. The i^{th} member stiffness matrix after it is damaged is found as follows

$$K_i^d = (1 - x_i)K_i^h \tag{2}$$

where K_i^h and K_i^d are the stiffness matrices of the i^{th} member in respectively healthy and damaged states. It is worth mentioning that the variations in the mass matrix have been neglected in the present research.

3. Defining damage detection in the form of an optimization problem

As mentioned earlier, damage in a member results in a decrease in its stiffness and the variations in the stiffness matrix of a structure causes variations in some such parameters as the structure's modal frequencies. Inverse damage detection methods can precisely detect the location and severity of damage by comparing the structure's pre- and post-damage responses using optimization search algorithms to find a set of damage variables that minimize or maximize a correlation index between the structure's pre- and post-damage responses. Therefore, damage detection can be stated as an optimization problem as follows

$$\begin{aligned} &Find \quad X^T = \{x_1, x_2, \ldots, x_{ne}\} \\ &to\ Optimize\ ObjectiveFunction(X) \\ &Subject\ to: \quad X^l \le X \le X^u \end{aligned} \tag{2}$$

where X is the damage variables vector and ne is the number of members in the structure. Many objective functions have been proposed for such an optimization problem among which the effective correlation index proposed by Nobahari and Seyedpoor (2011) used here. It states that

$$ECBI(X) = \frac{1}{2}\left[\frac{|\Delta F^T.\delta F(X)|^2}{(\Delta F^T.\Delta F)(\Delta F^T.\delta F(X))} + \frac{1}{nf}\sum_{i=1}^{nf}\frac{\min(f_i(X), fd_i)}{\max(f_i(X), fd_i)}\right] \tag{4}$$

where ΔF can be defined as follows

$$\Delta F = \frac{F_h - F_d}{F_h} \tag{5}$$

Here, the F_h and F_d are the frequencies of the healthy and damaged structures, respectively. fd_i and $f_i(X)$ are the i^{th} modal frequencies of the damaged structure and the analytical model, respectively. $\delta F(x)$ is the change in the natural frequency vector of the structure resulted from an analytical model as compared to the natural frequency of the healthy structure, expressed as

$$\delta F(X) = \frac{F_h - F(X)}{F_h} \tag{6}$$

It is worth mentioning that the first nf frequencies of the structure have been considered for damage detection. ECBI ranges from 0 to 1; 1 means that frequency vectors found from the analytical model conform rather well to the natural frequencies of the damaged structure; therefore, the values of the damage variables are indications of the location and severity of damage occurred in the structure.

4. Detecting damage using the residual force vector

The residual force vector was widely used by many researchers on structural damage identification. Chen and Garba (1998) proposed a method for structural damage assessment using the minimum norm solution of the residual force equation. Zimmerman and Kaouk (1994) proposed a two-step damage identification, in the first step of which they focused on damage localization using residual force vector. Chiang and Lai (1999) used residual force vector to localize damages in their proposed damage detection method. Using the residual force vector, the node residual force vector is defined to determine the suspected damaged members preliminarily by Yang and Liu (2007). For damage assessment in shear frames, Amiri *et al.* (2013) proposed two approaches, one of which was the residual force vector. Seyedpoor and Montazer (2016) proposed modal residual vector based indicator (MRVBI) to determine most probable damaged members.

In this section, using the residual force vector concept, a method is proposed for the detection of the damage-suspected members in truss structures. Neglecting the variations in the mass matrix of the structure due to damage, the eigenvalue equation for an n-degree freedom damaged structure is as follows:

$$\left(K^d - w_{dj}^2 M\right)\varphi_{dj} = 0 \qquad (7)$$

where w_{dj} and φ_{dj} are the frequency and mode shape vector of the j^{th} mode of the damaged structure, M is the mass matrix and K^d is its stiffness matrix as follows

$$K^d = \sum_{i=1}^{ne} K_i^d \qquad (8)$$

where K_i^d is the stiffness matrix of the i^{th} member of the damaged structure in the global coordinate. Substituting relations 2 and 8 in relation 7, we will have

$$R_j = \left(K^h - w_{dj}^2 M\right)\varphi_{dj} = \sum_{i=1}^{ne} x_i K_i^h \varphi_{dj} \qquad (9)$$

Where K^h is the stiffness matrix of the healthy structure and K_i^h is the stiffness matrix of i^{th} member in healthy state. It is notable that K_i^h is in the global coordinate and the dimension of K^h and K_i^h are similar. Rj is the residual force vector related to the j^{th} mode. As explained before, x_i is the damage variable of the i^{th} member and equals to 0 if the member is healthy. Therefore, only those components of the Rj vector are nonzero that are related to the nodal degree of freedom of the damaged members; hence, the sign of the components of the Rj vector will not be important. If the first nm modes of the structure are used, we can find ASR parameter by adding the absolute values of the Rj for all modes as follows

$$ASR = \sum_{j=1}^{nm} |R_j| \qquad (10)$$

Thus, ASR is an $n\times 1$ vector where n is the number of degrees of freedom of the structure. Using the values of the components of the ASR vector and considering the way members place to one another, we can determine the damage-suspected members as follows.

Suppose AB is a member of a 3D truss structure between nodes A and B. If the values of the ASR vector related to the DOF of these nodes are shown as ASR^A and ASR^B, we will have

$$ASR^A = \left\{ASR_x^A, ASR_y^A, ASR_z^A\right\}^T$$
$$ASR^B = \left\{ASR_x^B, ASR_y^B, ASR_z^B\right\}^T \qquad (11)$$

where superscript T is the vector transpose. It is worth noting that if one end of the member is connected to the support and is restrained, the ASR value of that restrained degree of freedom is not calculable and it is conservatively assumed equal to the ASR of the corresponding DOF of the other node of the member. If the absolute values of the cosines of the angles between member AB and the global coordinate axes x, y, and z are shown as C_x^{AB}, C_y^{AB} and C_z^{AB}, then RFV_{AB} will be determined as follows

$$RFV_{AB} = C_x^{AB}.ASR_x^A.ASR_x^B + C_y^{AB}.ASR_y^A.ASR_y^B + C_z^{AB}.ASR_z^A.ASR_z^B \qquad (12)$$

If AB is a damaged member, then both ASR^A and ASR^B vectors should have nonzero corresponding components. In such case, the RFV will have a positive value for a damaged member. Now, the damage index of the truss member AB is defined as follows

$$RFVI_{AB} = \frac{RFV_{AB}}{\mathrm{RFV}_{A,B}^{max}} \qquad (13)$$

where $RFV_{A,B}^{max}$ is the maximum RFV relative to the members entering nodes A and B. If this index is positive, the member is probably damaged or else, it is definitely healthy; in other words, the members with RFVBI = 0 are definitely healthy and can be excluded from other members, considered now as variables, to reduce size of the optimization problem.

Considering the noise measurement, the value of $RFVI$ may be positive for all members. To avoid determination of the healthy members as damaged members, a minimum $RFVI$ ($RFVI_{min}$) is defined as a boundary between damaged and undamaged states.

$$RFVI_{min} = \mu + \alpha\sigma \qquad (14)$$

Where μ and σ represent the average and standard deviation of the vector of $\{RFVI^i | i=1:ne\}$ respectively, and α is a coefficient between 0 and 1. Next, the proposed method will be assessed by attempting some numerical examples.

5. Numerical examples

In this section, 3 examples have been provided to check the efficiency and versatility of the proposed method. Example 1 is a 31-member planar truss with 25 degrees of freedom, example 2 is a 47-member planar truss with 41 degrees of freedom, and example 3 is a 52-member dome-shaped 3D truss problem with 39 degrees of freedom. The maximum stiffness reduction allowed here to a member in all examples is assumed to be 50%. This obviously does not indicate a 50% damage of the member. The number of population and the probabilities of the crossover and mutation operators are assumed to be 20, 1, and 0.005, respectively. The crossover operator used in the GA is of the uniform type. In the first two examples, the noise measurement is not considered, but the last example is studied for both noisy and free noise measurement.

5.1 The 31-member 2D truss

The31-member planar truss (Messina *et al.* 1998) used as the first example (Fig. 1) had equal member cross sectional areas. The elasticity modulus and density for the materials used were assumed to be 2e5MPa and 7850 kg/ m^3 respectively. Three damage scenarios (Table 1) were studied for this truss.

In the first step, the members suspected to damage (Table 2) were obtained using the proposed RFVBI. Considering those results, one realizes that the proposed index could detect the damaged members with only the data gained from the first mode. Thus, considering more modes will not affect the final answer.

Table 1 Three different damage scenarios set for the 31 member planar truss problem

Scenario 1		Scenario 2		Scenario 3	
Member No	Damage percentage	Member No	Damage percentage	Member No	Damage percentage
11	25	16	30	1	30
25	15			2	20

Table 2 Most probable damaged members predicted in the first stage; the 31

Damage scenario	Suspected members to damage		
	1 mode	4 modes	8 modes
Scenario1	11,25	11,25	11,25
Scenario2	16	16	16
Scenario 3	1,2,4	1,2,4	1,2,4

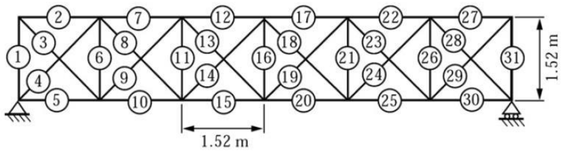

Fig. 1 The 31-member planar truss

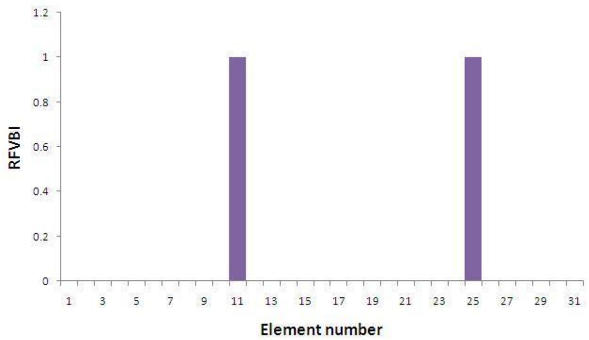

Fig. 2 RFVBI values for scenario 1 for the 31-member planar truss, considering first 6 modes

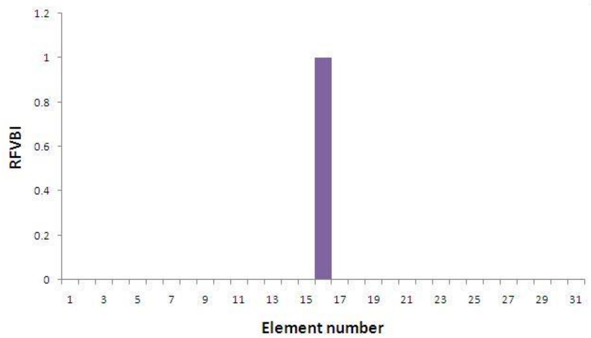

Fig. 3 RFVBI values for scenario 2 for the 31-member planar truss, considering first 6 modes

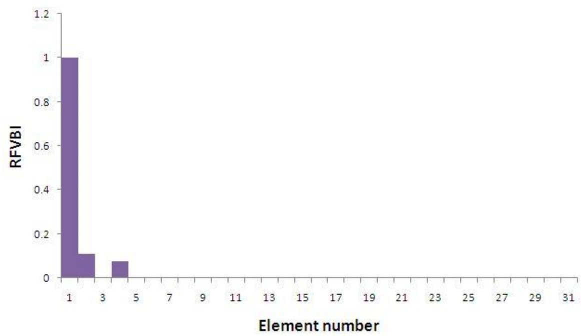

Fig. 4 RFVBI values for scenario 3 for the 31-member planar truss, considering first 6 modes

The RFVBI values of the truss members under different damage scenarios for the first 6 modes are shown in Figs. 2-4.

Table 3 The severity of found damaged members (11 and 25), for the 31-bar truss problem in scenario1

Run No	% severity of found damaged members		Required generations	No. of analyses carried
	11	25		
1	25	15	2	40
2	25	15	2	40
3	25	15	5	100
4	25	15	4	80
5	25	15	2	40
6	25	15	1	20
7	25	15	5	100
8	25	15	3	60
9	25	15	7	140
10	25	15	2	40
Average damage	25	15	3.3	66
Actual damage	25	15		

Table 4 The severity of found damaged members (only 16), for the 31-bar truss problem in scenario 2

Run No	% severity of found damaged members	Required generations	No. of analyses carried
	16		
1	30	1	20
2	30	1	20
3	30	1	20
4	30	2	40
5	30	1	20
6	30	2	40
7	30	1	20
8	30	1	20
9	30	1	20
10	30	2	40
Average damage	30	1.3	26
Actual damage	30		

Table 5 The severity of found damaged members (1 and 2), for the 31-bar truss problem in scenario3

Run No	% severity of found damaged members			Required generations	No. of analyses carried
	1	2	4		
1	30	20	0	8	160
2	30	20	0	6	120
3	30	20	0	7	140
4	30	20	0	8	160
5	30	20	0	11	220
6	30	20	0	3	60
7	30	20	0	9	180
8	30	20	0	10	200
9	30	20	0	3	60
10	30	20	0	9	180
Average damage	30	20	0	7.4	148
Actual damage	30	20	0		

Table 6 The results of the one-step method obtained by GA for 31-member planar truss

Damage scenario	% severity of found damaged members					Required generations	No. of analyses carried
	1	2	11	16	25		
Scenario1	0	0	28	0	18	445.5	8910
Scenario2	0	0	0	30	0	159	3180
Scenario3	30	20	0	0	0	332.5	6650

As shown, the proposed RFVBI has been able to detect the damaged members with high precision. Next, GA was used for the precise determination of the severity of the damage only on the suspected damaged members from the previous stage. Considering the stochastic nature of GA, each example was run 10 times, all results of which are shown in Tables 3-5 along with the total number of the analyses required at each run.

It is to be noted that GA is only involved in determining the damaged severity of those members suspected to damage from stage one.

To evaluate the capability of the proposed method in reducing the computational effort in structural damage identification, the average output for 10 independent runs using GA in a one-stage approach are shown in Table 6 for all damage scenarios.

5.2 The 47-member planar truss

The second example dealt with in this paper (Fig. 5) was a 47-member planar truss (Shirazi *et al*. 2014) which had equal cross sectional area members and the elasticity modulus and density of the materials used were assumed to be 2.1e5MPa and 8303 Kg/m^3 respectively. In this example, 4 different damage scenarios (Table 7) were studied.

In the first step, the damage suspected members (Table 8) were determined using the proposed RFVBI. In this example too, it can be observed that the proposed index can determine the damage-suspected members with the information of even one mode and considering more modes will not affect the final answer.

In the first 3 scenarios, not only the damaged members were detected correctly, but also there were no healthy members among the damaged ones. In the 4^{th} scenario, although there were 4 healthy members among the suspected ones, both the damaged members were detected as the suspected ones by the information of only the first mode. The RFVBI values of the truss members under different damage scenarios for the first 6 modes are shown in the diagrams of Figs. 6-9.

Next, GA was used for the precise determination of the location and severity of the damage after the suspected members were determined and the damage variables were considerably reduced. Considering the stochastic nature of GA, each example was run 10 times the results of all of which are shown in Tables 9-12 along with the number of the required analyses.

Table 7 Four different damage scenarios set for the 47-member planar truss problem

Scenario1		Scenario2		Scenario3		Scenario4	
Member No	Damage percentage	Member No	Damage percentage	Member No	Damage percentage	Member No	Damage percentage
10	30	30	30	10	30	40	30
-	-	-	-	30	30	41	20

Table 8 Most probable damaged members predicted in the first stage; the 47-member planar truss problem

Damage scenario	Suspected members to damage		
	1 mode	4 modes	6 modes
Scenario1	10	10	10
Scenario2	30	30	30
Scenario 3	10,30	10,30	10,30
Scenario 4	40,41,44,45,46,47	40,41,44,45,46,47	40,41,44,45,46,47

Table 9 The severity of found damaged members (only 10), for the 47-bar truss problem in scenario 1

Run No	% severity of found damaged members	Required generations	No. of analyses carried
	10		
1	30	1	20
2	30	1	20
3	30	1	20
4	30	1	20
5	30	1	20
6	30	1	20
7	30	1	20
8	30	1	20
9	30	1	20
10	30	1	20
Average damage	30	1	20
Actual damage	30		

Table 10 The severity of found damaged members (only 30), for the 47-bar truss problem in scenario 2

Run No	% severity of found damaged members	Required generations	No. of analyses carried
	30		
1	30	1	20
2	30	1	20
3	30	1	20
4	30	1	20
5	30	1	20
6	30	1	20
7	30	1	20
8	30	1	20
9	30	1	20
10	30	1	20
Average damage	30	1	20
Actual damage	30		

Table 11 The severity of found damaged members (10 and 30), for the 47-bar truss problem in scenario 3

Run No	% severity of found damaged members		Required generations	No. of analyses carried
	10	30		
1	30	30	3	60
2	30	30	1	20
3	30	30	4	80
4	30	30	2	40
5	30	30	1	20
6	30	30	5	100
7	30	30	1	20
8	30	30	5	100
9	30	30	5	100
10	30	30	2	40
Average damage	30	30	2.9	58
Actual damage	30	30		

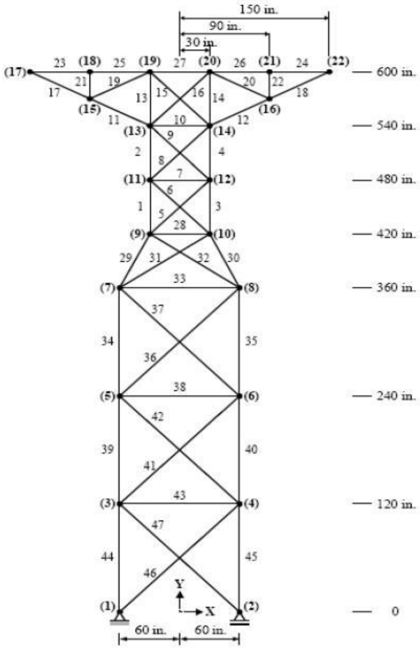

Fig. 5 The 47-member planar truss

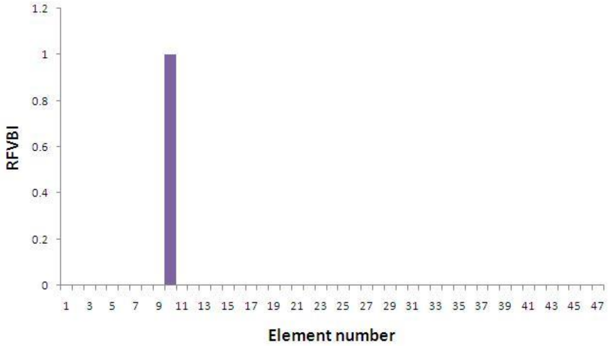

Fig. 6 RFVBI values for scenario 1 for the 47-member planar truss, considering first 6 modes

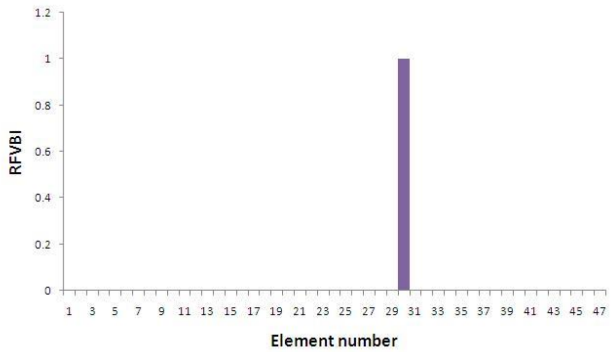

Fig. 7 RFVBI values for scenario 2 for the 47-member planar truss, considering first 6 modes

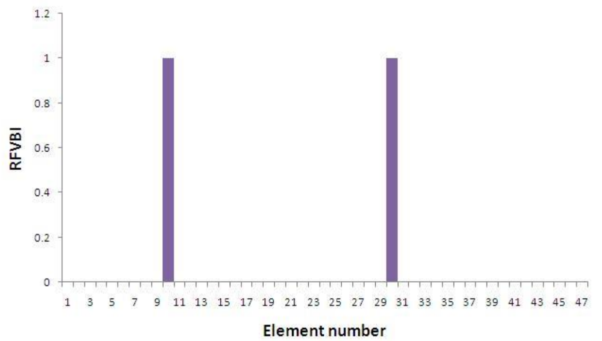

Fig. 8 RFVBI values for scenario 3 for the 47-member planar truss, considering first 6 modes

In this example, the results of the single step structural damage identification, obtained by GA, are shown in Table13.These are average results obtained by 10 independent runs of GA for each damage scenario.

Table 12 The severity of found damaged members (40 and 41), for the 47-bar truss problem in scenario 4

Run No	% severity of found damaged members						Required generations	No. of analyses carried
	40	41	44	45	46	47		
1	30	20	0	0	0	0	3	60
2	30	20	0	0	0	0	1	20
3	30	20	0	0	0	0	4	80
4	30	20	0	0	0	0	2	40
5	30	20	0	0	0	0	1	20
6	30	20	0	0	0	0	5	100
7	30	20	0	0	0	0	1	20
8	30	20	0	0	0	0	5	100
9	30	20	0	0	0	0	5	100
10	30	20	0	0	0	0	2	40
Average damage	30	20	0	0	0	0	2.9	58
Actual damage	30	20	0	0	0	0		

Table 13 The results of the one-step method obtained by GA for 47-member planar truss

Damage scenario	% severity of found damaged members									Required generations	No. of analyses carried
	9	10	11	30	32	35	40	41	46		
Scenario1	2	29.5	1.5	0	0	0	0	0	0	530	10060
Scenario2	0	0	0	28.5	0	2	0	0	0	670	13400
Scenario3	0	25.5	0.5	35	1	0	0	0	0	923	18460
Scenario4	0	0	0	0	0	0	35	20	0.5	812.3	16246

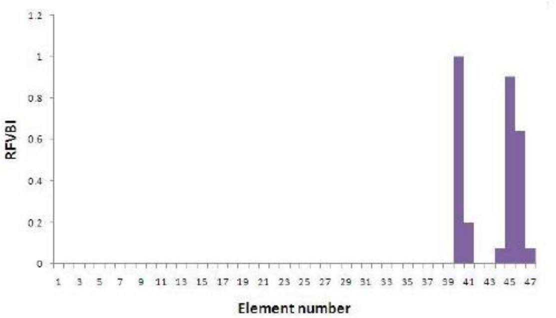

Fig 9 RFVBI values for scenario 4 for the 47-member planar truss, considering first 6 modes

5.3 The 52-member 3D truss

The 52-member steel dome structure (Naseralavi et al. 2012) (Fig. 10) was used in the third and last example. All the members had equal cross sectional areas and the modulus of elasticity and density of the consumed materials were 2e5MPa and 7850 kg/m^3. Two damage scenarios (Table 14) were considered for this truss. This example is studied in two cases of noise free and noisy measurement data.

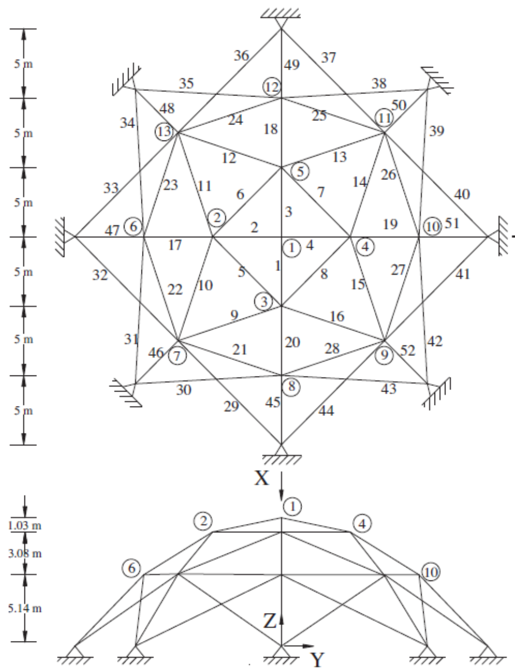

Fig. 10 The 52-member spatial truss

Table 14 Two different damage scenarios set for the 52-member spatial truss problem

Scenario 1		Scenario 2	
Member No	Damage percentage	Member no	Damage percentage
8	25	5	10
33	15	6	35

Table 15 Most probable damaged members predicted in the first stage; the 52-member spatial truss problem

Damage scenario	Suspected members to damage		
	1 mode	4 modes	6 modes
Scenario1	8,33,36,48	8,33,36,48	8,33,36,48
Scenario2	5,6	5,6	5,6

Table 16 The severity of found damaged members (8 and 33), for the 52-bar truss problem in scenario 1

Run No	% severity of found damaged members				Required generations	No. of analyses carried
	8	33	36	48		
1	25	15	0	0	34	680
2	25	15	0	0	28	560
3	25	15	0	0	72	1440
4	25	15	0	0	59	1180
5	25	15	0	0	47	940
6	25	15	0	0	71	1420
7	25	15	0	0	29	580
8	25	15	0	0	16	320
9	25	15	0	0	48	960
10	25	15	0	0	43	860
Average damage	25	15	0	0	44.7	894
Actual damage	25	15	0	0		

Table 17 The severity of found damaged members (5 and 6), for the 52-bar truss problem in scenario 2

Run No	% severity of found damaged members		Required generations	No. of analyses carried
	5	**6**		
1	10	35	3	60
2	10	35	1	20
3	10	35	4	80
4	10	35	2	40
5	10	35	1	20
6	10	35	1	20
7	10	35	3	60
8	10	35	1	20
9	10	35	5	100
10	10	35	4	80
Average damage	10	35	2.5	50
Actual damage	10	35		

Results of the first step without considering measurement noise are provided in Table 15. As shown, the proposed index has been able to detect the damaged members of the truss structure with the information of only the first mode. The RFVBI values of the truss members under different damage scenarios for the first 6 modes are shown in the diagrams of Figs. 11 and 12 and the final GA results of the detection of the location and extent of damage are provided in Tables 16 and 17.

As the second sub-problem, considering noise measurement for each damage scenario, results of 10 independents runs as the first stage are shown in Tables 19 and 21. The mean values of *RFVBI* for various damage scenarios can be seen in Figs 13 and 14. The values of $RFVI_{min}$ are shown as a red line in these Figs. The 6 first modes data in this example are utilized for damage assessment and α is selected as 0.2. In this example the noise measurement is considered by a standard error 0.2% for modal frequencies and 3% for mode shapes.

The results of the first stage exhibit that the proposed method could determine damaged members satisfactorily. According to Fig. 13 the proposed method could determine 68% of healthy members in the first scenario and condense the members suspected to damage from 52 to 18.

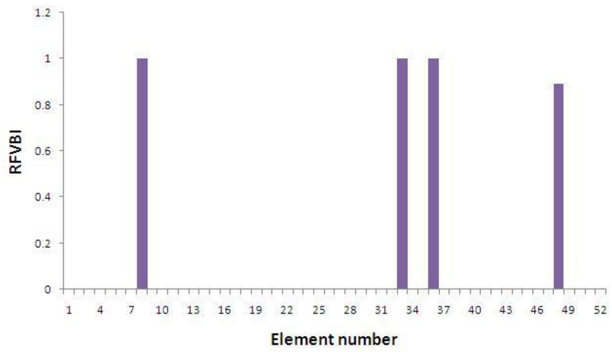

Fig. 11 RFVBI values for scenario 1 for the 52-member spatial truss, considering first 6 modes

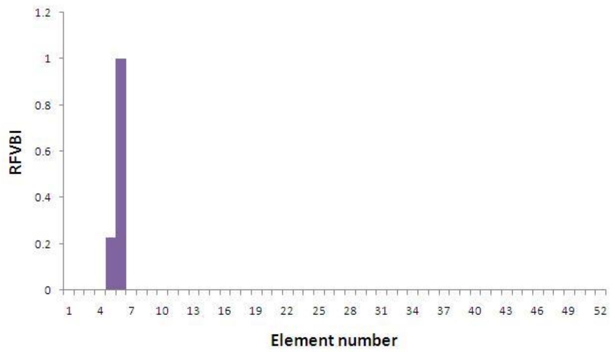

Fig. 12 RFVBI values for scenario 2 for the 52-member spatial truss, considering first 6 modes

Table 18 The results of the one-step method obtained by GA for the 52-member spatial truss

Damage scenario	% severity of found damaged members								Required generations	No. of analyses carried
	3	4	5	6	7	8	33	36		
Scenario1	0	0	0	0.5	1	27	12	1.5	923	18460
Scenario2	1.5	1	10	32	0.5	0	0	0	670	13400

Table 19 Most probable damaged members predicted in the first stage; the 52-member spatial truss problem considering measurement noise for scenario1

Run No.	Suspected members to damage
1	1,2,3,4,5,7,8,12,17,18,20,33,36,48,49
2	1,3,4,5,7,8,11,17,18,33,36,47,49
3	1,3,4,5,7,8,9,18,20,33,36,47,48
4	1,2,3,4,5,6,7,8,11,18,20,33,36,48,49
5	1,3,4,5,8,11,12,17,19,33,36,49
6	1,3,4,5,6,7,8,11,12,17,18,33,36,48,49
7	1,3,5,6,8,17,18,33,36,48,49
8	1,3,4,5,7,8,17,18,33,36,47,48,49
9	1,2,3,4,5,6,8,11,17,18,20,33,47,48,49
10	1,3,4,5,6,7,8,17,18,20,33,36,48,49

Table 20 The severity of found damaged members (8 and 33), for the 52-bar truss problem in scenario 1 considering noise measurement

Run No	% severity of found damaged members																			
	1	2	3	4	5	6	7	8	9	11	12	17	18	19	20	33	36	47	48	49
1	0	0	5	0	0	-	5	30	-	-	5	0	0	-	0	15	5	-	0	5
2	0	-	0	0	0	-	5	25	-	0	-	0	0	-	-	20	5	0	-	0
3	0	-	5	0	0	-	0	30	0	-	-	-	5	-	0	15	0	0	0	-
4	0	0	0	0	0	0	0	30	-	0	-	-	5	-	0	10	0	-	0	0
5	0	-	5	0	5	-	-	25	-	5	0	0	-	0	-	15	5	-	-	0
6	0	-	0	0	0	5	5	20	-	0	0	5	5	-	-	15	0	-	0	5
7	0	-	0	-	0	0	-	25	-	-	-	0	0	-	-	20	0	-	0	0
8	0	-	5	0	5	-	5	30	-	-	-	5	5	-	-	15	5	0	0	5
9	0	0	0	0	0	5	-	25	-	5	-	0	5	-	0	20	-	5	0	0
10	0	-	5	0	0	0	5	30	-	-	-	0	5	-	0	15	5	-	0	0
Average	0	0	2.5	0	1	1	2.5	26.5	0	1	0.5	1	3	0	0	15.5	2.5	0.5	0	1.5

In the second scenario, according to Fig. 14, the proposed method could predict 82% of healthy members correctly and thus condense the members suspected to damage from 52 to 11. Tables 20 and 22 present the final results of damage detection due to10 times independent runs for each damage scenario.

The convergence histories of the 52-member truss considering measurement noise are shown in Figs 15 and 16. Although achieving the target value of ECBI (1) by considering measurement noise is very difficult, if not impossible, according to diagrams shown in Figs 15 and 16, the proposed method could achieve 0.98 after approximately 400 generations in the first scenario and approximately 300 generations in the second scenario.

Table 21 Most probable damaged members predicted in the first stage; the 52-member spatial truss problem considering measurement noise for scenario2

Run No	Suspected members to damage
1	1,2,3,5,6,7,11,12,17,18,49
2	1,2,3,5,6,7,11,12,17,18,47,49
3	2,3,5,6,7,11,18,47
4	1,2,3,4,5,6,7,10,17,18
5	1,2,3,5,6,7,11,12,17,49
6	2,3,5,6,7,17,18,47,49
7	2,3,4,5,6,7,11,12,17,48,49
8	1,2,3,5,6,7,11,18,48,49
9	2,3,4,5,6,17,18,49
10	2,3,5,6,7,11,17,18,47,49

Table 22 The severity of found damaged members (5 and 6), for the 52-bar truss problem in scenario 2 considering noise measurement

Run No	% severity of found damaged members														
	1	2	3	4	5	6	7	10	11	12	17	18	47	48	49
1	0	0	5	-	15	30	0	-	0	0	5	0	-	-	5
2	0	5	5	-	10	30	0	-	5	0	0	0	0	-	0
3	-	0	5	-	10	30	0	-	0	-	-	5	0	-	-
4	0	0	0	5	15	30	0	0	-	-	5	0	-	-	-
5	5	5	0	-	10	25	0	-	5	0	0	-	-	-	5
6	-	0	0	-	15	30	10	-	-	-	0	0	0	-	0
7	-	0	5	5	15	25	0	-	5	0	0	-	-	5	0
8	5	0	0	0	10	30	5	-	5	-	-	0	-	5	0
9	-	0	5	0	15	30	-	-	-	-	0	5	-	-	5
10	-	0	0	-	15	30	0	-	5	-	0	5	0	-	0
Average	1	1	2.5	1	13	29	1.5	0	2.5	0	1	1.5	0	1	1.5

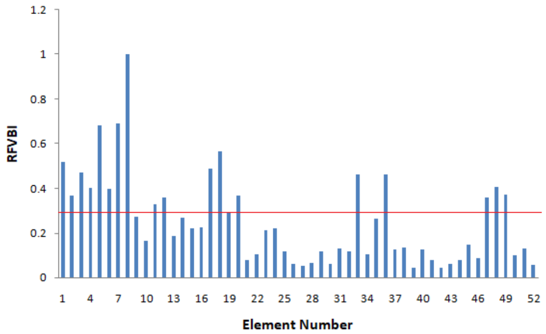

Fig. 13 RFVBI values for scenario 1 for the 52-member spatial truss, considering measurement noise

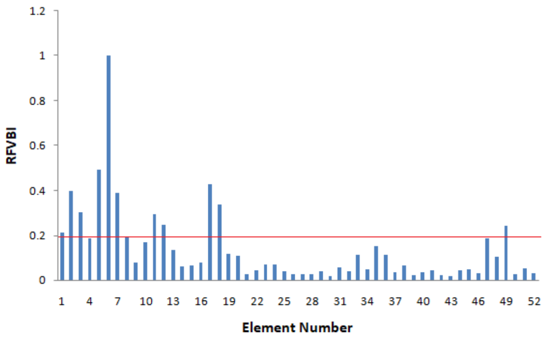

Fig. 14 RFVBI values for scenario 1 for the 52-member spatial truss, considering measurement noise

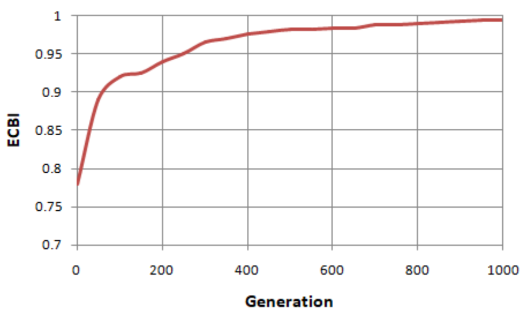

Fig. 15 Convergence history of 52-bar spatial truss for scenario 1 considering measurement noise

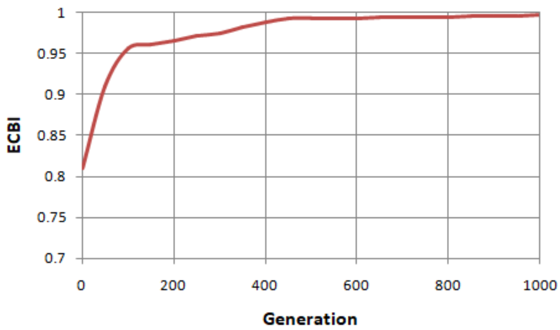

Fig. 16 Convergence history of 52-bar spatial truss for scenario 2 considering measurement noise

6. Conclusions

In this paper, a 2-step method has been proposed to enhance the precision and reduce the volume of the computations required in the solution of the problems that use optimization algorithms to detect damage in truss members. As the first step, the members suspected to damage are determined to be considered as the only variables suspected to damage for the next step. To do this, an index (called RFVBI) has been proposed using the residual force vector concept, as a result of which the suspected members to damage will be found. As the second step then, the severity of the damage for each member will be computed using the Genetic Algorithm (GA). To check the efficiency and precision of the proposed method, three examples were studied. The results showed that RFVBI is capable of detecting the damage location using the information of only the first mode; this is an advantage hard to overlook. Final results revealed that the proposed method is capable of detecting the damage location and severity with a significant limited volume of computations.

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