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Multi-stage approach for structural damage identification using particle swarm optimization

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Abstract. An efficient methodology using static test data and changes in natural frequencies is proposed to identify the damages in structural systems. The methodology consists of two main stages. In the first stage, the Damage Signal Match (DSM) technique is employed to quickly identify the most potentially damaged elements so as to reduce the number of the solution space (solution parameters). In the second stage, a particle swarm optimization (PSO) approach is presented to accurately determine the actual damage extents using the first stage results. One numerical case study by using a planar truss and one experimental case study by using a full-scale steel truss structure are used to verify the proposed hybrid method. The identification results show that the proposed methodology can identify the location and severity of damage with a reasonable level of accuracy, even when practical considerations limit the number of measurements to only a few for a complex structure.

Keywords: Particle Swarm Optimization (PSO); Damage Signal Match (DSM); truss; damage identification

1. Introduction

As civil infrastructure ages, the early detection of damage in a structure becomes increasingly important for both life safety and economic reasons, which is a vibrant area of current research in the civil engineering community. Structural damage generally produces changes in the static and dynamic characteristics of the structures, such as strain, deformation, as well as the inherent characteristics changes in frequencies, vibration modes, etc. In the past few decades, a lot of research has been dedicated to detect changes in the physical and/or geometric properties of a structure from data gathered at two different states, a reference state, considered as the undamaged state, and the current state. Changes can be caused by damage present in the structure. Recently, research efforts have been substantially expended in exploring the novel system identification techniques for damage detection (Hajela and Soeiro 1990, Viola and Bocchini 2011). A vast majority of the literature focus on laboratory tests and numerical simulations revealed numerous

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and diverse algorithms. The resulting literature was reviewed by Doebling *et al*. (1998), Sohn *et al*. (2003) and Peter and Fanning (2004).

These conventional damage identification methods may work satisfactorily when applied in laboratory or simulated environment, but theirs practical application still encounters some technical challenges, such as noise-contaminated measurements, incomplete model information and so on. The process of structural damage identification is commonly considered as an optimization problem in which an error measure that defines the discrepancy between computed and observed structural responses is minimized by updating a parameterized model (Hjelmstad and Shin 1997). Recently, some researchers tried to use heuristic intelligent optimization algorithms to tackle damage detection problems. These intelligent algorithms possess several advantageous features compared to many previous methods. One of the most important characteristics of computational intelligence methods is their effectiveness and robustness in coping with uncertainty, incomplete information, and noise. Several studies have applied intelligent optimization algorithms successfully in system identification and damage detection. Evolution strategy (ES) algorithms have been presented for the identification of multiple DOF systems (Franco *et al*. 2004). Tang *et al*. (2008) have applied a differential evolution (DE) strategy to parameter estimation of structural systems. Simulated annealing (SA) and genetic algorithm (GA) have been implemented for finite element model updating (Levin and Lieven 1998). The GA identification strategy was extended for structural damage detection whereby the undamaged state of the structure is first identified and used to direct the search for parameters of the damaged structure (Koh *et al*. 2003, Perry *et al*. 2006, Koh and Perry 2009). Mares and Surace (1996) used GA to adjust the structural parameters by minimizing the equation error (residual force) for locating and identifying structural damage from measured natural frequencies and mode shapes. Chou and Ghaboussi (2001) employed GA to identify damage severity of trusses by using a small number of measured static displacements. Ostachowicz *et al*. (2002) utilized GA to identify the location and magnitude of an added concentrated mass on a simulated rectangular plate by using the shifts in the first four natural frequencies. Raich and Liszkai (2007) used GA to identify location and severity of structural damage by minimizing the error between measured and analytically computed frequency response functions obtained through finite element model updating. Chiang and Lai (1999), Moslem and Nafaspour (2002) and Guo and Li (2009) described a two-stage process where the residual force vector is used to locate the damage initially and then in a second stage, a GA is used to quantify the damage in the identified elements. Srinivas *et al*. (2010) presented a damage detection scheme using modal strain energy and GA to assess the location and extent of damage.

As a novel evolutionary computation technique, the particle swarm optimization (PSO) algorithm (Eberhart and Kennedy 1995, Kennedy and Eberhart 1995) has attracted much attention, owing to its simple concept, easy implementation and quick convergence. PSO has been successfully applied in many fields, such as function optimization, artificial neural network training, fuzzy system control, simulation and identification, structural reliability assessment, automatic target detection, optimal design and parameter estimation (Eberhart and Shi 2001, Kennedy *et al*. 2001, Hu *et al*. 2004, Elegbede 2005, Meissner *et al*. 2006, Liang *et al*. 2006, He and Wang 2007, Tang *et al*. 2007). Recently, many successful applications of damage detection using the PSO algorithm have been reported in the literature (Perera *et al*. 2010, Begambre and Laier 2009).

The particle swarm optimizer shares the ability of the genetic algorithm to handle arbitrary nonlinear cost functions, but with a much simpler implementation. Boeringer and Werner (2003) have investigated the performance of GA and PSO for a phased array synthesis problem. The results show that some optimization scenarios are better suited to one method versus the other, which implies that the two methods traverse the problem hyperspace differently. In another publication (Mouser and Dunn 2005), the authors compared the performance of GA and PSO for optimizing a structural dynamics model. The results show that PSO significantly outperformed GA. Also, PSO is much easier to configure than GA and is more likely to produce an acceptable model.

When damage identification is cast as an optimization problem, especially for the identification of large-scale structures, great challenges arise such as large search domains and lack of sufficient information from tests performed on the structure. A large search domain will lead to excessive computational cost. This is because we have to evaluate the objective function at each stage of generation for the total population, which makes the computation very intensive and might involve problems of convergence. In order to reduce the computational cost of the optimization process and improve the convergence, it is therefore natural to reduce the dimension of optimization problem by considering the most potentially damaged elements as the search domains, instead of the total ones. For this purpose, the PSO algorithm combined with the Damage Signal Match (DSM) technique (Lam *et al*. 1998, Wang *et al*. 2001) can be utilized as an effective tool.

Usually, the first few natural frequencies and static displacements can be obtained relatively accurately for structures. In this study, a multi-stage approach is adopted using the first-order approximation of changes in static deformation and natural frequencies to identify the damage in structures. The methodology consists of two main stages. In the first stage, the DSM technique is employed to quickly identify the most potentially damaged elements. In the second stage, these identified damaged elements are analyzed further for exact identification and quantification of the damage using PSO-based optimization approach. The effectiveness of the proposed methodology is illustrated by numerical simulation as well as experimental study of a full size steel truss, of which the incomplete static response and the natural frequencies are obtained experimentally. The numerical and experimental results demonstrate that the combination of the DSM technique and PSO can produce an efficient tool to identify the structural damages.

2. Formulation of damage identification as an optimization problem

For a linear structure, the mathematical model for the system can be described as

$$\boldsymbol{K}(\boldsymbol{\alpha})\boldsymbol{u} = \boldsymbol{f} \tag{1}$$

where $\boldsymbol{K}(\boldsymbol{\alpha})$ is the stiffness matrix of structure, defined as a function of a vector of damage parameters $\boldsymbol{\alpha}$, $\boldsymbol{u}$ is the displacement vector under the applied static load vector $\boldsymbol{f}$. The damaged stiffness, $\boldsymbol{k}_i^{*e}$, corresponding to element i in the structure, can be computed from the undamaged stiffness, $\boldsymbol{k}_i^e$, and the corresponding damage parameter, $\alpha_i (0 \le \alpha_i \le 1)$, as

$$\boldsymbol{k}_i^{*e} = (1 - \alpha_i)\boldsymbol{k}_i^e \tag{2}$$

The global stiffness matrix is assembled from individual element contributions as

$$\boldsymbol{K}(\boldsymbol{\alpha}) = \sum_{i=1}^{ne} \boldsymbol{A}_i \boldsymbol{k}_i^{*e} \boldsymbol{A}_i^T \tag{3}$$

where $\boldsymbol{A}_i$ is the stiffness connection matrix constructed using connectivity and geometrical data of structure corresponding to the ith element, ne is the total number of the elements.

The displacement vector $\boldsymbol{u}$ can be calculated using

$$\boldsymbol{u} = \boldsymbol{K}(\boldsymbol{\alpha})^{-1}\boldsymbol{f} \tag{4}$$

Pre-multiply Eq. (4) by a Boolean matrix $\boldsymbol{Q}$, the measured displacement $\boldsymbol{u}_m$ extract from complete vector $\boldsymbol{u}$ is as follows

$$\boldsymbol{u}_m = \boldsymbol{QK}(\boldsymbol{\alpha})^{-1}\boldsymbol{f} \tag{5}$$

where $\boldsymbol{u}_{\mathrm{m}}$ is a vector of measured displacement. Eq. (5) can be extended for multiple loading conditions as follows

$$\boldsymbol{u}_{mj} = \boldsymbol{QK}(\boldsymbol{\alpha})^{-1}\boldsymbol{f}_j\,,\ j=1,\ \ldots,\ nlc \tag{6}$$

where nlc is the total number of the loading cases. The number of unknown damage parameters is still unchanged, but the number of equations is increased. If the total numbers of measurements are equal to the number of unknown parameters, the solution of Eq. (6) is determined and gives the damage parameters. In real applications, not all the degrees of freedom in a structure are usually measured. This gives rise to situations in which the number of parameters to be identified is larger than the number of measurements, resulting in a large number of possible solutions. Therefore, instead of solving Eq. (6), an alternative is to formulate the identification problem as an optimization problem and seek the best fit solution for Eq. (6).

The unknown damage parameters $\boldsymbol{\alpha}$ are obtained by minimizing an objective function formulated by the error between the computed response and the measured displacements of multiple tests. The error function used in this article is defined as

$$E(\boldsymbol{\alpha}) = \frac{1}{nlc}\sum_{j=1}^{nlc}\left\|\frac{\boldsymbol{u}_{mj} - \boldsymbol{u}_{cj}}{\max(\boldsymbol{u}_{mj})}\right\| \tag{7}$$

where, nlc is the total number of the static load cases; $\boldsymbol{u}_{\mathrm{mj}}$ and $\boldsymbol{u}_{\mathrm{cj}}$ are the measured and computed displacement vectors of the structure at sensor locations under the same load $\boldsymbol{f}_j$, respectively. The difference between displacements should be normalized to get a better representation of the relative change in response. The maximum displacement of all sensors is selected as the normalization parameter to cancel out spurious effects of very small displacements.

The optimal damage parameters, $\boldsymbol{\alpha}$, are obtained by solving the following constrained nonlinear optimization problem

$$\begin{aligned}&\underset{\boldsymbol{\alpha}}{Min}\,E(\boldsymbol{\alpha})\\&s.t.\quad 0 \le \alpha_i \le 1,\quad i = 1,\cdots,ne\end{aligned} \tag{8}$$

It is worth pointing out that, if total elements were treated as possible damage on the structure, the number of possible damages would be very large. This gives rise to the situation in which the search space of the identification optimization problem Eq. (8) is very large, resulting in much greater computational costs and problems of convergence.

3. PSO-based two-stage structural damage identification method

3.1 Identification of damage location

The main problem of damage identification using the optimization approach is that it imposes much computational effort to the process. In order to reduce the computational cost of the optimization process, some useful techniques should be employed. In this study, the DSM technique (Lam *et al*. 1998, Wang *et al*. 2001) is adopted to reduce the dimension of the optimization problem by considering the most potentially damaged elements instead of the total ones.

Generally, the structural damage can cause changes in the stiffness matrix by an amount $\Delta\boldsymbol{K}$. As it is assumed that damage does not change the mass of the structure, the changes in the displacements and the natural frequencies $\Delta\omega_j^2$ due to the existing damage can be evaluated from the following first-order approximation, respectively

$$\Delta\boldsymbol{u} \approx \boldsymbol{K}^{-1}\Delta\boldsymbol{K}\boldsymbol{K}^{-1}\boldsymbol{f} \tag{9}$$

$$\Delta\omega_j^2 = \frac{\boldsymbol{\varphi}_j^T\Delta\boldsymbol{K}\boldsymbol{\varphi}_j}{\boldsymbol{\varphi}_j^T\boldsymbol{M}\boldsymbol{\varphi}_j} \tag{10}$$

where $\boldsymbol{K}$ is the stiffness matrix of structure, $\boldsymbol{M}$ is the mass matrix; ω_j is the *j*th order of circular natural frequency and $\boldsymbol{\varphi}_j$ is the *j*th mode shape of the structure.

In order to identify the damage locations, the idea of DSM technique is adopted (Lam *et al*. 1998): If the changes of the static or dynamic response for all possible damage cases are predicted using an analytical model, the measured response changes can be compared with them one by one. Then, the damage location can be assessed by matching the Measured Damage Signatures (MDS) with the Predicted Damage Signatures (PDS) for different possible damage cases. The ratio of changes in static responses vector to changes in natural frequencies is defined as the Damage Signature (DS). In the proposed method, the MDS of load case *i* is defined from Eqs. (9) and (10) as

$$\{MDS_i\} = \left.\frac{\Delta\boldsymbol{u}_i}{\Delta\boldsymbol{\omega}^2}\right|_m \tag{11}$$

where the subscript *m* denotes that the measured data are employed. The change in one of the first few order frequencies is generally used as the reference value, in practicing.

Similarly, the PDS under load case *i*, assume that element *k* is damaged, can be calculated from Eqs. (9) and (10) as

$$\{PDS_{ik}\} = \left.\frac{(\Delta\boldsymbol{u}_i)_k}{(\Delta\boldsymbol{\omega}^2)_k}\right|_p \tag{12}$$

where the subscript *p* denotes that the value is predicted analytically.

It should be noted that calculations of MDS and PDS in the abovementioned equations involve only the DOFs where measurements have been made. The unmeasured DOFs of the changes of displacement can be set to zero or removed from the global vector. Then, the incomplete measured data will not influence the process described above, which is very useful in real application.

Finally, the total discrepancy between the measured and the predicted damage signature for possible damage in element k is defined as

$$D_k = \sum_{i=1}^{nlc} \left\| \{PDS_{ik}\} - \{MDS_i\} \right\| \tag{13}$$

where nlc is the total number of the static load cases.

For each possible damage location identified by DSM technique, the corresponding predicted damage signatures are compared with the measured damage signatures. The possible damage case with the smallest discrepancy D_k is believed to be the actual damage scenario on the structure. In another word, smaller D_k indicates the higher possibility of damage in the kth element.

3.2 Damage identification using PSO algorithm

In the first stage, possible localization of the damage was achieved by using the DSM technique so as to reduce the number of parameters of the searching space in the optimization approach. After obtaining the possible damage location, the reduced damage identification problem is solved using a particle swarm optimization method to truthfully determine the extents of actual damaged elements.

When the possible damage location is roughly determined, assuming the total number of possible damage elements in identification of damage location is np, the global stiffness matrix Eq. (3) will be rewritten as

$$\boldsymbol{K}(\boldsymbol{\alpha}) = \Delta \boldsymbol{K} + \sum_{i=np+1}^{ne} \boldsymbol{A}_i \boldsymbol{k}_i^e \boldsymbol{A}_i^T \tag{14}$$

where np is the total number of the possible damaged elements and

$$\Delta \boldsymbol{K}(\boldsymbol{\alpha}) = \sum_{i=1}^{np} \boldsymbol{A}_i \boldsymbol{k}_i^{*e} \boldsymbol{A}_i^T \tag{15}$$

Based on Eqs. (7), (8), (9) and (15), the model of Eq. (8) can further be cast into the following optimization problem for determining the damage extent, $\boldsymbol{\alpha} = \{\alpha_1, \alpha_2, \ldots, \alpha_{np}\}$.

$$\begin{aligned} &\underset{\boldsymbol{\alpha}}{Min}\, E(\boldsymbol{\alpha}) \\ &s.t. \quad 0 \le \alpha_i \le 1, \quad i = 1, \cdots, np \end{aligned} \tag{16}$$

Generally, $np << ne$, therefore, the dimension of solution parameters for the model of Eq. (16) can be reduced greatly comparing with the model of Eq. (8), which leads to the saving of computational resources and time, especially when dealing with large-scale structures. In this study, the PSO algorithm is proposed to solve this optimization problem.

3.3 Particle Swarm Optimization (PSO) algorithm

Particle swarm optimization algorithm is a population based stochastic optimization technique developed by Eberhart and Kennedy (1995), inspired by social behavior of animals such as bird flocking, insect swarming and fish schooling. 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 (*pbest*) of individual particles in each iteration. The fitness values of particles are obtained to determine which position in the search space is the best. The best value is a global best and is called *gbest*. The particle swarm optimization concept consists of, at each time step, changing the velocity of (accelerating) each particle toward its *pbest* and *gbest* locations.

In the illustrative examples presented in this paper, the searching procedure adopted is illustrated as following:

Let $f: R^m \rightarrow R$ be the fitness function that takes a particle's solution with several components in higher dimensional space and maps it to a single dimension metric. Let there be *n* particles, each with associated positions $x_i \in R^m$ and velocities $v_i \in R^m$, i=1,…,n.. Let $pbest_i$ be the current best position of each particle and let $gbest$ be the global best.

Initialize x_i and v_i for all *i*. One common choice is to take $x_{i,j} \in U\lfloor a_j, b_j \rfloor$ and $v_i = 0$ for all *i* and j=1,…,m, where a_j, b_j are the limits of the search domain in each dimension, and *U* represents the Uniform distribution.

$$pbest_i \leftarrow x_i \quad \text{and} \quad gbest \leftarrow \arg\min_{x_i} f(x_i),\ i = 1x_i, \cdots, n.$$

While the convergence is not met.

For each particle $1 \le i \le n$:

Create random vectors r_1, r_2: r_{1j} and r_{2j} for all *j*, by taking $r_{1j}, r_{2j} \in U[0,1]$ for j=1,⋯, m.

Update the particle velocities:

$$v_i \leftarrow \omega v_i + c_1 r_1 (pbest_i - x_i) + c_2 r_2 (gbest - x_i)$$

Update the particle positions: $x_i \leftarrow x_i + v_i$.

Update the local bests: If $f(x_i) < f(pbest_i)$, $pbest_i \leftarrow x_i$.

Update the global best If $f(x_i) < f(gbest)$, $gbest \leftarrow x_i$.

End For

End While

where, c_1 and c_2 are the acceleration constants reflecting the weighting of stochastic acceleration terms that pull each particle toward *pbest* and *gbest* positions, respectively. *w* is the particle inertia weight. The inertia weight is used to balance the global and local search abilities. For more information about the PSO algorithm, please refer to Eberhart and Kennedy (1995).

In this article, PSO parameters are set as 30 particles (swarm size), maximum of 500 generations (iterations), a linearly decreasing inertia function from 1.1 to 0.6 and acceleration constants are set to 2.05.

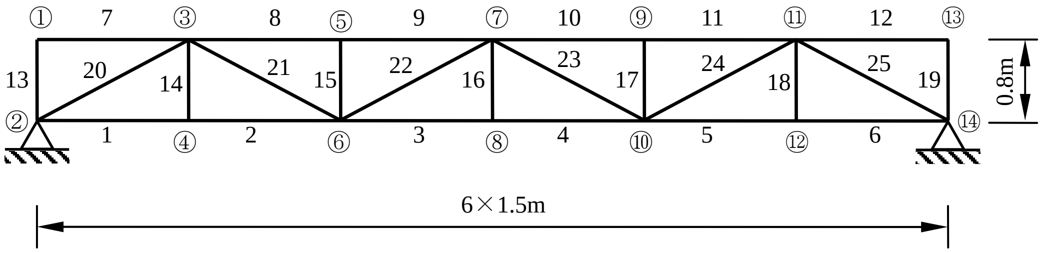

Fig. 1 Geometry for planar truss

Table 1 Load cases for the planar truss

Load case	Load at node
1	④
2	⑥
3	⑧
4	⑥, ⑧, ⑩, ⑫
5	④, ⑧
6	⑥, ⑫

Table 2 Damage cases for the planar truss

Damage case	Damaged element (Damage extent)
A	5(20%*)
B	23(20%)
C	5(20%), 16(20%)
D	5(20%), 16(20%), 23(20%)
E	5(20%), 16(10%), 23(50%)

*Note: 20% reduction in EA

4. Case studies

4.1 Numerical verification

Firstly, a mathematical model of a planar truss (Fig. 1) is used to verify the proposed method. The FEM analysis is carried out to simulate the experimental data by using two-node linear bar elements. The lumped-mass representation is adopted to generate the mass matrix for calculating the natural frequencies. Total numbers of elements and nodes are 25 and 14, respectively. The axial rigidity stiffness of each member in the structure, EA = 3.8 × 107 N, density= 7849 kg/m^3. Load cases are shown in Table 1, here, applied loads(vertically downward) at nodes are chosen to be 1000 N. Damage is simulated by reducing the axial rigidity stiffness of the member. Several damage cases for the planar truss are considered. Five damage cases shown in Table 2 are investigated, including single and multiple damage cases. Measurement locations for this example under the corresponding load case are selected. Here, horizontal displacement measurements of nodes 7 and 8 and vertical displacement measurements of nodes 5, 6, 9, 10, 11 and 12 are selected.

5% noise is added to the process of numerical simulation. The change in the first-order frequency, i.e., $\Delta\omega_1$, is used as the reference value, in practicing.

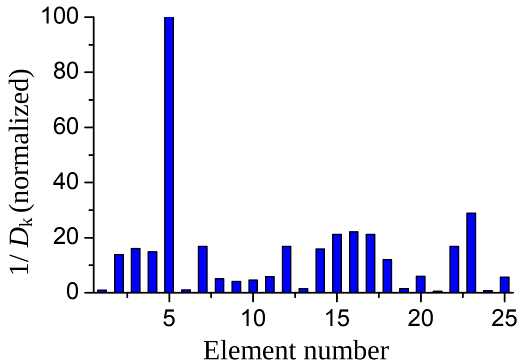

Fig. 2 Damage location results of damage case A

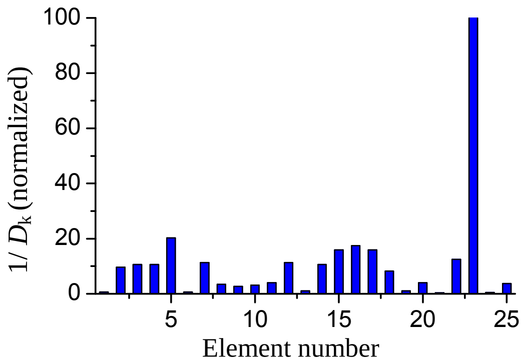

Fig. 3. Damage location results of damage case B

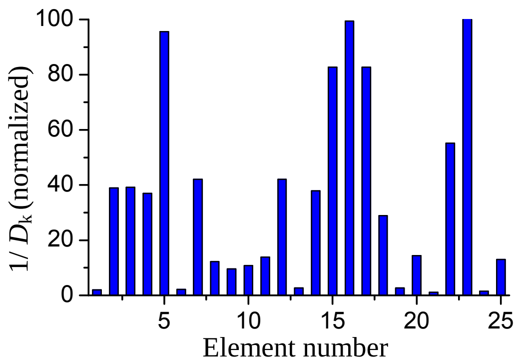

Fig. 4. Damage location results of damage case C

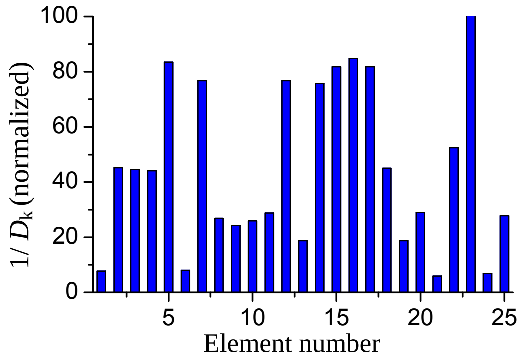

Fig. 5. Damage location results of damage case D

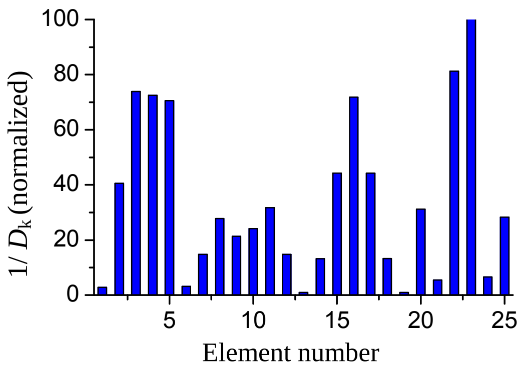

Fig. 6. Damage location results of damage case E

Usually the discrepancy D_k values are very small. For convenience, 1/ D_k is defined as damage index to judge the existence of damage in element *k*, when 1/ D_k is large, it can be thought that the possibility of damage in the *k*th element is very high. For each damage case, the 1/ D_k value, is normalized by the largest one of all candidates. All possible damages were calculated and shown in Figs. 2-6 respectively. From Figs. 2 and 3, it can be found that the proposed approach is very effective for the cases of single damage. For damage Case C, the result of damage location assessment is shown in Fig. 4. Although the damaged elements 5 and 16 can be identified obviously, the damage location figure becomes obscure in Fig. 4, and more wrong possible damaged elements, such as elements 15, 17 and 23 are also identified in this case. As we all know, the limited load paths and the sparsity of the measurements in damage identification problems lead to ill-posed inverse problems in which solution uniqueness is not guaranteed, consequently resulting in a large number of possible solutions. This problem can only be partially overcome by optimizing the scheme of loading and measurement according to the proper pre-analysis. For damage case D and E, the results are identical to those of damage case C shown in Fig. 4.

For assessing the damage extent, the estimated results of cases A, B, C, D and E are listed in Table 3. Results in Table 3 show that the exact value can be obtained using the particle swarm optimization algorithm, even in the case of multiple-damage. In general, for all cases studied, the results show small errors, only the element 16 in damage case E shows slightly high. These results show that the location and extent of damage can be identified successfully with an acceptable accuracy by using the proposed PSO-based two-stage damage identification method.

4.2 Experimental verification

To verify the ability of this method on detecting damage of structures in practical engineering, experiments on a full-scale steel truss structure were carried out. The elevation of the steel truss structure is shown in Fig. 7, and the experimental set-up is shown in Fig. 8. The truss is constructed from steel pipe truss members, whose material constants are the Young's modulus $E = 2.1\times10^2$ GPa, the section area of truss member $A = 2.135\times10^{-4}$ m^2 and the mass density ρ = 57.93103 kg/m^3. The finite element model of the structure consisting of 41 nodes and 128 bar elements is shown in Fig. 9. The node and member number of web, top and bottom chords for the experimental space truss are also shown in Fig. 9. The damage of the truss member is simulated by replacing a smaller cross-section with original members A14, B27 and C52 (marked in Fig. 9) and the stiffness of these members is reduced by 23.7%. Five damage cases shown in Table 4 are investigated, including the chord and web damage cases.

Table 3 Damage cases for the planar truss and identification results

Damage case	Possible damaged element	Damage extent
A	5	<u>5(21.06%)</u>
B	23	<u>23(19.75%)</u>
C	5, 15, 16, 17, 23	<u>5(19.45%)</u>, 15(0%), <u>16(22.26%)</u>, 17(0%), 23(0%)
D	5, 7, 12, 14, 15, 16, 17, 23	<u>5(23.22%)</u>, 7(0%), 12(0%), 14(0%), 15(0.12%), <u>6(21.45%)</u>, 17(0.13%), 23(18.25%)
E	2, 3, 4, 5, 15, 16, 17, 22, 23	2(0.12%), 3(0%), 4(1.65%), <u>5(20.40%)</u>, 15(0.15%), <u>16(3.68%)</u>, 17(0.21%), 22(0.17%), <u>23(50.31%)</u>

Fig. 7 Elevation of the steel truss structure

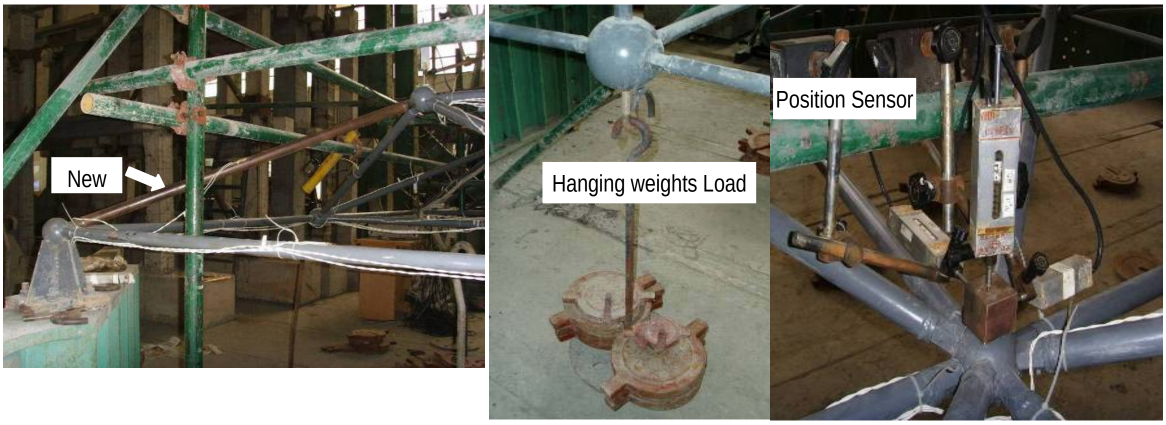

Fig. 8 Experimental set-up

Table 4 Damage cases for the experimental space truss

Damage case	Damaged element (Damage extent)
A	A14(23.75%)
B	C52(23.75%)
C	B27(23.75%)
D	A14(23.75%), C52(23.75%)
E	A14(23.75%), C52(23.75%), B27(23.75%)

Table 5 Load cases for experimental space truss

Load case	Load at node
1	11, 12, 13, 16, 17, 18, 22, 23
2	12, 16, 17, 18, 22, 34, 35, 38, 39
3	12, 17, 22, 34, 35, 38, 39
4	13, 14, 18, 19, 23, 24, 36, 40
5	31, 32, 33, 35, 36, 37, 39,40
6	22,23,34,35,36,38,39,40
7	6,7,11,12,13, 17,18,22,38

Table 6 Damage identification results of the experimental truss

Damage case	Possible damaged element	Damage extent
A14 (23.75%)	A1, A14, A23, C1, C14	A1(0%), A14(34.32%), A23(0.01%), C1(0%), C14(0%)
C52 (23.75%)	A1, A2, A3, A13, A14, A22, A23, C1, C14, C52, C63	A1(0%), A2(0%), A3(0%), A13(0%), A14(0.02%), A22 (0%), A23(0%), C1(0.04%), C14(0%), C52(28.4%), C63(0%)
B27 (23.75%)	A1, A2, A3, A13, A14, A23, C1, C14, C63	A1(0%), A2(0.12%), A3(0%), A13(0.18%), A14(0%), A23(0%), C1(0%), C14(0%), C63(0%)
A14 (23.75%), C52 (23.75%)	A10, A11, A14, A15, C52	A10(0%), A11(0%), A14(28.71%), A15(0.15%), C52(45.96%)
A14 (23.75%), C52 (23.75%), B27 (23.75%)	A2, A11, A14, A23, C1, C14, C52, C63	A2(0.07%), A11(0.13%), A14(31.86%), A23(0.09%), C1(0.12%), C14(0%), C52(49.62%), C63(0.13%)

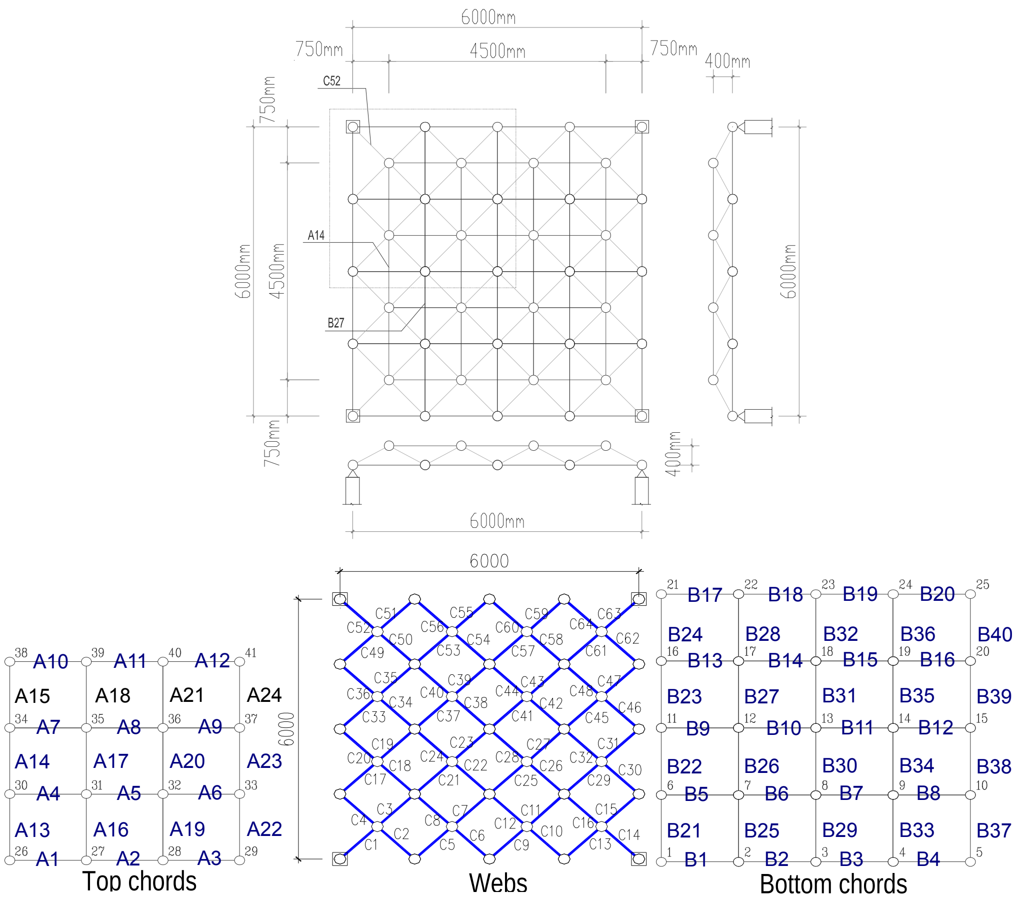

Fig. 9 Geometry for experimental truss

As we all know, selections of measurement locations and load cases have an important influence on the result of the damage detection. In this article, the method based on stored strain energy in elements and Fisher Information Matrix (Bakhtiari-Nejad *et al*. 2005) is used to select the load cases and measurement locations, respectively. Vertical loads are applied by hanging weights directly on the nodes. Applicable loads at the vertical degree of freedom are selected to be 1000 N. Seven groups of loads are listed in Table 5. Considering the measured information in real application is incomplete, and the vertical displacement meters are arranged only at the nodes (11, 12, 13, 16, 17, 18, 22, 23, 34, 35, 38 and 39) inside the dotted line part as shown in Fig. 9. The experimental results of the changes in deflections due to all damage cases under the 7 load cases are plotted in Figs. 10-14. A DASP-V10 modal test device was used for modal analyses. An accelerometer (EBM-941B) was employed to detect the dynamic response induced by the impulse hammer excitation and ambition vibration. The experimental frequencies and the static responses in 7 load cases of the intact and damaged structures were obtained. The change in the first-order frequency is used in this example.

For the damage location detection, the identification results of damage location using the DSM technique in the first stage are listed in Table 6. The results show that almost all damage cases,

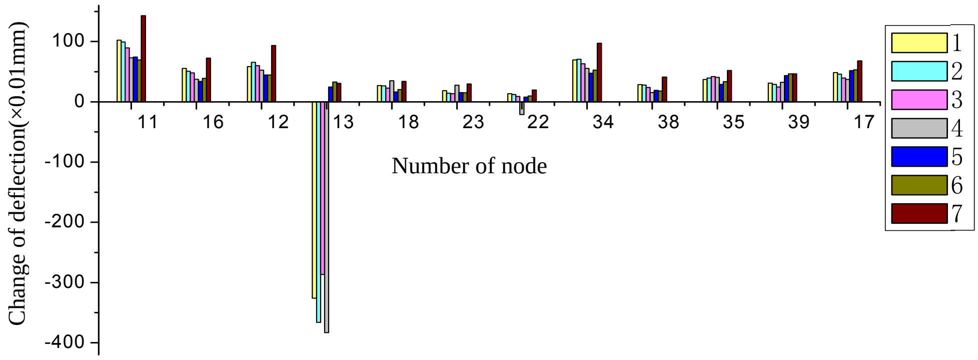

Fig. 10 Experimental results of the changes in deflections due to damage case A under 7 load cases

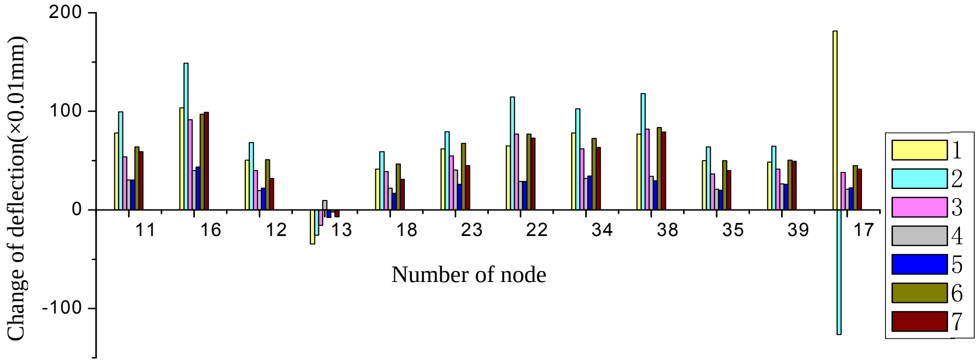

Fig. 11 Experimental results of the changes in deflections due to damage case B under 7 load cases

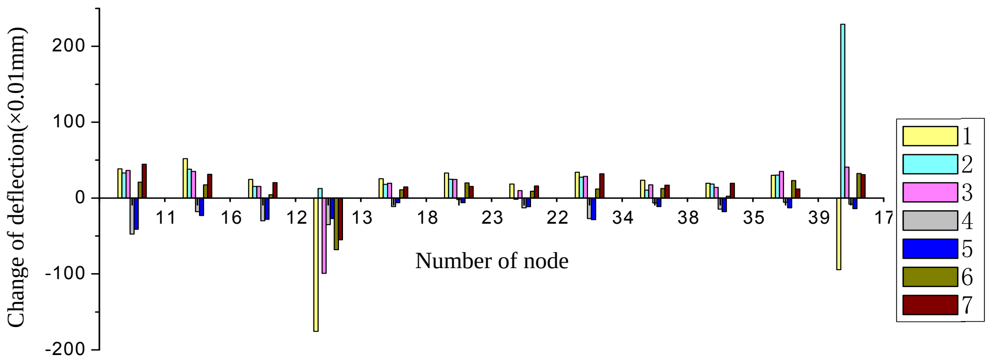

Fig. 12 Experimental results of the changes in deflections due to damage case C under 7 load cases

except for the damaged element B27, can be detected clearly when using the static test data and the first-order frequency. It should be noted that although several undamaged elements may be estimated as damaged ones, there have a lower numbers of damage variables compared to original ones.

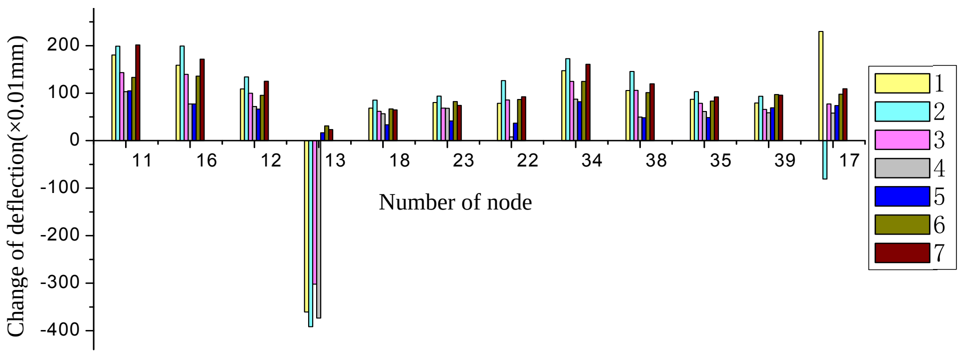

Fig. 13 Experimental results of the changes in deflections due to damage case D under 7 load cases

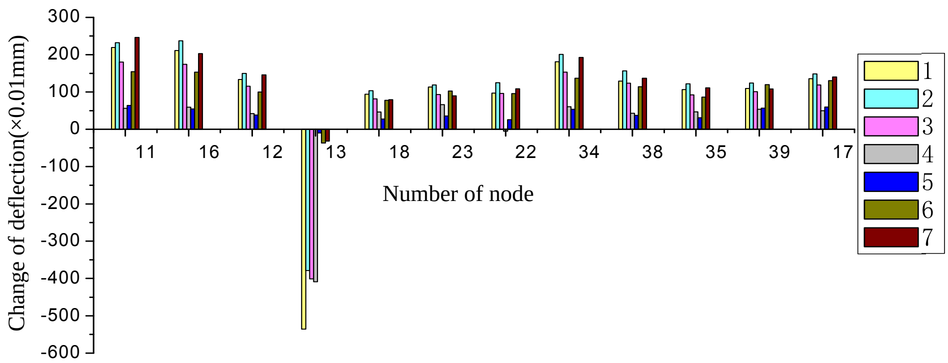

Fig. 14 Experimental results of the changes in deflections due to damage case E under 7 load cases

Table 7 The first-order natural frequencies of the experimental truss after the removing of elements A14, C52 and B27

Damage case	The first-order frequency（Hz）
original	12.285
A14 removed	9.188
C52 removed	4.749
B29 removed	12.182

The damage extent is estimated by choosing the possible damaged member. The estimated results of all damage cases are shown in Table 6. Apart from the damaged element B27, verification with these damage cases (single and multiple damages in the structure) proves the proposed method gives very satisfactory results. From this table, it can be observed that there are obvious errors in the damage extent, maximum error about 110% by comparing with the accurate damage extent, i.e., 49.62% reduction in stiffness of the damaged element C52. Although there are obvious errors in the damage extent, this step would be particularly valuable for removing the undamaged members from the possible candidates detected in the first step.

For the case that there is single or multiple damages in structure using the experimentally obtained data, the damage of element B27 cannot be detected, although almost the other damaged elements can be identified obviously. To illustrate this, a series of ambition vibration tests on this truss were carried out for sensitivity analysis. The first-order experimental natural frequencies of structure after the removing of elements A14, C52 and B27 are given in Table 7. From this table, it can be found that there is almost no change of the first-order natural frequency when the element B27 is removed. This means that the element B27 is insensitive to the integrated dynamic characteristics. For a real structure, the damaged components which have fairly little contribution to structural deformations under a certain load case will be difficult to be identified. Another main problem in the static identification methods lies in the effect of the damage may be concealed due to the limitation of load paths. This problem can be practically overcome by optimizing the loading scheme according to the proper pre-analysis or adopting several groups of loads synthetically.

5. Conclusions

In this study, an efficient two-stage damage identification technique is proposed to properly identify the damages in structural systems, which employs the incomplete measured information of structural static deformation and the first several natural frequencies. In the first stage, the basic idea of the DSM technique is employed for effectively detecting the damage locations. In the second stage, the damage identification problem, having a lower numbers of damage variables compared to original ones, is transformed into an optimization problem. These identified damaged elements were analyzed further for exact identification and quantification of the damage using PSO-based optimization approach. The efficiency of the proposed methodology has been demonstrated using two illustrative test examples: a numerical planar truss model and an experimental full-scale truss structure. From the identification results, it can be found that the proposed approach is very useful for identifying location and extent of damage in structures with sufficient accuracy.

It should be noted that single damage or multiple damages in the real structure using the experimentally obtained data, usually only the one whose location is the most important to the structural deformation can be identified. One of the main reasons is that the effect of the damage may be concealed due to the limitation of load paths. This problem can be practically overcome by optimizing the loading scheme. Future studies will aim to address this issue.

Although the proposed technique estimates the damage extent with approximate results when using experimentally obtained data, the damage extent prediction in the practical application may be useful for eliminating the undamaged members from the possible damaged candidates detected in the first step. This approach would be particularly valuable for large-scale and complex structures, where little information exists about the damage state, few measurements can be obtained in each test, and tests are very costly.

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