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Optimization-based method for structural damage detection with consideration of uncertainties- a comparative study

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Abstract. In this paper, for efficiently reducing the computational cost of the model updating during the optimization process of damage detection, the structural response is evaluated using properly trained surrogate model. Furthermore, in practice uncertainties in the FE model parameters and modelling errors are inevitable. Hence, an efficient approach based on Monte Carlo simulation is proposed to take into account the effect of uncertainties in developing a surrogate model. The probability of damage existence (PDE) is calculated based on the probability density function of the existence of undamaged and damaged states. The current work builds a framework for Probability Based Damage Detection (PBDD) of structures based on the best combination of metaheuristic optimization algorithm and surrogate models. To reach this goal, three popular metamodeling techniques including Cascade Feed Forward Neural Network (CFNN), Least Square Support Vector Machines (LS-SVMs) and Kriging are constructed, trained and tested in order to inspect features and faults of each algorithm. Furthermore, three well-known optimization algorithms including Ideal Gas Molecular Movement (IGMM), Particle Swarm Optimization (PSO) and Bat Algorithm (BA) are utilized and the comparative results are presented accordingly. Furthermore, efficient schemes are implemented on these algorithms to improve their performance in handling problems with a large number of variables. By considering various indices for measuring the accuracy and computational time of PBDD process, the results indicate that combination of LS-SVM surrogate model by IGMM optimization algorithm have better performance in predicting the of damage compared with other methods.

Keywords: Ideal Gas Molecular Movement (IGMM); Probability-Based Damage Detection (PBDD); Probability of Damage Existence (PDE); surrogate modeling; uncertainty quantification

1. Introduction

Structural systems in civil engineering are subjected to deterioration and damage during their service life. Damage is characterized as a weakening of the structure which may cause undesirable displacements, stresses, strain or vibrations to the structure leading to sudden and disastrous results. Damage can severely affect the safety and functionality of the structure and identification of it at early stage can increase safety and extend its serviceability. Thus, identification of damage is one of the most important factors in maintaining the safety and integrity of structures (Fan and Qiao 2011, Hakim and Razak 2014).

The structural damages are usually detected by the modal parameters of the structure (Boller *et al.* 2009), because not only are modal parameters (modal frequencies and mode shapes) functions of the physical parameters (mass and stiffness) and the existence of damage may lead to changes in the modal properties of the structure, but also modal parameters can be measured conveniently and accurately. Damage estimation techniques from modal data are often based on methods of model updating. These methods rely on a parametric model of the structure and the minimization of some objective functions based on the errors between the measured data and the predictions from the model (Ghasemi *et al.* 2018, Hakim and Razak 2014). The success of the finite element (FE) model updating method depends on the accuracy of the FE model, the quality of the modal tests, the definition of the optimization problem and the capability of the optimization algorithm.

The use of approximate models known as surrogate models with a much lower computational cost instead of expensive computer analysis codes (Finite Element Model) provides much of today's engineering design and optimization. These models are used to replace the actual expensive computer analyses packages, and to facilitate multidisciplinary, multi-objective optimization, reliability analyses and concept explorations (Ghiasi *et al.* 2016, Liu *et al.* 2011, Padil *et al.* 2017).

In fact detection of damage severity is effectively the solution to the inverse problem (Fathnejat *et al.* 2014, Torkzadeh *et al.* 2016). However, it may be necessary in many cases to solve the forward problem to generate data for the solution of the inverse problem. Now, since generation of data is usually computationally expensive, surrogate models may be created to reduce the computational cost (Mahmoudi *et al.* 2016). Simulation of efficient surrogate model of finite element (FE) as a response of updating damaged structure, could replace

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expensive numerical simulations while enhancing computation efficiency. It employed in the optimization loop through an inverse process to ascertain the damage severity and location as damage parameters. Torkzadeh *et al.* (2016) proposed solution procedure based on artificial neural network (ANN) to reduce the computational time of model updating during the process of damage severity detection.

Studies shows that ANNs are capable of providing correct damage identification, especially when the structural damage and the associated changes in vibration properties are simulated numerically and are error free (Ghiasi *et al.* 2017, Hakim and Razak 2014). However, in practice uncertainties in the FE model parameters and modelling errors are inevitable. The existence of error in the FE modelling, due to the inaccuracy of physical parameters and non-ideal boundary conditions and also finite element discretization together with nonlinear structural properties, may result in generating the vibration parameters from such a FE model not exactly representing the relationship between the modal parameters and the damage parameters of the real structure (Simoen *et al.* 2015). On the other hand, the existence of measurement error in the measured data, normally used as testing data in a surrogate model, is also unavoidable. Since the efficiency of a surrogate model prediction relies on the accuracy of both components, the existence of these uncertainties may result in false and inaccurate predictions. Therefore, the impact of uncertainties on the reliability of surrogate models for structural damage detection needs to be analysed.

The main objective of this paper is therefore to study the influence of uncertainty on damage identification using a combination of frequency and mode shape as the input variables. To consider the uncertainties in the FE modelling (aleatory uncertainty) and the measurement data (epistemic uncertainty), a novel approach based on a method introduced by Papadopoulos and Garcia (1998) is applied. On its basis, the probability of damage existence (PDE) can be estimated by comparing the probability distribution of the undamaged and damaged models. To consider the effect of FE modelling error, a surrogate model is trained with vibration data generated from the FE model, smeared though with random variations. To include the effect of noise in the measurement data, the testing data used as input to the surrogate model for damage identification are also smeared with random noises.

The basis of this paper is to introduce a novel technique for structural PBDD by correlating some superlative metaheuristic optimization algorithms and surrogate models. For optimization, three algorithms; Ideal Gas Molecular Movement (IGMM) (Varaee and Ghasemi 2017), Particle Swarm Optimization (PSO) (Kennedy 2010) and Bat Algorithm (BA) (Yang and Gandomi 2012) are modified to improve their performance, and for metamodeling, Cascade Feed Forward Neural Network (CFNN) (Hedayat *et al.* 2009), Least Square Support Vector Machines (LS-SVMs) (Suykens and Vandewalle 1999) and Kriging (Dubourg and Sudret 2011) are trained and tested. The executed results are the consequences of a just one-stage proposed algorithm.

To validate the proposed probability-based damage detection method, three examples are presented. In first example, the accuracy and the number of function evaluations of selected metaheuristic algorithms are compared together. In second example the possibility of using surrogate model as substitute of finite element analysis evaluated by comparison of various surrogate model. In third example the two previous part are merged to create mechanism for PBDD and this novel procedure is evaluated by various index.

The main contributions of this paper may be summarized as follows:

1. Following the new intelligent health-monitoring framework, a one-stage learning method will be proposed in this paper for PBDD. This framework consist on three interconnected loop: metamodeling loop, optimization loop and probability loop.
2. For metamodeling loop, three prominent surrogate model are constructed, trained and tested in order to inspect advantages as well as the shortcomings of each algorithm.
3. For optimization loop, three well-known optimization algorithms are chosen and performance of them are compared together. Furthermore, efficient schemes are implemented on these algorithms to improve their performance in handling problems with a large number of variables.
4. And finally, in probability loop to consider the uncertainties in the finite element (FE) modelling and the measurement data, a novel approach is introduced. Hence, a surrogate model is trained and tested with smeared vibration data and the statistical properties of Young's modulus value (E) for each segment are obtained by using Monte Carlo simulation

The paper is organized as follows. The brief introduction about model updating methodology and analytical formulation of damage index presented in Section 2 and 3. Section 4 and 5 then presents review of the metamodels and metaheuristic algorithms. Probability based model updating and the proposed damage detection procedure is described in Sections 6 and 7. Numerical examples are attempted in Section 8 and finally, Section 9 presents conclusions of the work.

2. Model updating methodology

Model updating methods are widely employed to develop a more accurate finite element (FE) model in giving the real structure to be used for optimization design, damage identification, structural control, and structural health monitoring. The basic procedure of a model updating is to continuously adjust the elemental parameters (usually stiffness properties) so as to predict the model, approving the actual measurements, as closely as possible (Xu *et al.* 2013). Fig. 1 shows general flowchart of the model updating based method for damage detection.

Features vectors of the real structure and the analytical model will be compared together by damage index, a detailed of which will be described in the section 3.

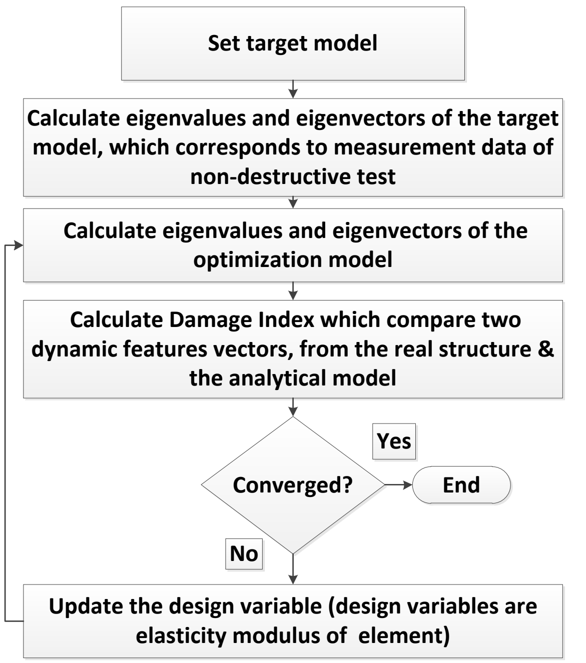


Fig. 1 General flowchart of the model updating based method for damage detection

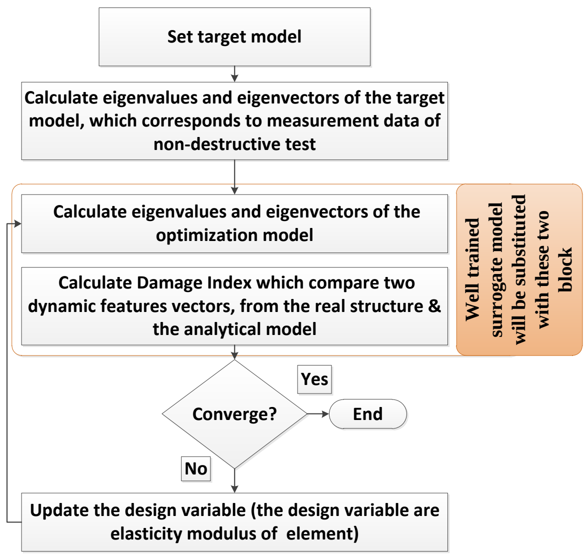


Fig. 2 Flowchart of the model updating based method for damage detection considering surrogate model

The conventional model updating procedure is usually expensive for a large-scale numerical model in terms of computation time and computer memory. For example, Xia *et al.* (2008) carried out a model updating exercise for the Balla Balla Bridge in Western Australia, which was modelled by 907 elements, 949 nodes and 5,400 degrees of freedom (DOFs). Convergence of the optimization took 155 iterations and cost about 420 hours. The considerable burden associated with the model updating method is due to two reasons: 1) the large-scale model is represented by large size system matrices, and the repeated analysis of the large-size matrices is a heavy workload. 2) Many uncertain

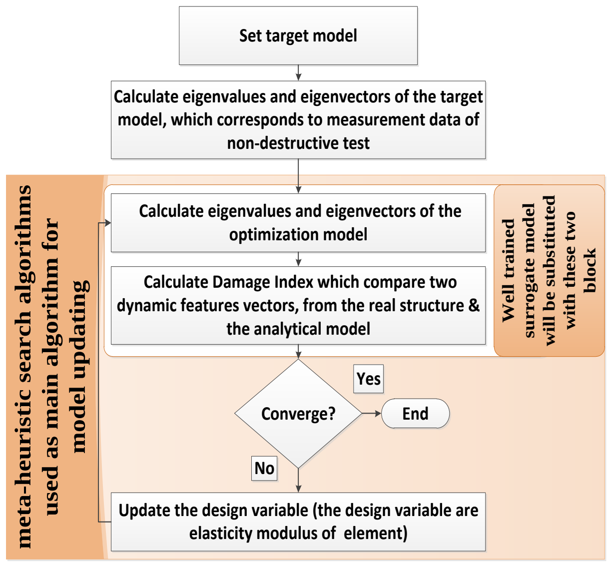


Fig. 3 Flowchart of the model updating based method for damage detection considering surrogate model and metaheuristic algorithms

Parameters need to be adjusted in a large-scale Numerical model, which makes convergence of the large-scale optimization problem much more difficult. The surrogate method was found a promising solution for reducing computation load in engineering applications. Therefore, in this paper well trained surrogate model will be substituted with two block of general flowchart of Fig. 1 as Fig. 2. The proposed surrogate models will be described in more detail in the section 4 and 7.

Furthermore, in order to deal with complex, high-dimensional, non-linear, non-differentiable and ill-condition function, used in structural health monitoring (SHM) process (Boller *et al.* 2009), some kind of a global optimization algorithm is required. For that purpose, meta-heuristic search algorithm will be used as the main algorithm of model updating process (Fig. 3). More details will be described in the section 5.

3. Multiple Damage Location Assurance Criterion (MDLAC)

Structural damage detection techniques are generally classified into two main categories. They include the dynamic and static identification methods requiring the dynamic and static test data, respectively. Furthermore, the dynamic identification methods have shown their advantages in comparison with the static ones (Nobahari *et al.* 2017). Among the dynamic data, the modal analysis information of a structure such as the natural frequencies and mode shapes were widely used for damage detection (Ghiasi *et al.* 2015, Seyedpoor 2012, Shirazi *et al.* 2013). Determination of the level of correlation between the measured and predicted natural frequencies or mode shapes can provide a simple tool for identifying the location and severity of structural damages. When the natural frequencies are employed to identify the damage, two parameter vectors may be determined. One parameter vector consists of the ratios of the first n_f natural frequency changes ΔF due to structural damage, i.e.

$$\Delta F = \frac{F_h - F_d}{F_h} \tag{1}$$

where F_h and F_d indicate the natural frequency vectors of the healthy and damaged structure, respectively. Another parameter vector can be similarly defined as

$$\delta F(ESV) = \frac{F_h - F(ESV)}{F_h} \tag{2}$$

where $F(ESV)$ is a natural frequency vector that can be extracted from an analytic model and elemental stiffness vector (ESVs) $ESV^T = [E_1, \ldots, E_i, .., En]$ which represents a damage variable vector containing the elasticity modulus of structural elements $(E_i, i = 1, \ldots, n)$ of all n structural elements.

Given the pair of parameter vectors, one can estimate the level of correlation in several ways. An efficient way is to evaluate a correlation index called the multiple damage location assurance criterion ($MDLAC$) which is expressed in the following form(Seyedpoor 2012)

$$MDLAC(ESV) = \frac{|\Delta F^T \delta F(ESV)|^2}{(\Delta F^T \Delta F)(\delta F^T(ESV)\delta F(ESV))} \tag{3}$$

The $MDLAC$ compares two frequency change vectors, one of which is obtained from the examined structure and the other from an analytical model of the structure. The $MDLAC$ varies from a minimum value 0 to a maximum value 1. It will be maximal when the vector of analytical frequencies equates to the frequency vector of damaged structure, i.e.

$$F(ESV) = F_d \tag{4}$$

4. Review of the selected metamodels

Basically, the analysis procedure within the concept of SHM, falls into two main classes: parametric (also known as model-based) methods and non-parametric (also known as model-free or data-driven) methods (An *et al.* 2015).

These methodologies follow specific procedures and are applicable in distinct contexts. These interpretation methods will be preferred over each other based on desired objectives. If the objective is to provide a better physical conceptualization or developing a prediction model, then parametric methods may be better alternatives while dependency on behavior model is the main downside associated with this type of algorithm (Malekzadeh and Catbas 2016).

Alternatively, non-parametric methods, are superior since creating a behavioral model is either time consuming or expensive. This aspect is considered as their leading advantage over parametric methods (Malekzadeh *et al.* 2015, Malekzadeh and Catbas 2016).

Indeed, model-free approaches are free of geometrical and material information. Also, interpreting a finite element model is not needed for such methods. Their main shortcoming however is that having a predictive model based on existing data driven methods is not possible.

The data-driven approaches are generally divided into two categories (An *et al.* 2015): (1) the artificial intelligence approaches that include neural network (NN), fuzzy logic and new methodologies such as Deep Learning (Al-jarrah *et al.* 2015, Farrar and Worden 2012); and (2) the statistical approaches that include the Gaussian Process (GP) regression, relevance/support vector machine, least squares regression, the gamma process, the Wiener processes, hidden Markov model, and new method such as Polynomial Chaos expansion NARX models (An *et al.* 2015, Spiridonakos and Chatzi 2015b). Among these algorithms, three algorithms mentioned in the introduction are most commonly used for SHM, and thus, will be utilized and discussed in this paper.

4.1 SVM Summarization

Support vector machine (SVM), a novel machine learning method based on statistical learning theory (SLT), is a small-sample statistical theory, introduced by Cortes and Vapnik (1995). The SVM training process always seeks a global optimized solution and avoids over-fitting, so it is powerful for the problems characterized by small samples, non-linearity and high dimension. In simple terms, the SVM can be thought of as creating a line, or hyper-plane between two sets of data. Imagine two different class of data, class A and class B, as a two-dimensional case that each of them is composed of a series of data. The SVM attempts to place a linear boundary between the two different classes, and orientate it in such a way that the margin is maximized. In other words, the SVM tries to orientate the boundary in such a way as to ensure that the distance between the boundary and the nearest data point in each class is maximal (Fig. 4). The optimal hyperplane can be obtained as a solution of the constrained quadratic programming (QP) optimization problem.

The boundary is then placed in the middle of this margin between the two points.

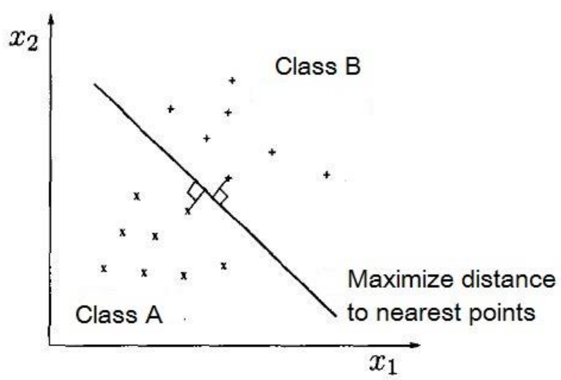


Fig. 4 Definition of a unique hyperplane which corresponds to a maximal distance between the nearest points of the two classes A and B

The nearest data points are used to define the margin, and are known as support vectors. SVM can be used for multi-class categorizations and regression problems as well. The basic idea of the support vector regression is to map the input data into a feature space via a nonlinear map. In the feature space, an optimum linear decision function is constructed based on the structural risk minimization (SRM) principle; then SVM nonlinearly maps the inner product of the feature space to the original space via kernels (Cortes and Vapnik 1995). SVM has offered promises to overcome the conditional neural networks shortcoming such as the local minimizing and inadequate statistical capabilities (Suykens and Vandewalle 1999).

For the outstanding learning performance of SVM, it has been applied to structure health monitoring (Ghiasi *et al.* 2016). The LS-SVM is a kind of expansion of standard SVM. In the LS-SVM, Vapnik's ε-insensitive loss function has been replaced by a sum-squared error (SSE) cost function. Moreover, the LS-SVM considers equality type constraints instead of inequalities as in the classic SVM approach (Suykens and Vandewalle 1999). This reformulation greatly simplifies a problem such that the LS-SVM solution follows directly from solving a set of linear equations rather than from a convex quadratic program (QP).

4.2 Cascade feed-forward neural network

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

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

4.3 Kriging

Kriging, which is widely used, is a combination of polynomial regression and Gaussian stochastic processes (Dubourg and Sudret 2011). The regression model fits the samples according to the rule of least-squares estimation. The correlation model adjusts the prediction error by using maximum likelihood estimation. Kriging is formulated as (Xu *et al.* 2013)

$$\hat{y} = Y(x) + Z(x) = \overbrace{\sum_{i=0}^{n} \beta_i f_i(x)}^{regression} + \underbrace{Z(x)}_{correlation} \tag{5}$$

Where $Y(x) = \sum_{i=0}^{n} \beta_i f_i(x)$ is the regression model, which usually adopts polynomials up to the second order to represent the global trend of the sample points $Z(x)$ is the correlation model, which is a Gaussian process with mean value 0 and covariance σ. The correlation model is given by

$$cov\left(Z(x_j), Z(x_k)\right) = \sigma^2 R_{ij}(\theta, x_j, x_k) \tag{6}$$

where R_{ij} is the Gaussian correlation function on the *p*-dimensional design space

$$R_{ij}(\theta, x_j, x_k) = \prod_{i=1}^{p} e^{-\theta_i(|x_{ji} - x_{ki}|^2)} \tag{7}$$

In Eqs. (6) and (7), θ is the coefficient vector of the correlation model. The optimal coefficients θ^* are found for maximum likelihood estimation. It is important to choose proper formulations of the regression functions which represent the system behavior as precisely as possible. Higher-order polynomial regressions have the capability of approximating more complex responses, but they require more sample points to determine the polynomial coefficients. By properly selecting the polynomial orders and mixed terms of design variables using knowledge of a system, the number of coefficients in regression functions can be greatly reduced.

5. Optimization techniques

In order to obtain the most probable values of the model parameters, the objective function should be minimized through an optimization algorithm. Three meta-heuristic search algorithms are used in this study to meet this goal: a Particle swarm optimization (PSO), Bat Algorithm (BA) and Ideal Gas Molecular Movement (IGMM). PSO and BA have been widely used in the area of damage identification (Ghiasi *et al.* 2014, Torkzadeh *et al.* 2016) and IGMM is a relatively new but previously proven very effective in some aspects (Ghasemi and Varaee 2017a, b). These three algorithms have been chosen to assess the validity of the current study and to demonstrate the value of the newly presented IGMM over PSO and BA to the SHM community. In the following sub-sections, the algorithms are described in more details.

5.1 Bat optimization algorithm

Bat algorithm (BA) is a meta-heuristic population-based optimization technique, inspired first from the search of bats for food (Yang and Gandomi 2012). Bats send some signals to the environment and then listen to their echoes, called echolocation process. BA is mainly constructed by the use of three main ideas (Yang and Gandomi 2012).

All bats use echolocation to sense distance, and they also "know" the difference between food/prey and background barriers; a bat b_i flies randomly with velocity v_i at position x_i with a frequency f_i, varying wavelength λ and loudness A_i to search for prey. They can automatically adjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission $r_i \in [0,1]$, depending on the proximity of their target; Although the loudness can vary in many ways, (Yang and Gandomi 2012) assumed that the loudness A_i varies from a large (positive) A_0 to a minimum constant value A_{min} .For more detail information on process of BA algorithm, readers are referred to original papers (Yang and Gandomi 2012, Ghiasi *et al*. 2018)

5.2 Particle swarm optimization

The PSO has been inspired by the social behavior of animals such as fish schooling, insect swarming and bird flocking (Eberhart and Kennedy 1995). It involves a number of particles, which are initialized randomly in the search space of an objective function. These particles are referred to as swarm. Each particle of the swarm represents a potential solution of the optimization problem. The particles fly through the search space and their positions are updated based on the best positions of individual particles in each iteration. The fitness values of particles are obtained to determine which position in the search space is the best. In K^{th} iteration, the swarm is updated using the following equations

$$V_i^{k+1} = \rho^k V_i^k + c_1 r_1 \left(P_i^k - X_i^k\right) + c_2 r_2 (P_g^k - X_i^k) \qquad (8)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \qquad (9)$$

where X_i and V_i represent the current position and velocity vectors of the ith particle, respectively; P_i is the best previous position of the ith particle and P_g is the best global position among all the particles in the swarm; r_1 and r_2 are two uniform random sequences generated from interval [0,1]; c_1 and c_2 are the cognitive and social scaling parameters, respectively and ρ^k is the inertia weight used to discount the previous velocity of particle preserved. The inertia weight ρ^k may be defined to vary linearly from a maximum value ρ^{max} to a minimum value ρ^{min}. Velocity vector V_i is limited to a lower bound V^l and an upper bound V^u. For more detail information on process of PSO algorithm, readers are referred to original paper (Eberhart and Kennedy 1995).

5.3 Ideal gas molecular movement

The behavior of gas molecules in an isolated medium shows that they disperse rapidly in different directions and cover all the space inside. The essence of such manner lies on two factors; the high speed of ideal gas molecules and their collisions. Recently the conventional IGMM was introduced by the Varaee and Ghasemi (2017) and its application in solving engineering problems was assessed then (Ghasemi *et al*. 2017a, b, Ghasemi and Varaee 2017a, b). The algorithm utilizes the governing equations for speed and collision of molecules in order to determine their new location. The speed of molecules thus is proportional to the temperature and inversely proportional to its mass. Besides they collide with each other with a certain probability, increasing gradually with their motions. Ideal gas molecules have fully elastically collisions and elastic collision governing equations can be used to determine the new position of gas molecules after collision. For more detail on fundamental steps of the IGMM algorithm readers are referred to original paper (Varaee and Ghasemi 2017).

5.4 Efficient reduction of variables

In some optimization problems, the number of variables is very large. For example, in an optimization based damage detection problem, damaged elements and damage extents are searched through an optimization process until the response of hypothesized damaged structure equals those of a real damaged structure. When a real structure is largely scaled, the number of elements, being as variables, will increase (Torkzadeh *et al*. 2013). Hence, when the optimization method tries to minimize the objective function, it must handle a huge bunch of variables which decreases the convergence speed of the algorithm. In this situation the commonly used method in literatures divides the damage detection process into two steps. In the first step, suspected damaged elements are detected using various index such as MDLAC or modal strain energy-based index (MSEBI) (Fathnejat *et al.* 2014). In the second step, severity and exact locations of damage are obtained using various search algorithms such as PSO, genetic algorithm (GA), etc. (Nobahari *et al*. 2017b). Meanwhile these procedures are time consuming and in most cases high noise level makes them inaccurate and unreliable. Hence, in this paper innovative scheme is implemented to develop a one-stage method for a noise resistant damage identification.

In damage detection process, after generating the initial population as the first stage, each molecule/particle/bat has a velocity vector that represents its speed in an n-dimensional space. Each variable of this vector represents elasticity modulus of structural elements.

In the proposed method, first, the number of variables in first stage of the search algorithm is considered as the total number of elements. Then, all the intact elements are eliminated along each stage carried and the algorithm converges to the exact locations and severity of the true damaged elements. Zero values for the variables signifies that the i-th element of the structure is intact and a non-zero value refers to the damaged element. To reach to this goal, if the variables with near zero values $(Stiffness\ reduction\ ratin\ (SRF_i) \leq 0.05)$ do not alter for 10 iteration, this variable will be eliminated. This scheme is implemented for three aforementioned algorithm.

As far as the objective function is concerned, it is defined here as an unconstrained optimization problem as follows

$$\begin{aligned}&Find: ESV_i = \{E_1, E_2, E_3, \ldots, E_n\}\\&Minimize: F(ESV) = \|1 - MDLAC\|^2\\&Where: E_{min} \leq E \leq E_{max}\end{aligned} \tag{10}$$

Where $F(ESV)$ is the minimization problem and E_{min} and E_{max} are the lower and upper bounds of the damage vector, respectively. It is necessary that the bounds represent the physical behavior of the structure. Using an optimization algorithm and solving Eq. (10), the damage variables are determined.

6. Monte Carlo simulation for probability based model updating

Since uncertainties like noises inevitably exist in the measured vibration data, the updated ESV (E) is subjected to uncertainty as well. As mentioned before, the uncertainties in the measured modal data are assumed as independent normally distributed random variables with zero means and particular covariance. In this regard, the eigenvalues and mode shapes can be expressed as (Wang *et al.* 2013)

$$\begin{aligned}&\lambda_i^E = \lambda_{i,0}^E(1 + X_{\lambda i})\\&i = 1,2, \ldots, n_m\end{aligned} \tag{11}$$

$$\begin{aligned}&\phi_i^E = \phi_{i,0}^E\left(1 + X_{\phi i}\right)\\&i = 1,2, \ldots, n_m\end{aligned} \tag{12}$$

Where 0 represents the true values, $X_{\lambda i}$ and $X_{\phi i}$ denote relative random noises in the measured frequencies and mode shapes, respectively. The mean value of vector X is zero and the standard deviation represents the noise level.

The statistics (mean value and standard deviation) of E can then be calculated by the perturbation method (Hua *et al.* 2008) or Monte Carlo simulation (MCS). The latter method can also give statistical samples of the updated ESVs, from which the statistical distribution can be obtained. Studies have demonstrated that the statistical distribution of the ESVs in the updated model is also normal (Hao and Xia 2002), verified by the goodness-of-fit test (Kottegoda and Rosso 1997). Again when the measured modal data in both undamaged and damaged states are available and the model updating method is employed, the statistics of ESVs in both states (E^h and E^d) can be calculated.

The PDE can be estimated from statistical distributions of the stiffness parameters of the undamaged and damaged models. For example, if the stiffness parameter (α_j) of the undamaged segment J is normally distributed with mean $E(\alpha_j)$ and standard deviation $\sigma(a_j)$, the probability density function can be obtained as illustrated in Fig. 5, where L_{α_j} is the lower bound of the healthy parameter.

In this study, the confidence level is set to 95%, thus the lower bound is $L_{\alpha_j} = E(\alpha_j) - 1.645\sigma(\alpha_j)$, which indicates that there is a probability of 95% that the healthy stiffness parameter falls in the range of $[E(\alpha_j) - 1.645\sigma(\alpha_j), \infty]$. Similarly, for the stiffness parameter of segment j in the damaged state (α_j'), the distribution is again assumed as normal with mean $E(\alpha_j')$ and standard deviation $\sigma(\alpha_j')$, and the corresponding probability density function is also plotted in Fig. 5. The PDE is defined as the probability of not being α_j' within the 95% confidence healthy interval. Thus the PDE of segment j is

$$\begin{aligned}P_d^j &= 1 - prob\left(L_{a_j} \leq x_{a'} \leq \infty\right)\\&= prob(-\infty \leq x_{a'} \leq L_{a_j})\end{aligned} \tag{13}$$

PDE is a value between 0 and 1, and if the PDE of a segment is close to 1, then it is most likely that the element is damaged. If the PDE is close to 0, damage existing in the element is very unlikely (Bakhary *et al.* 2007, Padil *et al.* 2017). It should be noted again that the stiffness parameters of the undamaged and damaged state have normal distributions because the random variations in (11) are assumed as zero mean normally distributed random variables.

In most surrogate applications for damage detection, the training data are obtained from FE analysis, which involves generating large number of damage cases based on an initial baseline FE model. Once the surrogate model is well-trained, the testing data are applied to the model to obtain the locations and severities of any damages. In most of the previous studies, both training and testing data are assumed to be free from modeling and measurement error. In practice, however, modeling error and measurement noise are inevitable.

According to Xia *et al.* (2002), the inaccuracy due to modeling and measurement error can be overcome by taking into account the uncertainties through a statistical method. In this study, modeling error and measurement noise are assumed to be normally distributed with zero means and specific variance. The noise is applied in terms of coefficient of variations (COV). The statistical properties of E value for each segment are obtained by using Monte Carlo simulation. This is followed by calculation of the PDE of E values for each segment.

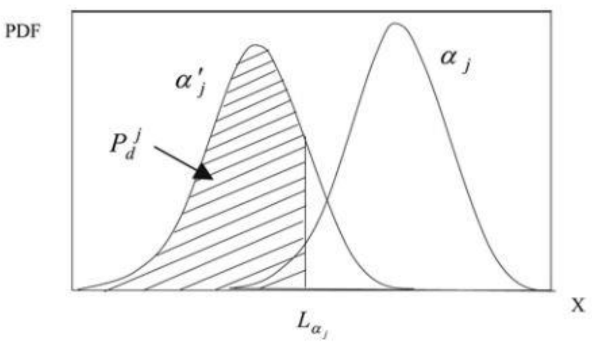


Fig. 5 Probability density functions for α_j and α_j' and probability of damage existence P_d^j

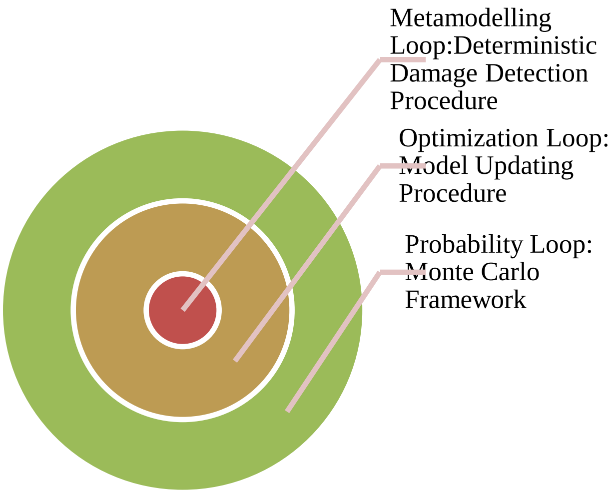


Fig. 6 General flowchart of the proposed PBDD

7. Main steps for proposed damage detection method

For the clarity, the general flowchart of the proposed PBDD method is depicted in Fig. 6. It consists of three interconnected loops. A more detailed flowchart is shown in Fig. 7.

The main steps for the proposed PBDD method using surrogate model and metaheuristic optimization algorithm are summarized as follows:

Step 1: Generate failure scenarios with the damage severity range between 0.05 and 0.40 with the pace of 0.05

Step 2: Develop FE model which computes the natural frequencies of the structure and finally the MDLAC corresponding to the failure scenarios that have been defined in the previous step.

Step 3: Use finite element (FE) model of the structure in order to generate training and testing datasets for development of surrogate model that is used in the optimization process of damage detection.

Step 4: Create MCS samples based on section 6 and set the initial number of design variables equal to the total number of elements.

Step 5: Engage directly the surrogate model by the optimizer to evaluate the objective function to be minimized to determine the damage of elements. (Apply surrogate model).

Step 6: Find i as $X_i = 0$ for all components of damage vector and determine the total number of intact elements.

Step 7: Remove the intact elements from the damage vector. Thus reduce number of variables from the optimization problem.

Step 8: Perform optimization algorithm once again based on the new optimization size from step 7.

Step 9: Check the convergence criterion by computing $1 - MDLAC$ from Eq. (10). If two response vectors are almost indifferent, save the results and terminate the optimization process then go to step 4, otherwise, go to the step 6.

Step 10: Calculate PDE of elements using the statistics (mean value and standard deviation) of E that calculated based on result of step 9.

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

8. Numerical results of damage detection

In this study, three structures are selected as the numerical examples to reveal the robustness and the degree of accuracy of the proposed damage detection method. These structures are:

(1) 72-bar space truss problem
(2) 120-bar Dome Truss problem
(3) Five-Story, Four-Span Frame

In first example, the accuracy and robustness of selected metaheuristic algorithms are evaluated based on statistical results. In second example the possibility of using data driven methods as substitute of finite element analysis evaluated by comparison of various surrogate model. The third example will merge the two previous parts together to create a mechanism for PBDD and this novel procedure is evaluated by various indices. Therefore, a 72-bar spatial truss is chosen as the first numerical example based on conveniently of implementation of its FE code in MATLAB for using it as core model for comparison the performance of metaheuristic algorithms.

A 120-bar dome truss is considered as the second example to show robustness of proposed method in substitution with FE model in larger structure. Finally The third example is a five-story, four-span frame, which is selected for demonstrate the capability of proposed method for damage detection of various structural configuration, in example 1 and 2, 3D truss structures which has only compression-tension members is examined and in last example frame structure that has flexural members with rigid connection is considered.

The mass matrix is assumed to be constant and the damage in the structures is simulated as a relative reduction in the elasticity modulus of individual element. Stiffness reduction ratio (SRF) is defined as

$$SRF_i = \frac{E - E_i}{E}, i = 1, \ldots, n \tag{14}$$

Where E is the original modulus of elasticity and E_i is the final modulus of elasticity of the i-th element. Due to the stochastic nature of optimization algorithm, twenty independent runs for each problem are carried out. Number of molecules/particles/bats was fixed to 50 for each run with a maximum of 200 iterations allowed. The number of maximum function evaluations is, therefore summed to 10,000. The mean values and standard deviations of E for estimating PDE is calculated from 500 samples, based on the Monte Carlo simulation framework.

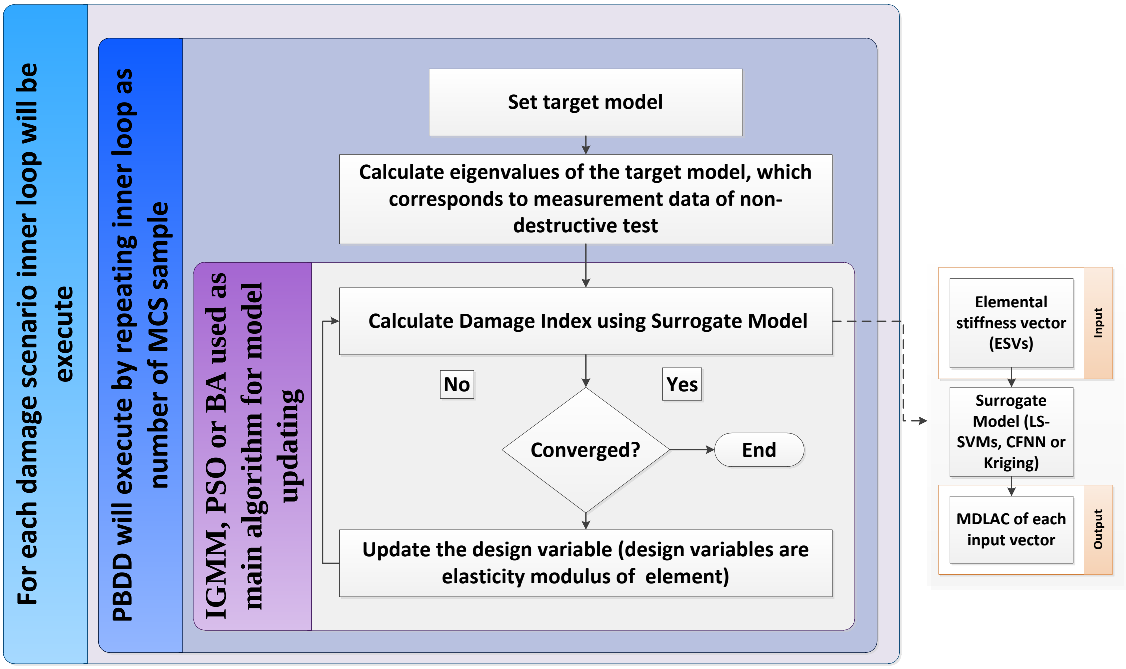


Fig. 7 Detailed flowchart of the proposed PBDD Method

Table 1 Properties of 72-bar space truss

E,modulus of elasticity(N/m^2)	ρ, material density(kg/m^3)	Added mass (kg)	A, cross-sectional area of the members(m^2)
6.98×10^{10}	2770	2270	0.0025

8.1 The 72-bar space truss

A 72-bar spatial truss is considered as the first numerical example, shown in Fig. 8. Four non-structural masses of 2270 kg are attached to the nodes 1–4. This structure has also been investigated as an example in the field of structural optimization under frequency constraints, by different researchers (Dizangian and Ghasemi 2016, Kaveh and Zolghadr 2014). As it can be seen from Fig. 8, the structure has 48 degrees of freedom. Table 1 represents the properties for this example.

Two cases of damage are assumed for this structure:

Damage case 1: 15% of damage in element 55; (15% of damage in each of the vertical members of the first story will result in the same set of natural frequencies).

Damage case 2: 10% of damage in element 4 and 15% of damage in element 58; (90, 180, and 270 degrees rotation along the z axis will result in the same set of natural frequencies).

In this section, the validity of IGMM in dealing with PBDD problems will be investigated, and a comparison of results with some available metaheuristic algorithms will be presented. The convergence measure applied for engineering optimization problems is based on the proximity of the fit-test design in the current iteration with that of 20 iterations before. Thus, if the difference between these two values is less than a small allowable tolerance value, it is recorded as converged. The desired value for this example is set to 10^{-3}. If not converged, the algorithm will be terminated by implementing a maximum number of iterations set fixed. The statistical data on 20 independent runs for damage cases of 1 and 2 are presented in Tables 2 and 3.

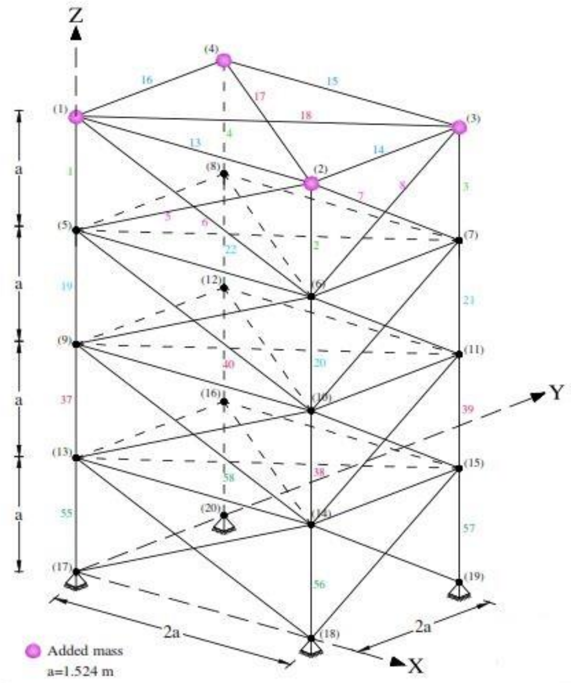


Fig. 8 72-bar spatial truss

Table 2 Statistical results of different approaches for damage case 1 of the 72-bar truss

	PSO	BA	IGMM
Damaged Element	55	55	55
Actual Damage Severity	0.15	0.15	0.15
Best	0.156	0.151	0.15
Mean	0.152	0.157	0.153
Worst	0.12	0.139	0.142
SD	0.02	0.011	0.007
Success %	90	100	100
NFEs	950	660	400
Rank	3	2	1

Table 3: Statistical results of different approaches for damage case 2 of the 72-bar truss

	PSO		BA		IGMM	
Damaged Element	4	58	4	58	4	58
Actual Damage Severity	0.1	0.15	0.1	0.15	0.1	0.15
Best	0.09	0.15	0.10	0.15	0.10	0.15
Mean	0.09	0.15	0.10	0.15	0.10	0.15
Worst	0.06	0.18	0.07	0.13	0.08	0.16
SD	0.01	0.01	0.01	0.01	0.01	0.00
Success %	90		100		100	
NFEs	1250		960		650	
Rank	3		2		1	

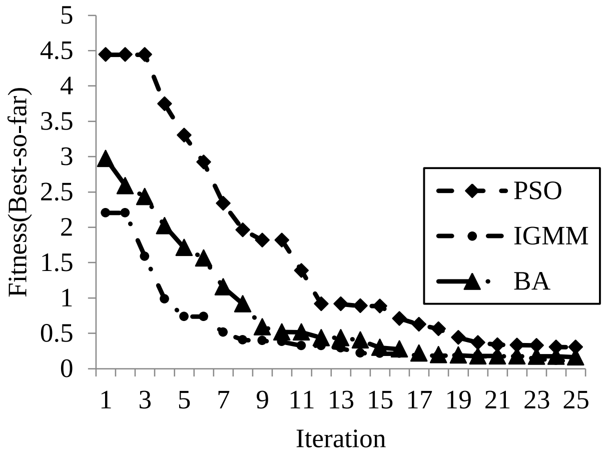


Fig. 9 Comparison of IGMM, PSO and BA for PBDD of 72-bar truss

The statistical data presented in Table 2 and 3 indicate that the standard deviation of IGMM-based optimum solutions is the lowest among other selected algorithm, showing its robustness compared to other techniques. Furthermore, the maximum numbers of function evaluations presented in Tables 2 and 3 show that the IGMM requires much less computational cost to determine the global optimum against PSO and BA.

8.2 120-bar dome truss

A 120-bar dome truss, shown in Fig. 10 is considered as the second example (Kaveh and Talatahari 2009). In this example, three metamodel are constructed, trained and tested to evaluate their performance in PBDD in civil structures. The variation of running time, mean square error (MSE), and the accuracy in the prediction of PDE for each element is calculated in order to inspect pros and cons of each algorithm.

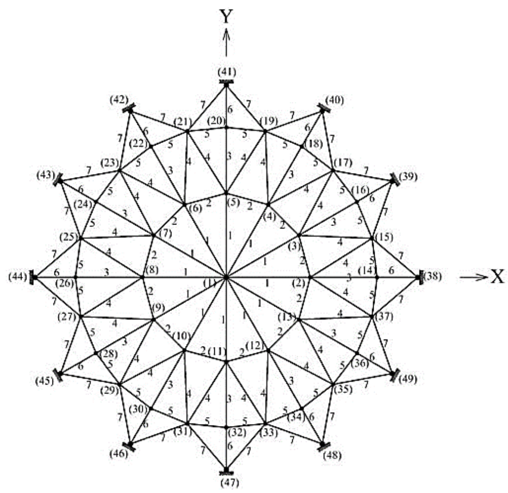
The diameter and the height of the dome are 31.78 m and 7 m, respectively. The material is a seamless steel pipe with a modulus of elasticity equal to 30,450 ksi (210,000 MPa) and the material density is 0.288 lb/in3 (7971.810 kg/m3). The external diameter of the pipes is 0.2 m and the thickness is 0.006 m. For generating training and testing datasets of the FE program, OpenSees (Mazzoni *et al.* 2006) is used for structural analysis. Different damage scenarios are considered as shown in Table 4.

Using the trained surrogate model with 2% and 15% random errors (COV) in frequencies and mode shapes, and the testing data with the same level of noise, the mean values and standard deviations of structural stiffness parameters corresponding to the two damage scenarios are estimated based on proposed procedure. From the normally distributed probability density function of the damaged and undamaged states, the PDEs can be calculated. The reason of difference between level of noise in frequencies vs. mode shapes is that modal frequencies can be measured from just a few accessible points on the structure and are less vulnerable to experimental noise than mode shapes (Nobahari *et al*. 2017a, b).

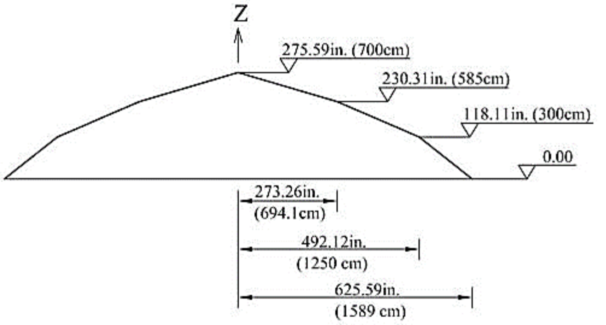
It is worth noting, because the established surrogate model is trained based on data generated from the FE model and tested with the measured data, the existence of errors in the FE model and noise in the measured data provide more significant contributions to the failure in detecting damage rather than significant changes in modal data (Padil *et al.* 2017).

Table 4 Different damage scenarios for the 120-bar Dome Truss

Case 1		Case 2	
Element Number	SRF	Element Number	SRF
12	0.30	4	0.35
38	0.20	30	0.20
53	0.25	51	0.35
79	0.2	58	0.25
		89	0.2
		105	0.40



(a) Plan view



(b) Section view

Fig. 10 120-bar dome truss

Table 5 Probability of damage existence for damage case 1 of the 120-bar Dome Truss

Element Number	Actual Damage (PDE)%	FE Model (PDE)%	LS-SVM (PDE)%	CFNN (PDE)%	Kriging (PDE)%
10	0.00	2.00	9.00	11.00	3.00
11	0.00	0.00	1.00	0.00	0.00
12	100.00	98.00	94.00	94.00	96.00
13	0.00	0.00	2.00	1.00	1.00
36	0.00	0.00	5.00	8.00	5.00
37	0.00	0.00	4.00	3.00	0.00
38	100.00	95.00	94.00	90.00	90.00
39	0.00	10.00	14.00	10.00	11.00
51	0.00	0.00	1.00	2.00	2.00
52	0.00	0.00	0.00	2.00	1.00
53	100.00	100.00	100.00	100.00	98.00
54	0.00	0.00	0.00	0.00	1.00
77	0.00	0.00	0.00	1.00	1.00
78	0.00	3.00	2.00	10.00	5.00
79	100.00	98.00	96.00	98.00	95.00
80	0.00	0.00	1.00	1.00	1.00
Total time	-	3510	251	200	990
MSE*	-	6.00e-04	2.02e-03	4.11e-03	1.02e-02

*MSE: Mean squared error

Therefore, it is essential to consider the existence of uncertainties in both the FE model and the measured data when performing damage detection using an surrogate model. Based on the proposed approach, the uncertainties in the FE model and the measurement data are considered.

The PDEs for scenarios 1 and 2 are depicted in Tables 5 and 6, respectively. There is illustrated the comparing results between the solution methods in terms of computational speed and accuracy. To compute process time when using a surrogate model, data generation time, the training and testing time and the IGMM implementation time are all considered together. (core™ i7 2.67 GHz CPU).

From Tables 5 and 6, one may observe that in scenario 1 and 2, the PDEs of damaged element is very high and the PDEs of the other elements are low. These results show that using the proposed LS-SVM surrogate model, coupled with IGMM, the damages are detected with high confidence and undamaged segments are less likely to be falsely identified. Moreover, in these tables, the improved algorithm's capability to find all the global optimal solutions (damage states) is apparent.

Furthermore, engaging IGMM by efficient surrogate model, maintains the acceptable accuracy of damage detection. Meanwhile, in comparison with the kriging and CFNN models, the LS-SVM model gives a better performance and has higher PDEs for damaged elements and lower PDEs at the undamaged elements.

This due to that LS-SVM was very effective for sparse and high dimensional data. Furthermore, LS-SVM have better generalization abilities than the ANN (CFNN). The major drawback of using ANN was computational cost for the potentially large size of the hidden layer which could be equal to the size of the input vector.

Thirdly, it is found that, relatively speaking, model construction is time-consuming for kriging. Kriging requires a k dimensional optimization to find the maximum likelihood estimates of the parameters used to fit the model, which can become computationally expensive when the problem scale and the sample size are large.

As can be considered, using proposed solution procedure contributes to a substantial reduction in the number of FE structural analysis which shows itself in damage detection of large-scale structures.

By this proposed solution method, computation time of the proposed procedure is reduced to one-tenth of the former time. Therefore, using LS-SVM model in process of damage detection carried by optimization algorithm accelerates this process besides for maintaining the acceptable detection accuracy.

8.3 Five-story, four-span frame

The third example is a five-story, four-span frame, as illustrated in Fig. 11 (Kaveh *et al.* 2014). The sections used for the beams and columns are (W12×87) and (W14×145), respectively. The material density is 7780 kg/m3 and the modulus of elasticity is 210 GPa. Different damage scenarios are considered, as shown in Table 7. Table 8 show the performance of the proposed method for damage scenario 1.

Table 6 Probability of damage existence for damage case 2 of the 120-bar Dome Truss

Element Number	Actual Damage (PDE)%	FE Model (PDE)%	LS-SVM (PDE)%	CFNN (PDE)%	Kriging (PDE)%
2	0.00	0.00	3.00	2.00	1.00
3	0.00	1.00	2.00	1.00	4.00
4	100.00	99.00	96.00	95.00	92.00
5	0.00	0.00	1.00	3.00	1.00
30	100.00	100.00	100.00	92.00	98.00
31	0.00	1.00	0.00	1.00	0.00
32	0.00	4.00	9.00	8.00	7.00
33	0.00	0.00	1.00	0.00	0.00
50	0.00	7.00	7.00	4.00	9.00
51	100.00	100.00	100.00	100.00	100.00
52	0.00	0.00	2.00	6.00	6.00
56	0.00	0.00	1.00	2.00	2.00
57	0.00	0.00	0.00	0.00	1.00
58	100.00	97.00	95.00	90.00	97.00
87	0.00	0.00	0.00	5.00	5.00
88	0.00	5.00	4.00	0.00	0.00
89	100.00	94.00	94.00	92.00	92.00
90	0.00	7.00	9.00	8.00	11.00
103	0.00	0.00	0.00	1.00	0.00
104	0.00	1.00	2.00	5.00	1.00
105	100.00	100.00	99.00	99.00	100.00
106	0.00	7.00	18.00	15.00	15.00
Total time	-	4000	360	300	1200
MSE	-	5.02e-04	2.08e-03	5.16e-03	1.21e-02

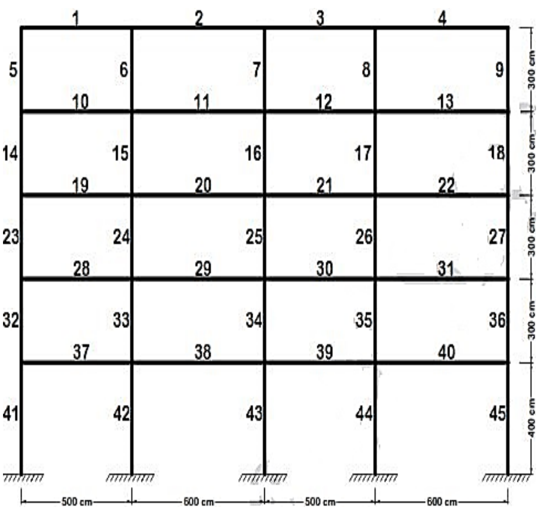


Fig. 11 A four-span five-story frame

Table 7 Different Damage Scenarios for Planar Frame

Case 1		Case 2	
Element Number	SRF	Element Number	SRF
10	0.25	14	0.35
30	0.20	28	0.30
40	0.25	38	0.35

Table 8 Mean value of SRF for damage scenario 1 ($\xi_\lambda = 10\%$)

Damaged Element	10	30	40	MSE of surrogate Model	Time (s)
Actual Damage	0.25	0.2	0.25	-	-
LS-SVM+PSO	0.254	0.2	0.26	3.87E-05	412
LS-SVM+BA	0.249	0.186	0.26	9.90E-05	350
LS-SVM+IGMM	0.25	0.195	0.252	9.67E-06	300
CFNN+PSO	0.21	0.198	0.22	8.35E-04	320
CFNN+BA	0.23	0.212	0.22	4.81E-04	290
CFNN+IGMM	0.24	0.21	0.24	1.00E-04	250
Kriging+PSO	0.19	0.17	0.21	2.03E-03	560
Kriging+BA	0.22	0.187	0.21	8.90E-04	500
Kriging+IGMM	0.23	0.196	0.24	1.72E-04	430

Table 9 Mean value of SRF for damage scenario 2 ($\xi_\lambda = 10\%$)

Damaged Element	14	28	38	MSE of surrogate Model	Time (s)
Actual Damage	0.35	0.3	0.35	-	-
LS-SVM+PSO	0.301	0.29	0.32	1.13E-03	561
LS-SVM+BA	0.32	0.26	0.33	9.67E-04	510
LS-SVM+IGMM	0.368	0.304	0.364	1.79E-04	480
CFNN+PSO	0.3	0.28	0.29	2.17E-03	521
CFNN+BA	0.31	0.3	0.37	6.67E-04	501
CFNN+IGMM	0.33	0.32	0.35	2.67E-04	450
Kriging+PSO	0.28	0.25	0.301	3.27E-03	900
Kriging+BA	0.29	0.27	0.32	1.80E-03	861
Kriging+IGMM	0.33	0.299	0.33	2.67E-04	600

The results demonstrate the fact that coupled IGMM with LS-SVM could effectively explore the correct locations and severity of the damages. For a larger noise level, that is $\xi_\lambda = 10\%$, the statistics of SRF for damage scenario 2 are presented in Table 9. In comparison to the lower uncertainty level, the proposed method shows larger errors, but it can still acquire accurate mean values and small standard deviations of the SRFs. All these results demonstrate that the proposed one-stage method for damage identification, using IGMM as the main algorithm for model updating and LS-SVM as surrogate model, is robust to measurement noise. Also, these tables illustrate that the proposed method is very efficient for multiple structural damages, even though the damage severity is low.

The numerical results reveal the high level of reliability in the performance of the proposed method for accurately detecting the location and the severity of various damage scenarios. The probability-based damage detection (PBDD) methods lead to higher SRF values at the damaged elements and give lower SRF values for the undamaged elements.

9. Numerical results of damage detection

This paper provides a comprehensive comparison of coupling metamodelling techniques with metaheuristic optimization algorithm for probability-based damage detection of structures. As common prognostics algorithms, LS-SVM, CFNN and kriging are coupled with IGMM, PSO and BA. They were then employed for case studies to discuss their attributes, pros and cons and applicable conditions. Furthermore, efficient schemes are implemented on optimization algorithms to improve their performance in damage detection of large scale structure.

The present work performs a surrogate method that accounts for the inevitable FE modeling error (aleatory uncertainty) and measurement noise (epistemic uncertainty) for structural damage detection. Monte Carlo simulation framework is used to derive the statistical surrogate model and to identify the structural condition. Both the modeling error and measurement noise are assumed to have normal distribution and zero means. Using this method, the probability of damage existence can be estimated.

The numerical and experimental results demonstrated that, the computational time of damage detection using IGMM coupled with LS-SVM model as a surrogate of FE model, is significantly reduced about ten times when compared with direct FE model utilization based on IGMM. This solution procedure contributes to a substantial reduction in the number of FE structural analysis which is further highlighted in damage detection of large-scale structures.

However, further investigation needs to be conducted in order to investigate the applicability of proposed PBDD framework for real-time damage monitoring of in-service structures.

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