Damage localization in irregular shape structures using intelligent FE model updating approach with a new hybrid objective function and social swarm algorithm

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H I G H L I G H T S

- A hybrid algorithm is evolved to solve structural damage identification problems.
- The hybrid algorithm is verified using well-known test functions.
- A new hybrid objective function is utilized.
- The developed method was tested on three-dimensional irregular-shape frames.
- The proposed method succeeded to detect damage until the level of 10% noise.

A B S T R A C T

Health monitoring of structures and damage diagnosis are important research disciplines under investigation worldwide. Soft computing techniques are usually used to solve the uncertain complex inverse problem of revealing structural damage. In the current research, FE model updating (FEMU) paradigm is embraced for solving the damage tracking problem in three dimensional irregular shape structures. By taking into account the complexity of problem, the pivotal point is to efficiently educe damage through well-evolved objective function. Therefore, a novel objective function merging the modal characteristics of modal strain energy (MSTEN) and mode shape curvature (MSC) is established. Posteriorly, to solve the FEMU problem, a hybrid algorithm combining the particle swarm optimization with a new social version of the sine–cosine optimization algorithm (SPSOSCA) is proposed. The SPSOSCA is considered to take advantage of two enhanced search mechanisms to overcome the overall problem complexity. The proposed paradigm is evaluated using many damage scenarios even under noise conditions and the total outcome reveals outstanding performance with fair computational time.

1. Introduction

Damage determination in structures under service has gained a remarkable heed in the last decade due to its importance in ensuring the structures' reliability and usability. Structural damage identification techniques have been developed thanks to the innovation of reliable sensing tools and signal acquisition instruments as well as the effective non-destructive tests. Structural damage can be deduced from the dynamic responses of a structure, which in turn can reflect the damage locations and the damage severity [1–3].

For damage identification in structures, a comparison can be made between dynamic features of a structure in use and simulated dynamic responses usually taken from a finite element (FE) model. This comparison can discover the existence of damage by analyzing the differences between both measured and simulated dynamic responses. This aforementioned framework is defined as FE model updating (FEMU) process, in which the "FE model of an intact structure is gradually modified by minimizing the variation between both simulated and measured dynamic responses of a structure. The minimization process is basically described as a complex optimization problem that requires a powerful and reliable optimizer" [4].

Computational intelligence techniques have been widely applied for structural damage identification [5,6]. Their capabilities in extracting the complex features underlying in dynamic responses of structures can provide great abilities for solving large scale inverse problems especially when linked to damage detection procedures [7–9]. Among the computational intelligence techniques, evolutionary computation (EC) is a remarkable optimization tool being implemented for solving complex

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problems including highly non-linear, multimodal and large-scale optimization problems [4].

EC has been recently used alone or combined with FEMU for solving damage detection problems. The Genetic algorithm (GA) has been implemented for structural damage identification by various researchers. Various versions of GA were used for damage inference in beam, frame, and truss structures [10–12]. Raich and Liszkai [13] used implicit redundant representation GA for damage locating in simple 2-D structures using FRF based residual. PSO is one of the most effective algorithm being used by researchers worldwide. It has many advantages such as, the ability to interchange position information between various particles along the search space, the ability to follow the elite particles in order to converge into the near optimum region in the search space, the powerful feature of overcoming optimization problems with many local optima and multi-modality [14,15], etc. It has also been employed for solving various engineering problems. AlRashidi and El-Hawary [16] reviewed the applications of PSO for tackling the electrical power engineering problems. Martínez et al. [17] applied PSO algorithm for solving the optimization of energy management in Plug-in hybrid electric vehicles focusing on powertrains. Moreover, PSO was successfully utilized in the field of damage detection in structures. Qian et al. [18] developed a hybrid PSO simplex method for delamination detection in laminated beams using delamination parameters based objective function. Results showed good accuracy and robustness of the proposed method. Other PSO implementation in 2D structures were reported in [19,20]. Ding et al. [21] proposed a hybrid ABC technique for successful damage prediction in various 2D structures. Seyedpoor et al. [22,23] utilized ECs and model features for damage recognition in 2D structures. Other stochastic algorithms were applied such as the work of. Kaveh and Maniat [24], Kaveh and Zolghadr [25], Dinh-Cong et al. [26,27], Shobeiri and Ahmadi-Nedushan [28], Cha and Buyukozturk [29], etc. To epitomize, it is clear that ECs have revealed a superb performance in damage realization, nevertheless, it was basically employed on 1D or 2D problems. Damage identification in the three-dimensional structures experiences tremendous difficulties such as the high number of degrees of freedom, the large number of nodes and elements to be tackled, the minor damages along a few structural members have little impact and effect on the modal characteristics, natural frequencies do not carry useful information about structural damage, etc. [29]. Over and above, there is a need to develop powerful algorithms that overcome the difficulties in complex structures. Therefore, a novel algorithm combines the powerful search features of PSO and another new algorithm called sine–cosine optimization algorithm (SCO) [30], is presented. According to Mirjalili [30], the SCO algorithm has a great exploration of the search space due to sinusoidal functions utilization, a local optima overcoming ability, a smooth transmission from exploration to exploitation, elite population-based mechanism implementation, etc. The new algorithm, called social particle swarm optimization sine–cosine algorithm (SPSOSCA), merges the social terms of PSO into SCO to produce better searching tools which in turn can overcome the optimization problem of FEMU-based structural damage identification.

In order to combine EC into FEMU paradigm, the key point is to choose the dynamic characteristics required for objective function formulation. Modal analysis can be used to derive the modal characteristics that are useful for extracting the damage information along the structure. Alkayem et al. [4] reviewed various dynamic characteristics used for FEMU procedures. Natural frequencies, mode shapes, modal strain energy and modal flexibility are the most commonly used for damage detection based on FEMU [4,31,32]. Moreover, mode shape curvature (MSC) or modal curvature developed by Pandey et al. [33] is a sensitive modal feature that can be used efficiently for damage identification process. Various researchers have successfully implemented the modal curvature into damage detection processes such as, damage localization in bridges [34], beam structure [35,36], composite laminated plates [37], frames [38], etc. By studying the available literature, it is observed that the modal curvature can be used for damage identification based on FEMU. Hence, it is essential to explore the potential application of modal curvature into FEMU-based damage localization in structures. Another modal characteristic that is modal strain energy (MSTEN) is an efficient damage index utilized by many researchers [39–42]. MSTEN can be used efficiently for detecting minor damage in three dimensional structures [29] even under noisy conditions [4]. By taking into account the above mentioned information, a hybrid objective function based on MSC and MSTEN subobjectives is developed. The intended objective function is thought of because, this research is studying the damage identification in complex three dimensional irregular-shape structures. Therefor, it is necessary to extract different damage information from more than one dynamic characteristic that finally can describe various common structural damage types.

The contributions of the current work can be summarized as: Firstly, a new hybrid objective function combining the modal characteristics of MSTEN and MSC is developed for solving the complex problem of damage identification in irregular shape structures. For effective correlation between the MSC of the healthy and damaged structure, a mode shape curvature assurance criteria (MSCAC) is utilized within the objective function. Secondly, in order to study the damage identification problem using the proposed framework, two irregular shape three-dimensional frame structures are evolved based on the famous IASC-ASCE benchmark model. Thirdly, a hybrid SPSOSCA optimization algorithm is proposed to solve the optimization problem of FEMU-based structural damage inference. The SPSOSCA algorithm is benchmarked and compared with other six EC algorithms which shows its robustness and reliability. Finally, various damage scenarios are studied in order to illustrate the successful application of SPSOSCA even when noisy conditions exist. Also, a complete discussion about the results and the effectiveness of the proposed approach are well illustrated. Moreover, various levels of noise are studied in order to determine the margin of noise that the proposed framework can be applied on.

The rest of the paper can be outlined as follows. Section 2 presents an overview about the dynamic characteristics and the objective function used in this work. Section 3 explains the proposed hybrid SPSOSCA algorithm as well as the structural damage identification problem. Section 4 focuses on the development of the irregular shape structures. The structural damage localization using SPSOSCA algorithm is illustrated in Section 5, followed by the future research scope presented in Section 6. Finally, concluding remarks are summarized in Section 7.

2. Dynamic characteristics and objective function

As it has already been discussed, in structural damage localization using EC with FEMU, the basic connotation is to first choosing the adequate dynamic characteristics that can well reflect the occurrence of structural damage. Thereafter, the objective function that measures the response correlation between the healthy structure's model and the structure experiencing damage should be developed. In this research, a hybrid MSC-based and MSTEN-based objective function is designed for the purpose of revealing damage using FEMU with EC.

MSC is a modal characteristic usually utilized to replace the original mode shape in order to derive better damage information mainly when damage is occurred due to stiffness reduction. When the stiffness is decreased, the MSC will increase providing a good indicator of damage [34–38]. Pandey et al. [33] defined the MSC by the second derivative of mode shape. The second derivative is calculated by using the central finite difference method as

$$\varphi_i'' = \frac{\varphi_{i-1} - 2\varphi_i + \varphi_{i+1}}{l^2}, \tag{1}$$

where φ_i is the ith mode shape of the structure; l is the element length or the distance between two measured points.

To develop an efficient MSC correlation method, similar to modal assurance criterion (MAC) [43], a correlation matrix called mode shape curvature assurance criterion (MSCAC) is utilized. By taking into account the mode shapes φ^I and φ^D for both the model of the structure and the damaged-structure, respectively, the MSCAC is able to find the variation between a reference MSC and the measured MSC. The MSCAC matrix can be defined as

$$\mathrm{MSCAC}\left(\left\{\varphi^I\right\}'', \left\{\varphi^D\right\}''\right) = \frac{\left|\left\{\left(\varphi^I\right)''^*\right\}^T \left\{\left(\varphi^D\right)''\right\}\right|^2}{\left\{\left(\varphi^I\right)''^*\right\}^T \left\{\left(\varphi^I\right)''\right\} \left\{\left(\varphi^D\right)''^*\right\}^T \left\{\left(\varphi^D\right)''\right\}}, \tag{2}$$

where T refers to the transpose; and * to the complex conjugate. If a MSCAC is 1, there is no variation between the studied MSCs, else if MSCAC is 0, it means there is a complete mismatch between the studied MSCs.

Based on MSCAC, the MSC subobjective can be stated as

$$MSCSO(\varphi) = \sum_{i=1}^{N} \left(1 - dg\left(MSCAC_i\left(\left\{\left(\varphi_i^I\right)''\right\}, \left\{\left(\varphi_i^D\right)''\right\}\right)\right)\right), \tag{3}$$

where $MSCSO(\varphi)$ is the mode shape curvature subobjective; $MSCAC_i$ is the MSCAC with respect to the ith mode shape; $\left(\varphi_i^I\right)''$ and $\left(\varphi_i^D\right)''$ are the MSCs taken from the intact structure and the damaged structure, respectively; $dg(MSCAC)$ is the diagonal of the MSCAC matrix.

In order to complete the objective function, MSTEN based subobjective function is developed. MSTEN can serve well in conveying damage information when structural damage occurs due to stiffness reduction, i.e. structural elements cracks, construction imperfection, etc. Also, MSTEN is able to illustrate minor damage along the structure [4]. MSTEN is dependent on the mode shape φ as well as the stiffness matrix K of the structure. The K matrix is derived from the initial FE model of the intact structure because the damaged stiffness matrix cannot be achieved. Hence the MSTEN can be written as

$$MSTEN_i^I\left(\varphi_i^I, K\right) = \frac{1}{2}\varphi_i^{I^T} K \varphi_i^I, \tag{4}$$

$$MSTEN_i^D\left(\varphi_i^D, K\right) = \frac{1}{2}\varphi_i^{D^T} K \varphi_i^D, \tag{5}$$

where, $MSTEN_i^I$ and $MSTEN_i^D$ refer to the modeled (undamaged) and the real (damaged) modal strain energy, respectively.

The global MSTEN subobjective (MSTENSO) can be deduced as

$$MSTENSO\left(\varphi, K\right) = \sum_{i=1}^{N} \frac{1}{\varphi_i^{D^T} K \varphi_i^D} \sqrt{\left(\varphi_i^{I^T} K \varphi_i^I - \varphi_i^{D^T} K \varphi_i^D\right)^2}, \tag{6}$$

By combining MSC and MSTEN subobjectives, the total objective function can be explained as

$$\begin{aligned} &Min\left(MSCSO\left(\varphi\right) + MSTENSO\left(\varphi, K\right)\right) \\ &= Min\left(\sum_{i=1}^{N}\left(1 - dg\left(MSCAC_i\left(\left\{\left(\varphi_i^I\right)''\right\}, \left\{\left(\varphi_i^D\right)''\right\}\right)\right)\right)\right. \\ &\quad \left. + \sum_{i=1}^{N} \frac{1}{\varphi_i^{D^T} K \varphi_i^D} \sqrt{\left(\varphi_i^{I^T} K \varphi_i^I - \varphi_i^{D^T} K \varphi_i^D\right)^2}\right), \end{aligned} \tag{7}$$

Usually, in structural damage detection problems, the maximum amount of information about the structural changes are required. Therefore, the structural health monitoring engineers look for the responses that provide the highest level of damage detectability as well as the lowest possible effects of noise. In Eq. (7) two sub-objectives are used. Even though, one subobjective can be used rather than two, palpable difficulties in localizing structural damage are observed during the first implementation of the framework when individually using MSC or MSTEN as objective functions. The difficulties are observed especially when working under noisy conditions. The MSTEN subobjective can work well when detecting linear types of damage, or in other words, when the stiffness of the structure is reduced. Such types of damage occur when a structure is subjected to cracks, erosion, loosening of links and bolts, etc. In addition to MSTEN, MSC can work well to describe other types of structural damage such as delamination and debonding in composite structures, oxidation and contamination is some types of welded structures, etc. Also, the use MSC can help to study the responses besides the effect of stiffness changes even under noisy environments. Therefore, the combination between MSC and MSTEN subobjectives are preferred to be used together and with the same significance in order to localize all possible types of damage even under noisy conditions.

When structural damage takes place, it is literally explained as changes in the physical parameters of the structure [44]. Those changes can be attached to FEMU process, "in which the physical parameters are gradually updated till a relative consistency is achieved between the measured dynamic responses and the calculated ones" [4]. The physical parameters chosen for FEMU can be material properties, geometrical properties, etc. [45,46]. The use of material parameters is more common because it can reflect the changes in the model's matrixes and are linked directly to the model elements [47,48]. In a FEMU framework, the damage index vector with a number of elements el is usually stated as a vector of damage parameters $\Delta = [\delta_1, \delta_2, \ldots, \delta_{el}] \epsilon [0 - 1]$. By considering X is vector of chosen updating parameters or damage indicators x, Δ is utilized to examine the variation in damage indicators. The calculated changes in Δ can reflect the existence and severity of damage along the structure and can be derived as

$$x_i^D = x_i^I - \delta_i . x_i^I, \tag{8}$$

where x^U and x^D are the updating parameters of the damaged and undamaged structure, respectively. Hence, the stiffness and mass matrixes can be updated as

$$\begin{aligned} M_i^D &= M_i^I + x_i^D . M_i^I \\ K_i^D &= K_i^I + x_i^D . K_i^I \end{aligned} , \tag{9}$$

where M_i^D, M_i^I, K_i^D and K_i^I are the damaged and undamaged mass and stiffness matrixes, respectively.

In this work, the structural damage is considered as a reduction in K due to a reduction in modulus of elasticity (E). This assumption may cover all structural damage variations. But, it is suitable for explaining some common structure failures such as, cracks, corrosion, etc.

3. Damage prognostic using SPSOSCA and FEMU

The implementation of EC to solve the optimization problem of FEMU for damage tracking can be classified into two main categories, single-objective EC and the multi-objective EC. The differences between both paradigms can be well observed in

[4,49]. In order to solve the optimization problem of damage detection using FEMU, a novel hybrid algorithm called SPSOSCA integrates the powerful search strategy of PSO [50] and inserts the social behavior of PSO into a newly developed algorithm called Sine–Cosine Optimization algorithm [30]. The aim of that combination is to evolve an efficient algorithm able to overcome the complex problem of damage identification using model updating framework by using two distinctive search strategies. Moreover, the hybrid algorithm is intended to track damage in complex three dimensional irregular-shape structures. First, a brief review of both PSO and SCO should be provided as

• PSO is a well-known population-based optimization algorithm simulates the social behavior of swarms. The main search engine in PSO is the following equation:

$$\begin{aligned} x_i^{G+1} &= x_i^G + U_i^{G+1}, \\ U_i^{G+1} &= \Omega . U_i^G + A_1 R_1 \left(x_{Gbest} - x_i^G \right) + A_2 R_2 \left(x_{i,Lbest}^G - x_i^G \right), \end{aligned} \tag{10}$$

where, x_i is the ith particle in the population; x_{Gbest} is the global best particle; x_{Lbest} is the local best particle performance; U_i is the velocity of the ith particle; Ω is the inertia parameter; A_1 and A_2 are acceleration factors; $R_!$ and R_2 are coefficients chosen randomly $\in [0, 1]$; G is the generation number.

• SCO is a recent algorithm developed by Mirjalili [30]. SCO is a population-based optimization method that implements sinusoidal functions in order to oscillate initial random solutions around the global solution. SCO depends on the two following equations:

$$x_i^{G+1} = x_i^G + \sigma_1 \times \sin(\sigma_2) \times \left| \sigma_3 . DP_i^G - x_i^G \right|, \tag{10.1}$$

$$x_i^{G+1} = x_i^G + \sigma_1 \times \cos(\sigma_2) \times \left| \sigma_3 . DP_i^G - x_i^G \right|, \tag{10.2}$$

where $\sigma_1 = a - it \times \left(\frac{a}{max_{it}} \right)$, a is a constant, it is the iteration number, max_{it} is the maximum number of iterations, σ_2 and σ_3 are random numbers $\in [0, 2\pi]$; DP is the target solution which is chosen to be the best solution achieved in each iteration; $\|$ denote the absolute function.

Eqs. (10.1) and (10.2) are merged as

$$x_i^{G+1} = \begin{cases} x_i^G + \sigma_1 \times \sin(\sigma_2) \times \left| \sigma_3 . DP_i^G - x_i^G \right|, \sigma_4 < 0.5 \\ x_i^G + \sigma_1 \times \cos(\sigma_2) \times \left| \sigma_3 . DP_i^G - x_i^G \right|, \sigma_4 \geq 0.5 \end{cases} \tag{11}$$

where σ_4 is another random number $\in [0, 1]$.

Bu utilizing the concepts of PSO and SCO, the hybrid SPSOSCA which merges the social behavior of PSO with a new implementation of a social form of SCO, is developed. Within the hybrid formulation of SPSOSCA, the global best and the local best particles gained from PSO search paradigm are inserted inside the SCO framework. Hence the Eq. (11) can be modified as

$$x_i^{G+1} = \begin{cases} x_i^G + \sigma_1 \times \sin(\sigma_2) \times \left| \sigma_3 . x_{Gbest} - x_i^G \right|, \sigma_4 < 0.25 \\ x_i^G + \sigma_1 \times \cos(\sigma_2) \times \left| \sigma_3 . x_{Gbest} - x_i^G \right|, 0.25 < \sigma_4 \leq 0.5 \\ x_i^G + \sigma_1 \times \sin(\sigma_2) \times \left| \sigma_3 . x_{i,Lbest}^G - x_i^G \right|, 0.5 < \sigma_4 \leq 0.75 \\ x_i^G + \sigma_1 \times \cos(\sigma_2) \times \left| \sigma_3 . x_{i,Lbest}^G - x_i^G \right|, \sigma_4 > 0.75 \end{cases} \tag{12}$$

This can improve the performance of PSO to and SCO to deal with the complex FEMU for damage diagnosis problem. The SPSOSCA algorithm is designed as

1. Create a population of initial particles randomly.
2. Create the set of particles' velocities.
3. Evaluate and sort the population using the objective function values.
4. Define the global best solution x_{Gbest} and the local best solutions x_{Lbest} for all the corresponding particles.
5. **Do**
   (a) Use the search engine of PSO to create new solutions using Eq. (10).
   (b) Evaluate all the new solutions using the objective function and determine x_{Gbest} and x_{Lbest} for all solutions.
   (c) Compare the new particles with the original particles and update the population.
   (d) Implement the social SCO paradigm using Eq. (12).
   (e) Evaluate all the new solutions using the objective function and determine x_{Gbest} and x_{Lbest} for all solutions.
   (f) Compare the new solutions with the updated PSO population and modify the population.
6. **While (The termination criterion is not satisfied).**
7. End

The developed SPSOSCA algorithm is compared to six well-known powerful optimization algorithms including the original PSO and the original SCO as well as the differential evolution (DE) [51], firefly algorithm (FA) [52], the artificial bee colony (ABC) [53], and the genetic algorithm (GA) [54]. The comparison is conducted using 10 benchmark objective functions including many local minima, bowl-shape, plate-shape, valley-shape functions as in Table 1. Each algorithm is executed 20 times using the default parameter settings and a fixed number of population size equal to 100 individuals with maximum number of iterations equals to 500 iterations. The average minimum, mean, maximum and standard deviation (STD), related to the implementation of each algorithm, are recorded and tabulated in Tables 2, 3, 4 and 5, respectively. Although there is no free lunch theorem, by studying the results, it is observed that the PSO has overcome the other algorithms in some of the tests. Moreover, the SPSOSCA algorithm has improved the performance of PSO and outperformed all other algorithms. This is because, the combined social mechanisms of PSO is able to overcome the multi-modality and many local minima as well as locally improving the global search mechanism of PSO.

In the structural damage detection problem using FEMU, there is no direct correlation between the objective function and the updating parameters. The correlation exists between the measured and calculated dynamic responses, as well as between the model matrixes and the updating parameters. Other problems appear during any structural damage detection process such as the noise originated from several sources which cannot give clean responses. Moreover, in structural damage detection techniques, achievements of unique solutions and consistent performance are not guaranteed. Thus, the optimization problem cannot be a deterministic problem and it suffers from uncertainty which is tackled by using EC algorithms in particular.

Structural damage tracking using FEMU with SPSOSCA algorithm is sketched in Fig. 1. From the figure, we can summarize the framework as: First, the structure is modeled using finite element method and the damage identification variables are chosen. Then, the procedure is separated into two processes. First, damage is simulated in order to derive the FE model's matrixes of the damaged structure as well as the mode shapes and mode-shape curvatures are calculated so that the MSTEN and MSC subobjectives can be defined. After that, the process of damage inference starts by initializing a set of random particles containing damage indexes. Then, the model is altered within the population to derive the updated responses essential for calculating the MSTEN and MSC subobjectives as in Eq. (7). Thereafter, instantly after checking evaluating the termination criterion, the SPSOSCA

Table 1
The benchmark test functions [55].

F	Name	Formula	Parameters	Global minimum	Range
F1	Ackley	$f(x) = -a\exp\left(-b\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) - \exp\left(-\frac{1}{d}\sum_{i=1}^{d}\cos(cx_i)\right) + a + \exp(1)$	$a = 20$, $b = 0.2$, $d = 20$, $c = 2\pi$.	$f(x^*) = 0,\ at\ x^* = (0, \ldots\ldots, 0)$	$x_i \in [-32.768, 32.768]$
F2	Griewank	$f(x) = \sum_{i=1}^{d} \frac{x_i^2}{4000} - \prod_{i=1}^{d}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	$d = 20$	$f(x^*) = 0,\ at\ x^* = (0, \ldots\ldots, 0)$	$x_i \in [-600, 600]$
F3	Rastrigin	$f(x) = 10d + \sum_{i=1}^{d}\left[x_i^2 - 10\cos(2\pi x_i)\right]$	$d = 5$	$f(x^*) = 0,\ at\ x^* = (0, \ldots\ldots, 0)$	$x_i \in [-5.12, 5.12]$
F4	Levy	$f(x) = \sin^2(\pi\omega_1) + \sum_{i=1}^{d-1}(\omega_i - 1)^2\left[1 + 10\sin^2(\pi\omega_i + 1)\right] + (\omega_d - 1)^2\left[1 + \sin^2(2\pi\omega_d)\right]$	$\omega_i = 1 + \frac{x_i - 1}{4}$ $for\ i = 1, \ldots, d$, $d = 20$	$f(x^*) = 0,\ at\ x^* = (1, \ldots\ldots, 1)$	$x_i \in [-10, 10]$
F5	Perm Function 0, D, β	$f(x) = \sum_{i=1}^{d}\left(\sum_{j=1}^{d}(j+\beta)\left(x_j^i - \frac{1}{j^i}\right)\right)^2$	$d = 5$	$f(x^*) = 0,\ at\ x^* = \left(1, \frac{1}{2}, \ldots\ldots, \frac{1}{d}\right)$	$x_i \in [-d, d]$
F6	Sum Squares	$f(x) = \sum_{i=1}^{d} i x_i^2$	$d = 30$	$f(x^*) = 0,\ at\ x^* = (0, \ldots\ldots, 0)$	$x_i \in [-10, 10]$
F7	Rotated Hyper-Ellipsoid	$f(x) = \sum_{i=1}^{d}\sum_{j=1}^{i} x_j^2$	$d = 20$	$f(x^*) = 0,\ at\ x^* = (0, \ldots\ldots, 0)$	$x_i \in [-65.536, 65.536]$
F8	Power Sum	$f(x) = \sum_{i=1}^{d}\left[\left(\sum_{j=1}^{d} x_j^i\right) - b_i\right]^2$	$d = 4$, $b = (8,18,44,114)$	$f(x^*) = 0,\ at\ x^* = (1, 2, 2, 3)$	$x_i \in [0, d]$
F9	Rosenbrock	$f(x) = \sum_{i=1}^{d}\left[100\left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2\right]$	$d = 4$	$f(x^*) = 0,\ at\ x^* = (1, \ldots\ldots, 1)$	$x_i \in [-5, 10]$
F10	Dixon-Price	$f(x) = (x_1 - 1)^2 + \sum_{i=2}^{d} i\left(2x_i^2 - x_{i-1}\right)^2$	$d = 10$	$f(x^*) = 0,\ at\ x^* = 2^{\frac{2^i - 2}{2^i}}$	$x_i \in [-10, 10]$

Table 2
The average minimum of the compared algorithms.

F	SSCA-PSO	PSO	SCA	GA	FA	ABC	DE
F1	**7.99E−15**	**7.99E−15**	3.37E−05	4.86E−05	3.6E−05	0.001499	5.35E−05
F2	**0**	4.11E−15	3.53E−05	5.24E−10	4.11E−08	0.015464	1.89E−06
F3	**0**	**0**	**0**	0.994959	0.994959	0.1682	5.61E−12
F4	**1.50E−32**	3.26E−19	1.056931	6.06E−13	7.53E−11	0.000138	6.41E−10
F5	**0**	2.31E−05	0.063319	2.48E−06	3.12E−10	0.001526	0.001473
F6	**1.83E−13**	5.05E−13	0.000932	5.43E−06	7.05E−09	0.089155	5.79E−05
F7	**9.44E−18**	2.22E−17	7.29E−07	2.91E−08	7.16E−08	5.49E−05	1.13E−07
F8	**4.901E−11**	3.97E−09	0.010418	0.000104	6.31E−10	0.002016	0.00111
F9	6.098E−06	0.000728	0.288333	0.044047	**4.56E−12**	0.004665	0.003089
F10	**2.890E−24**	1.84E−12	0.666668	0.000315	0.666667	0.49198	1.19E−11
Sum	6.098E−06	0.000751	2.08667	1.039482	1.661662	0.774698	0.005786

Table 3
The average mean of the compared algorithms.

F	SSCA-PSO	PSO	SCA	GA	FA	ABC	DE
F1	**1.51E−14**	2.22E−14	0.001065	2.575442	5.02E−05	0.007597	9.12E−05
F2	0.044263	0.058921	0.476874	0.066437	0.009865	0.30549	0.000138
F3	**9.32E−11**	1.989918	**9.32E−11**	5.969749	12.93446	1.7846	9.66E−09
F4	**2.01E−30**	2.58E−17	1.542788	0.998176	1.33E−10	0.001936	2.03E−09
F5	0.139004	0.031277	1.372324	0.142668	0.031277	**0.025481**	0.105156
F6	**2.25E−11**	3.05E−11	2.772696	0.243497	1.15E−08	0.22102	0.000135
F7	**3.57E−15**	5.91E−15	0.001364	0.002864	1.09E−07	0.000214	2.97E−07
F8	0.002805	0.00171	1.294515	0.303761	**0.000303**	0.031805	0.040618
F9	0.007294	0.007062	1.238042	3.750229	**8.66E−11**	0.20106	0.083512
F10	**0.666667**	**0.666667**	0.666776	0.666984	**0.666667**	0.66741	0.809476
Sum	**0.860033**	2.755554	9.366444	14.71981	13.64262	3.246612	1.039126

Table 4
The average maximum of the compared algorithms.

F	SSCA-PSO	PSO	SCA	GA	FA	ABC	DE
F1	**1.51E−14**	2.22E−14	0.001065	2.575442	5.02E−05	0.007597	9.115E−05
F2	0.044263	0.058921	0.476874	0.066437	**0.009865**	0.30549	0.0001379
F3	**9.32E−11**	1.989918	**9.32E−11**	5.969749	12.93446	1.7846	9.662E−09
F4	**2.01E−30**	2.58E−17	1.542788	0.998176	1.33E−10	0.001936	2.03E−09
F5	0.139004	0.031277	1.372324	0.142668	0.031277	**0.025481**	0.1051555
F6	**2.25E−11**	3.05E−11	2.772696	0.243497	1.15E−08	0.22102	0.0001353
F7	**3.57E−15**	5.91E−15	0.001364	0.002864	1.09E−07	0.000214	2.968E−07
F8	0.002805	0.00171	1.294515	0.303761	**0.000303**	0.031805	0.0406182
F9	0.007294	0.007062	1.238042	3.750229	**8.66E−11**	0.20106	0.0835117
F10	**0.666667**	**0.666667**	0.666776	0.666984	**0.666667**	0.66741	0.8094757
Sum	**0.860033**	2.755554	9.366444	14.71981	13.64262	3.246612	1.0391258

Table 5
The standard deviation of the benchmark function corresponding to all compared algorithms.

F	SSCA-PSO	PSO	SCA	GA	FA	ABC	DE
F1	**3.57E−15**	4.62E−15	0.001369	1.018412	3.25E−06	0.001404	1.256E−05
F2	0.015585	0.016933	0.123477	0.022227	0.003325	0.068601	**3.602E−05**
F3	3.82E−11	0.797275	**2.25E−11**	1.269868	2.843636	0.564121	2.271E−09
F4	**6.82E−31**	7.43E−18	0.108798	0.24496	1.47E−11	0.000399	3.669E−10
F5	0.048483	0.007194	0.378893	0.041203	0.007278	**0.007033**	0.0266109
F6	**5.82E−12**	8.5E−12	0.856613	0.054409	1E-09	0.032701	2.073E−05
F7	**9.63E−16**	1.55E−15	0.000327	0.000636	1.11E−08	4.03E−05	4.467E−08
F8	0.000794	0.000411	0.420658	0.06781	**0.0001**	0.00767	0.0117578
F9	0.002003	0.001942	0.292245	1.000912	**2.08E−11**	0.048245	0.0224386
F10	0.205196	0.149071	2.66E−05	0.149006	**2.9E−11**	0.041691	0.2236169
Sum	**0.27206**	0.972827	2.182406	3.869443	2.854342	0.771905	0.2844936

Table 6
Material properties of the structure [57].

Property	Columns	Beams
Section type	B100×9	S75×11
Cross-sectional area (m^2)	1.133×10^{-3}	1.43×10^{-3}
Moment of inertia I_y (strong direction) (m^4)	1.97×10^{-6}	1.22×10^{-6}
Moment of inertia (weak direction) I_z (m^4)	0.664×10^{-6}	0.249×10^{-6}
St. Venants torsion constant J (m^4)	8.01×10^{-9}	38.2×10^{-9}
Young's modulus E (Pa)	2×10^{11}	2×10^{11}
Shear modulus G (Pa)	*E/2.6*	*E/2.6*
Mass per unit volume ρ (kg/m^3)	7,800	7,800

is employed to achieve an updated, better vectors of damage indexes. The process iterates until the termination criterion is satisfied, i.e. when the updated model can effectively localize the structural damage. In the end, the damage locations are noted down and the severity of damage in each location is derived.

4. Three dimensional irregular shape structures

In order to verify the effectiveness of the proposed method and the reliability of using the new objective function formulation, two irregular-shape modular structures in the three dimensional domain are evolved using the MATLAB software. The two models consist of four stories with dimensions similar to the famous benchmark model [56,57], as shown in Fig. 2. The models have the dimensions of 2.5 m ×2.5 m ×3.6 m. Beams and columns of the structure are made of hot rolled grade 300 W steel having 300 MPa nominal yield stress and considered to be Euler–Bernoulli beams. The properties of the structures' material are shown in Table 6 [57]. Both models are composed of 68 elements. Each element has 12 × 12 K and M matrices, i.e. 12 DOFs.

In the next section, four damage scenarios divided to two damage scenarios for each FE model are examined as shown in Fig. 3. All damage scenarios simulate the 10% reduction in stiffness by means of decreasing 10% of modulus of elasticity (E). For each FE model, the number of damage indicator parameters is equal to 68 parameters. The dynamic characteristics are taken for the overall DOFs which is not very precise in practice. Nevertheless, because of the difficulty in constructing such models due to financial and logistical problems, the whole DOFs are considered. In practice, some issues should be taken into account. Firstly, the use of efficient data acquisition instrumentation is required in order to obtain accurate responses from the structure. Also, effective signal processing techniques must be implemented to reduce the noise effects. Moreover, in case the responses cannot be observed for all DOFs due to limited number of sensors or complexity of the structure, the optimal sensor planning is required in the pre-detecting phase in addition to data compensation techniques. Finally, in case of large scale structures, computationally efficient computers are required to solve the structural damage detection problem.

5. Damage localization

The proposed SPSOSCA algorithm for the purpose of solving the FEMU-based structural damage identification using the new objective function, previously stated in Eq. (7), is executed. By following back the original PSO algorithm [50] and the parametric study on PSO conducted by Alkayem et al. [58], the value of momentum coefficient ∈ [0, 1.5], the first acceleration coefficient ∈ [1, 5], and the second acceleration coefficient ∈ [0.5, 3.5], are recommended to initiate the PSO algorithm execution. Nevertheless, in this work, the parameters of SPSOSCA are determined similar to the constriction PSO [59,60] by initialization of the coefficient κ as:

$$\kappa = \frac{2G}{|2 - 2\Phi - \sqrt{4\Phi^2 - 8\Phi}|}, \tag{13}$$

where G is the generation number, and $\Phi = 2.05$ a predefined number calculated in [59]. Hence, the inertia factor and the acceleration coefficients are calculated, respectively, as:

$$A_1 = A_2 = \kappa * \Phi, \tag{14}$$

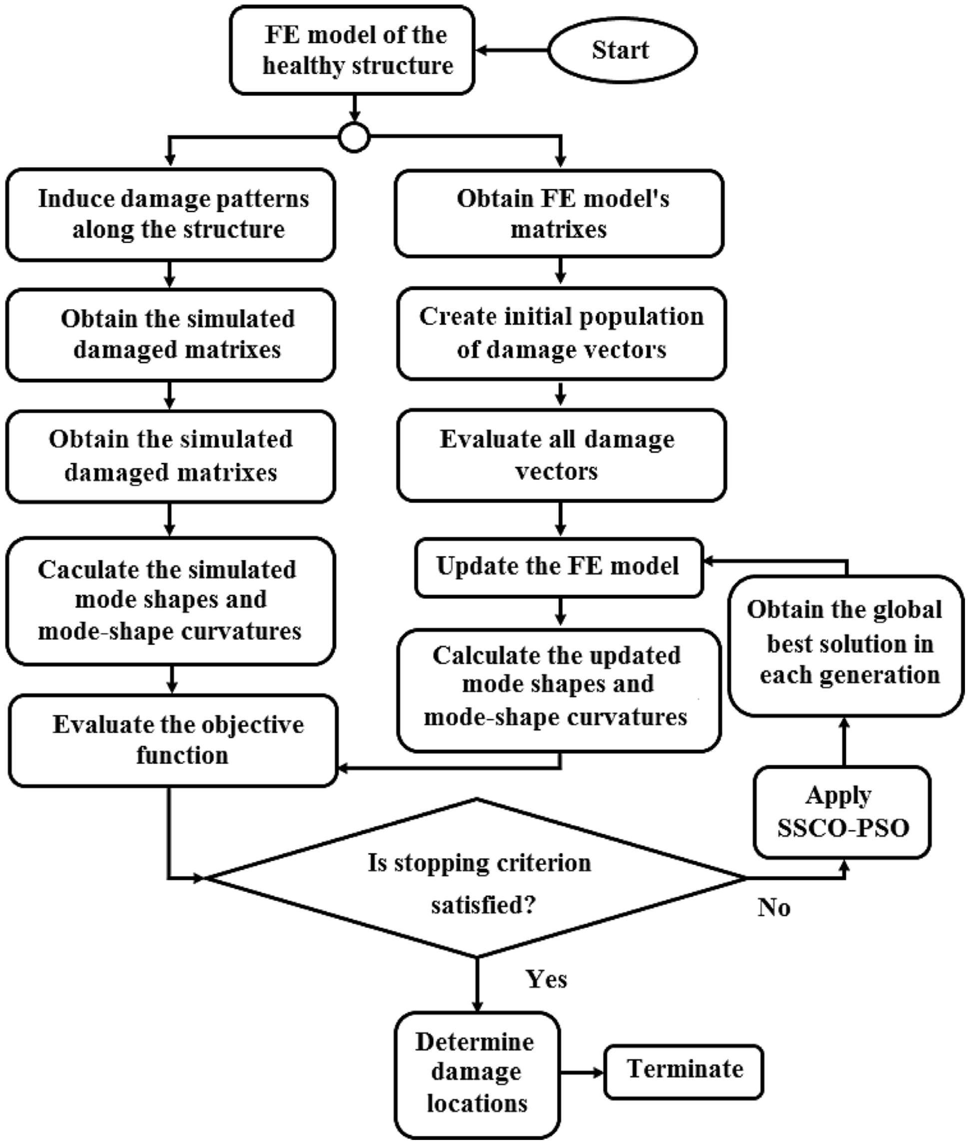

Fig. 1. Structural damage identification using and FEMU with SPSOSCA.

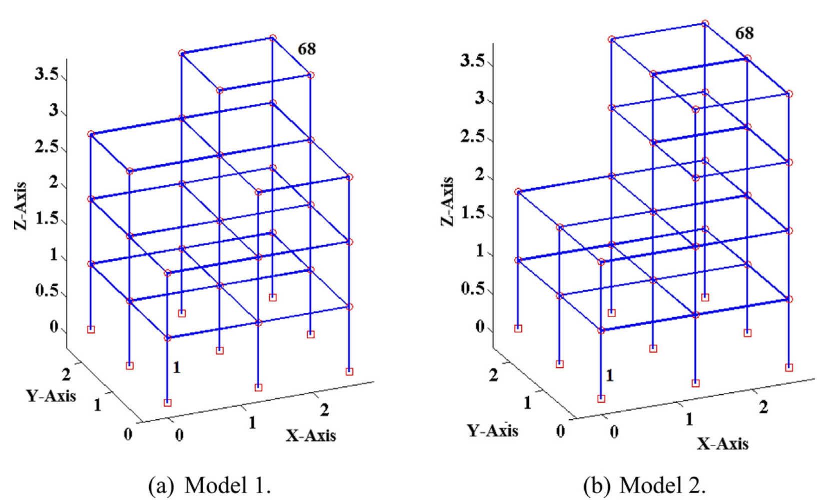

Fig. 2. Three dimensional irregular-shape modular structures.

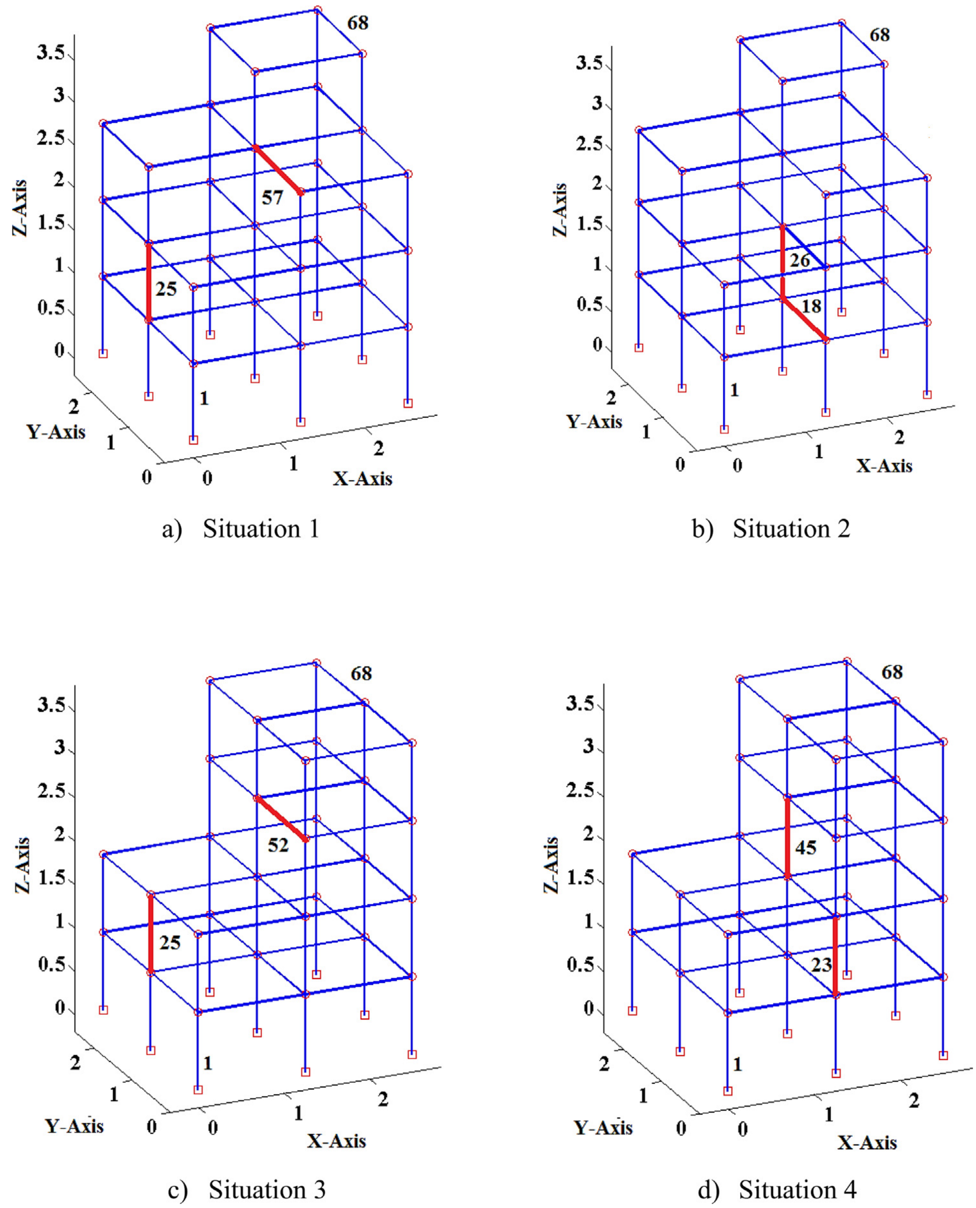

Fig. 3. Damage scenarios.

$$\Omega^{G+1} = \Omega^{G} * \Omega_{damp}, \tag{15}$$

where $\Omega_{damp} = 0.99$. Therefore, the acceleration coefficients are $A_1 = A_2 = 1.494 \approx 1.5$ using Eq. (14). The inertia factor is initiated as $\Omega^1 = 1$ and damped in each generation using Eq. (15) as well as the constant a is set to default value of 2. After several trials, the population size is set to 100 because no further improvements were recorded after the population size of 100 and with an intensive increase of computational time for higher population size. The algorithm is run for 20 times and the minimum, mean and maximum objective values as well as the standard deviation are recorded. The outcomes of damage localization process corresponding to FE model 1 and the convergence of the algorithm towards the optimum can be deduced from Figs. 4–6. Also, the results of implementation on model 2 are shown in Figs. 7–9. By checking the results, it is observed that the proposed SPSOSCA algorithm serves well when used to solved the hybrid new objective function that utilized the MSTEN and MSC subobjectives, though some minor and acceptable errors are reported during the damage detection paradigm.

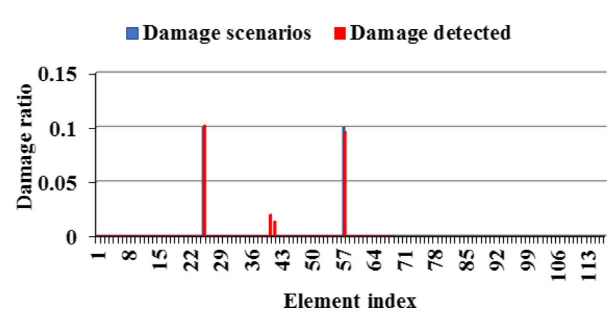

Fig. 4. Damage locations (model1 — damage case1).

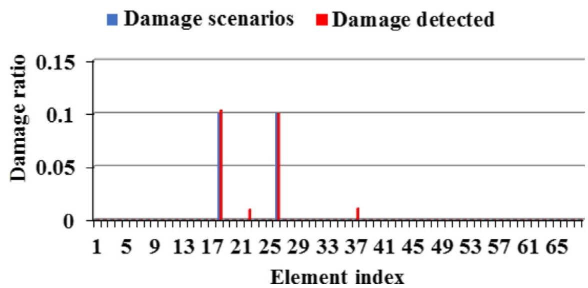

Fig. 5. Damage locations (model1 — damage case2).

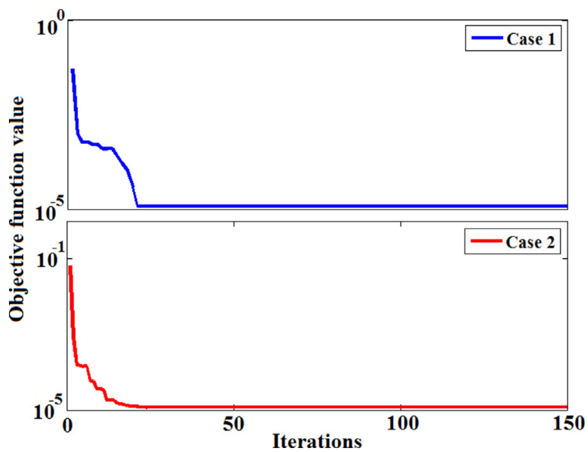

Fig. 6. Convergence of SCCO-PSO algorithm (model1 — damage cases 1 and 2).

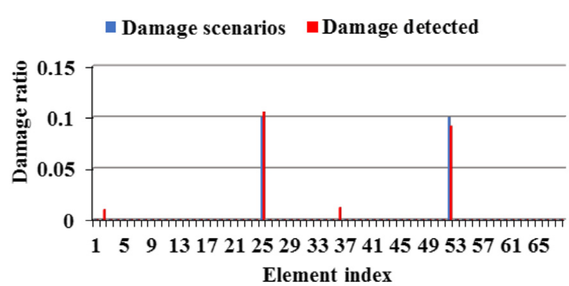

Fig. 7. Damage locations (model2 — damage case3).

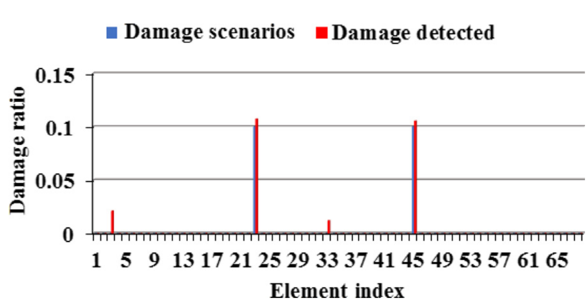

Fig. 8. Damage locations (model2 — damage case4).

To evaluate the overall performance of the above mentioned framework, the simulated damaged mode shapes related to damage case 1 and damage case 4 in model 1 and model 2, respectively, which in turn provide the core parameters for MSTEN and MSC, are contaminated with Gaussian noise having the maximum absolute amplitude of 5%. The SPSOSCA algorithm is run using the

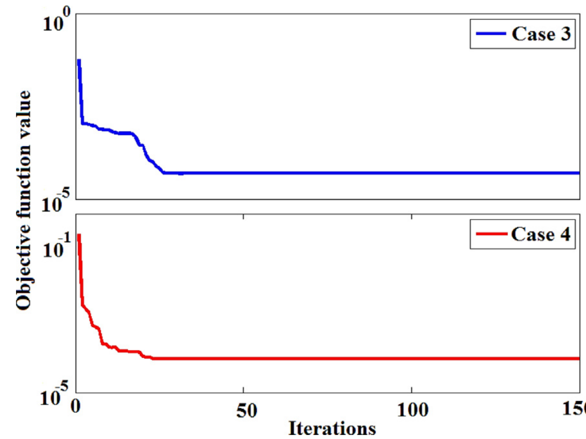

Fig. 9. Convergence of SCCO-PSO algorithm (model2 — damage cases 3 and 4).

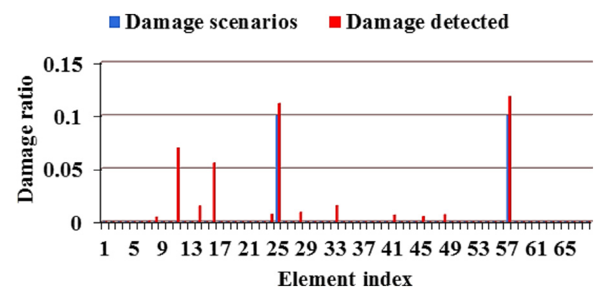

Fig. 10. Damage locations (model1 — damage case1) subject to noise simulation.

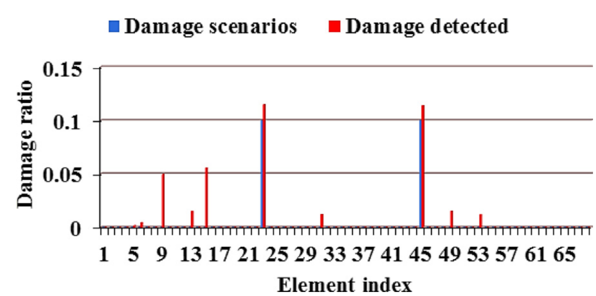

Fig. 11. Damage locations (model2 — damage case4) subject to noise simulation.

same settings and the damage identification results with respect to damage case 1 and damage case 4 are shown in Fig. 10 and Fig. 11, respectively.

Last but not least, comparisons are made between the suggested SPSOSCA and the original PSO with respect to computational efforts, standard deviation, as well as minimum, mean maximum objective function values. Moreover, a non-parametric test called Wilcoxon Rank Sum (WRS) [61] test is used to show if the results are statistically significant or not. The significance level "p-value" which should be less than 0.05 is used to authenticate the statistical significance of SPSOSCA against the original PSO. The *p*-value which is above 0.05 means that there is no difference between the two studied results and vice versa. The recorded performances for both algorithms are summarized in Table 7. By studying the results, it is well observed that the developed SPSOSCA has shown a prominent performance comparing to the original PSO. By comparing the computational effort of SPSOSCA and PSO, PSO takes less computational time because of the additional SSCO part in SPSOSCA. Nevertheless, SPSOSCA is

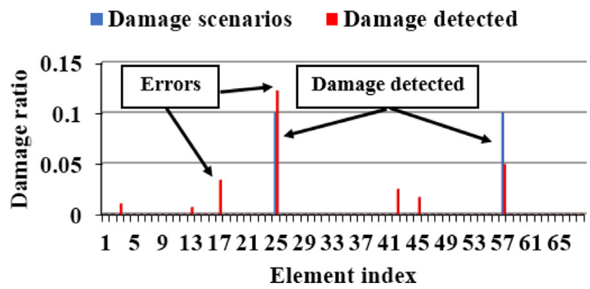

Fig. 12. Damage locations (model1 — damage case1) under noisy conditions (8%).

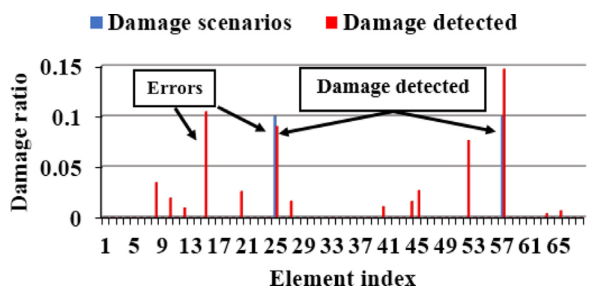

Fig. 13. Damage locations (model1 — damage case1) under noisy conditions (10%).

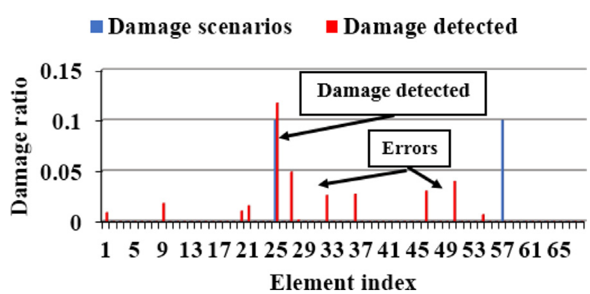

Fig. 14. Damage locations (model1 — damage case1) under noisy conditions (12%).

statically significant according to the WRS test conducted against the original PSO.

Finally, to check to which level of noise the algorithm fails, the mode-shapes of the model1 — damage case1 are contaminated with higher levels of Gaussian noise, specifically, 8%, 10%, and 12%. The results of executing the SPSOSCA algorithm are shown in Figs. 12–14, corresponding to the three levels of noise mentioned above, respectively. Fig. 12 shows the successful damage detection of SPSOSCA with a considerable negative effect of noise. Moreover, SPSOSCA is able to identify damage under the condition of 10% noise as in Fig. 13, nevertheless, it has given a wrong high prediction of damage in other two locations. Finally, it is clear from Fig. 14 that the SPSOSCA has failed to reveal damage in one of the locations and succeeded to detect damage in the other location.

6. Future research scope

This paper hints some potential future research directions to better improve the application of FEMU for damage deduction in complex structures as follows:

- By considering the difficulty of detecting damage in large scale complex structures, it is highly suggested to do further research on the application of machine learning tools to first localize the possible substructures that experience damage and then apply FEMU with ECs in order to reduce the expensive computational time and provide convenient online damage detection process.
- The use of modal characteristics can be combined with other types of dynamic responses derived from signal processing technology, such as, wavelet transforms, Hilbert–Huang Transform, etc. Such utilization may give more damage information from the structure and provide better assistance to damage identification procedure.
- Damage detection in structures, especially when with FEMU, is practically facing major issues including the response measurement difficulties and incomplete data. Therefore, further industrial applications should be conducted and effective noise removal methods with data compensation technologies have to be employed.
- Many new EC algorithms are being developed having their specific features and characteristics. No usage of such algorithms for solving structural mechanics and damage inference problems has been reported. Hence, it is worth to utilize those algorithms and improve their performances using modified and hybrid paradigms to solve the existing structural damage identification problems, in addition to other more complex problems.

7. Concluding remarks

In this work, damage estimation in complex irregular-shape structures using a hybrid MSC and MSTEN objective function within a FEMU procedure was presented. A novel objective function merging MSC and MSTEN was developed to indicate maximum dynamic information of the structure. A new hybrid EC optimization algorithm combining PSO and SCO algorithms was evolved to solve the problem of FEMU for damage prediction in complex-shape structures. The novel methodology named SPSOSCA was prepared mainly by using social interaction between PSO and SCO to overcome the highly non-linear and multimodal optimization problem of FEMU-based damage deduction. To check the reliability of the developed paradigm, two irregular-shape structures were constructed and four damage situations were studied. For each damage situation, the modal characteristics of MSC and MSTEN were derived and Gaussian noises were used to contaminate the derived modal characteristics aiming to study the durability of the method under noisy environments. The developed method proved a very good solidity and stability when applied on different damage situations in irregular-shape structures. With a relatively low computational efforts, noise overcoming abilities and steady performance, the FEMU-based damage inference in complex irregular-shape structures using the newly developed objective function and SPSOSCA algorithm can be highly recommended and promoted for structural damage prognostication.

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Table 7
Performance comparisons between SPSOSCA and PSO.

Damage situation	EC	Mean computational time (s)	Min objective function value	Mean objective function value	Max objective function value	STD	WSR test (*P*-value)
Situation 1	PSO SPSOSCA	2512 3304	3.44E−06 **1.54E−06**	8.16E−05 **3.13E−05**	0.000344 **0.000139**	0.000118 **3.47E−05**	0.04648
Situation 2	PSO SPSOSCA	2652 3402	4.85E−07 **1.31E−07**	0.000126 **2.37E−05**	0.000534 **0.000258**	0.000155 **5.62E−05**	0.00181
Situation 3	PSO SPSOSCA	2112 3592	**1.07E−06** **1.07E−06**	0.00012 **1.86E−05**	0.000696 **0.00013711**	0.000212 **3.79E−05**	0.00013
Situation 4	PSO SPSOSCA	2470 3366	1.25E−05 **1.46E−07**	0.00024 **6.15E−05**	0.00105 **0.000182**	0.000297 **5.66E−05**	0.04272
Situation 1 with noise	PSO SPSOSCA	3490 3902	0.007707 **0.007179**	0.007868 **0.007277**	0.008169 **0.007413**	0.000186 **7.19E−05**	0.00004
Situation 4 with noise	PSO SPSOSCA	3304 4002	**0.0138936** **0.0138936**	0.0140945 **0.0140206**	0.0148389 **0.0146258**	3.07E−4 **02.09E−4**	0.00022

Declaration of competing interest

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.asoc.2019.105604.

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