Comparison of Different Model Updating Algorithm to Detect Damage in Beam Structure Using Mode Shape Data

Nur Atikah Zainudin, Norhisham Bakhary

[1]Faculty of Civil Engineering, Universiti Teknologi Malaysia, Malaysia

norhisham@utm.my

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Abstract. The effects of vibrations lead to hazards and operating limitations ranging from discomfort, malfunctioning, perfomance reduction, early breakdown, structural failure and even worse, catastrophic case. Hence, accurate mathematical models is important in designing stage within the purpose to foresee the probable damage due to the vibrations. In providing this mean, model updating method has been given considerable attention in vibration-based damage detection for global damage detection. However, conventional model updating method demands finite element (FE) model for sensitive computation during the iteration process which leads to high time consumption and slow convergence. Thus, in conjunction with SDTools, FE model updating has been alternatively build in simpler manner and time-efficiciently processed where conventional FE model is replaced with SDT model. Focusing on single objective-optimisaton, mode shape has been chosen as the paramater in objective function. In this study, three algorithms are used in updating procedure in order to obtain the effecient algorithm for damage detection. The algorithms are Least Square Optimisation (*lsqnonlin*), Constrained Optimisation (*fmincon*) and Multiobjective Optimisation (*fgoalattain*). However, limitation of termination criteria restricts the updating procedure to proceed the iteration in order to find the optimal damage. Thus, a better SDT updating procedure employing variation of tolerances and increment of maximum function evalution is proposed in the second part of this study. The implementation of the proposed study involves increment of maximum function evaluation up to 1500 counts and variation of tolerances consists of 1e-6,1e-10, 1e-15 and 1e-20 where these termination criteria are subsequently applied on each of the algorithms. Both first and second part of this study is implemented to detect damage on simulated 15 elements simply supported beam model with four different damage cases. This study only employed numerical modeling without experimental work being carried out. The updated results are further used in sensitivity analysis considering efficiency of algorithms in detecting damage and the effects of tolerances within the same purpose. The results from the sensitivity analysis show that the proposed method is able to provide reliable damage localization. Algorithm fgoalattain is able to provide the least error for damage detection in terms of intensities and locations. As for the tolerances, the accuracy of the damage prediction increased when the tolerances is increased. Nevertheless, the increment of tolerances demands longer time for iteration to take place until the termination criteria is fulfilled. Due to limitation of no experimental work being carried out, the data only can be used in simulation work. Besides suggestion to conduct experimental work simultaneously, it is also suggested to incorporate frequency as another objective function to improve the applicability in real practice.

Introduction

Damage identification and integrity assessment of structural buildings has attracted increasing interest during the last several decades as many civil structures are now, or will soon be, approaching the end of their design lives due to the aging and time-according-deterioration [1]. Based on previous research, traditional methods that have been used to quantify the damage are current damage detection methods, either visual or local experimental methods such as ultrasonic methods, magnetic field methods, radiograph, eddy-current methods and thermal field methods [2]. However, these methods are limited to local damages, and only applicable at accessible area or area near the surface of the structure. Structural Health Monitoring (SHM), a global damages detection, is basically a process to assess conditions and foresee probable failures of designated structure in order to monitor the structural health of the structure. Due to the limitation, Vibration-Based Damage Detection (VBDD) method as a global damage identification technique is developed to overcome these difficulties [3].

Modal updating method is the main focus of this study. Therefore, this study aims to investigate the applicability of modal updating method for damage detection of a single span beam structure. Moreover, this study also investigates the efficiency and effects of different types of modal updating algorithms as well as the effect of different tolerances values for damage detection based on modal data. Thus, this study demonstrates the applicability of the vibration data, precisely, modal domain data, for damage detection purpose. In conventional model updating-based method, finite element (FE) model is required for sensitive computation during the iteration process which leads to high time consumption and slow convergence. Due to the less practical of conventional methods, in conjunction with SDTools, FE model updating has been alternatively build in simpler manner and time-efficiciently processed where conventional FE model is replaced with SDT model. In this study, single objective function using mode shape, is utilised. In comparison with frequency, mode shape has higher sensitivity in producing better damage localisation. In addition, selection of algorithms also contribute to a large role in providing reliable damage localisation. Thus, this study employs three types of algorithms consists of lsqnonlin, fmincon and fgoalattain in order to obtain the relevant algorithm for damage detection purpose. However, due to the limitation in optimisation termination criteria provided at default condition, this study provide the extension to the damage detection purpose in which, variation of tolerances are applied in damage cases. The tolerances consist of ($1e-6$ (default),$1e-10$, $1e-15$ and $1e-20$). Hence, this study proposed a new model updating method employing SDT for damage detection by considering both variation of algorithms and tolerances for better damage detection purpose.

Previous Studies

Civil engineering structures are prone to deterioration, overstressing of increasing load applied and misuse of the structural parts. These damages are always being pictured as a whole if there is no significant analysis being carried out. The damages will alter the properties of stiffness, mass and energy-dissipation (damping) the structure which eventually lead to altered measured dynamic response of the system as the output [2]. Due to the changes of properties, this will adversely affect the performance of the structure. Thus, it is necessary to conduct a continuous assessment towards a structural system to identify precisely the damage and the behavior of the damages and also the structure being exerted with it. In comparison with the traditional inspection method which demand higher cost of man hours and structure down-time, Structural Health Monitoring (SHM) is a good method applied to the structure in providing those means.

Structural Health Monitoring

SHM as for the definition is a process where it should be able to diagnose the state of the component material of different parts and the full assembling of all the parts as a whole structure, at every moment during the life span of the structure [4]. Damage detection is determined by the changes of dynamic properties or the response of the structure. The core of global damage detection methods assumed that the modal parameters (frequency, mode shape, damping) are the functions of the physical parameters (mass, stiffness and damping). Any changes occurred in these physical parameters will eventually lead to modal parameters changes [5]. For instance, damage detection is carried out by determining structural stiffness values and comparing them with previously determined reference values or originally intended values determined by design drawings [6]. [4] mentioned that researchers have come to an agreement of five general realizations respect to SHM and the process towards the development of it. Three of the ‘rules’ are:

1. Damage assessment needs to be made by comparison of two structural health states.

2. A trade-off exists between sensor precision (sensitivity) and its disturbance of a changing environment and general noise.
3. The size or amount of damage detected is inversely proportional to the frequency being measured.

The rest of the general realizations require more explanation and can be found in the noted reference.

In previous researches, there are few traditional methods introduced for the purpose of structural monitoring and damage detection. These methods comprised of visual or local non-destructive evaluation such as radio X-ray, radiographic, eddy current and acoustic or ultrasonic techniques. All of these experimental techniques necessitate the proximity of the damage is known *a priori* and the portion of the structure to inspected is readily accessible. Due to these limitations, the methods stated are only able to detect damage on or near the surface of the structure [2]. Hence, for these methods, it is hardly can be used to detect damages at deeper-state or at inaccessible location. As the need for global damage-detection methods is growing, especially for the application towards complex structures, there has been continued research regarding the methods that examine the vibration characteristics of the structure [2]. Thus, this global method, similarly known as vibration-based damage detection method, is the main focus of this study and will be discussed further in the following sub-chapter.

Vibration-based Damage Detection

VBDD methods are classified as global damage detection methods which are able to identify and locate damage in large, complicated, and inaccessible structures. Generally, different types of VBDD methods can be categorized into methods which are based on modal parameters, mathematical or finite element model, signal processing, and pattern recognition techniques [7].

One of the most common damage detection methods is based on studying changes in structural modal parameters such as frequencies, mode shapes and modal damping. According to [3], the fundamental idea for vibration-based damage identification is that the damage-induced changes in the physical properties (mass, damping, and stiffness) will cause detectable changes in modal properties (natural frequencies, modal damping, and mode shapes). For instance, reductions in stiffness will results in crack. Hence, damage can be identified by analyzing the changes in vibration properties of the structure. The advantage of using VBDD is that it allows bigger changes on the structures to be detected in higher precision with only small number of sensors utilized.

In VBDD methods, three types of vibration data can used in order to extract damage sensitive features (DSF). The vibration data comprised of time domain data, frequency domain data and modal domain data. Focusing on modal domain data, it involves further reduction in data volume compared to the frequency domain. However, it can be contaminated by modal extraction error and can only be extracted from a very limited frequency range around the resonance. According to [8], several authors questioned the suitability of modal data for the purpose of damage detection. The arise argument is that modal data is the reflection of the global system properties while damage is a local phenomenon. Previous research has proven that a local damage does not necessarily change the mode shapes more significantly at the damaged location or in the proximity areas, than the other areas. To conclude the result of the experiment, it can be said that the lower natural frequencies are often fairly uninfluenced by the local damage. In other word, low sensitivity of frequency shifts to damage demand either high precision measurements of frequency change or significant levels of damage, especially when involving the applications towards large civil engineering structures.

According to [9], a system of classification for damage-identification methods are classified into four levels as follows :

1. Level 1 : Determination that damage is present in the structure
2. Level 2: Determination of the geometric location of the damage 3
3. Level 3: Quantification of the seventy of the damage
4. Level 4: Prediction of the remaining service life of the structure

Level 1 involves modal testing for the acquisition of modal parameters such as natural frequencies, mode shapes and damping properties. Some of the other features that are similar to these three features are time histories and frequency response functions (FRFs). Damage detection algorithms are needed for level 2 and 3 where the vibration characteristics are used and analysed in order to evaluate the damage. Level 4 of the damage identification procedure is used for evaluating the need for repair and/or replacement of the structure. The accuracy of algorithm and its effectiveness which contribute to the quality of NDE technique is one of the main importance in the damage identification procedure [10].

There is a great number of studies regarding SHM methodologies that has been made throughout the development period of this global damage identification method. This study is focusing on Model updating-based method.

Model Updating-based Method

In order to conduct an overall inspection of a structure, it is required to analyse the dynamic behavior to observe and examine the structure itself. Visual inspection solely is not sufficient in providing those means as it is limited to detect the damage only near to the surface but not be able to classify invisible damage occurred in the structure. Adding to the need of modal analysis, structures can resonate although only small forces being exerted on it where the resonant result in important deformation and damage induced in the structure. Interaction between the inertial and elastic properties of the materials within a structure leads to resonant vibration event. Thus, identification and quantification of resonant frequencies of a structure is required in order to gain better understanding of any structural vibration problem. In order to overcome the limitation, modal analysis has the ability to fulfill the requirements of global in nature and automated that examine changes in the vibration characteristics of the structure [11]. Modal analysis is able to examine the frequency response of a structure and further extract the dominant modes of the structure's vibration behavior. To gain basic understanding in modal analysis, modes of vibration of a simple plate is often referred.

According to [2], structural model parameters updating method focused in the modification of structural model matrices such as mass, stiffness, and damping with the aim to reproduce as closely as possible the measured static or dynamic response from the data. A constrained optimization problem based on the structural equations of motion, the nominal model, and the measured data is formed to solve the updated matrices. The idea is similar to the main topic, vibration-based damage detection, where the updated matrices are compared to the original correlated matrices thus providing an indication of damage and also the damage location and extent of the damage. The method provides differences in various algorithms depending on objective function to be minimized, constraints placed on the problem and numerical scheme used to implement the optimization.

Methodology

In this study, three basic stages involves are : (i) preparation of undamaged and damaged beam structure to obtain modal data at intact and damage phase, (ii) approximation function or SDT function is build and (iii) optimization procedure of modal updating. In this study, a paper by (Ren, 2005) is used for the purpose of model validation since there is no experimental work being carried out. The beam model is simulated by using two dimensional (2D) simulation, indicating that each node has two-way deflection and one rotation. At initial stage, an intact beam structure is simulated by using SDT with relevant input parameters. Overall length of the model is 6m in which further divided into 15 similar elements. The parameters involved are Young's modulus, E = 3.20 GPa, density, D = 2500 kg/m^3, moment of inertia, I = 1.66 x 10^{-4} m^4 and Poisson's ratio, ρ = 0.2. The simply supported beam is pinned at the first end (node 1) and restrained from vertical deflection at the other end (node 16). In the vicinity of this study, the domain mode shapes are on the first 3 mode shapes for further analysis and result verification. Figure 1 shows the model of th beam whereas Table 1 shows the comparison of frequencies at first three modes of referred paper and simulated beam model. The first three modes of the intact beam is shown in Figure 2.

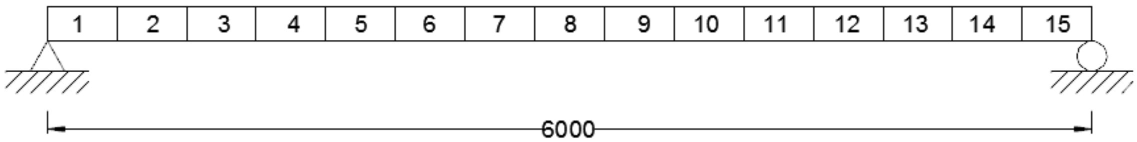
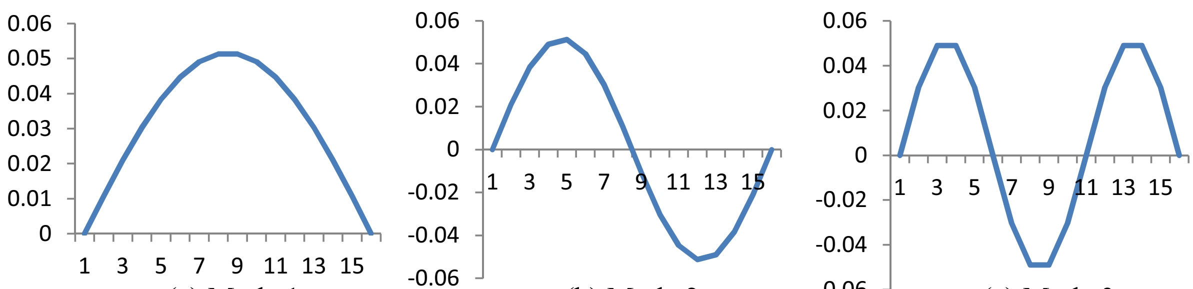


Figure 1: Model of Beam

Table 1: Comparison of Frequencies of Undamaged Beam

Mode	Study (Hz)	[12] (Hz)	Differences (%)
1	9.009	8.990	0.21
2	35.99	35.915	0.21
3	80.79	80.632	0.20



(a) Mode 1 (b) Mode 2 (c) Mode 3

Figure 2: First three modes of Undamaged Beam

Stage (i) : Undamaged and Damaged Beam Model

At Stage (i), four damage cases are developed consisting of two single damage cases and two multiple damage cases. For single damage, the damage cases are : (i) Case 1 : 30% reduction of Young's Modulus at Node 3 where E = 2.24 GPa and (ii) Case 2 : 45% reduction of Young's Modulus at Node 6 where E = 1.76 Gpa. For multiple damage, the damage cases are : (i) Case 3 : 30%, 60% and 40% reduction of Young's Modulus at Node 3, 8 and 13 where E = 2.24 GPa, E = 1.28 GPa and E = 1.92 GPa respectively and (ii) Case 4 : 20%, 35% and 55% reduction of Young's Modulus at Node 2, 6 and 14 where E = 2.56 GPa, E = 2.08 GPa and E = 1.44 GPa respectively. Table 2 shows the frequencies of the damaged beam at their respective first three modes.

Table 2: Frequencies of Damaged Beam

Case	Frequencies at Respective Modes		
	1	2	3
Case 1	8.944	35.25	78.74
Case 2	8.624	35.03	80.3
Case 3	8.102	34.13	70.23
Case 4	8.672	34.16	75.88

Stage (ii) : SDT Model

At Stage (ii), SDT model is developed based on the parameter to be iterate in which this study employ Young's Modulus as the parameter. The E values for each elements (E1, E2,… Ek) are taken as the inputs to build the SDT approximation function. In order to obtain high performance algorithms, the input and target data are normalized in order to linearly rescale every feature in the data. The relationship employed for data normalization in this study is as follows :

$$Normalized\ value = \frac{[A]^T\ x\ [B]}{[B]^T\ x\ [B]} \tag{1}$$

where A indicate Young's Modulus (E) at undamaged state whereas B indicate Young's Modulus (E) at damaged state.

Stage (iii) : Model Updating

Stage (iii) is where the damage localisation is conducted. For the construction of updating program, the upper boundary and lower boundary is set to $3.2e-10$ (E_o) and $1.2e-10$ respectively. The objective function employed in this study is MAC of the mode shapes. The equation of MAC is shown below in Equation (2).

$$MAC = \frac{|\{\emptyset_{SDT}\}^T.\{\emptyset_{EXP}\}|^2}{\{\emptyset_{SDT}\}^T.\{\emptyset_{SDT}\}.\{\emptyset_{EXP}\}^T.\{\emptyset_{EXP}\}} \tag{2}$$

The modal updating procedure is divided into two main procedure which are : (i) employment of three types of algorithm consist of *lsqnonlin*, *fmincon and fgoalattain* for modal updating utilising only default setting and (ii) employment of variation of tolerances for *TolFun*, *TolCon and TolX* ($1e-6$ *(default)*,$1e-10$, $1e-15$ *and* $1e-20$) and increment of maximum function evaluation (1500). The values of tolerances and maximum function evaluation are subsequently applied to each of the algorithm for each damage cases.

*lsqnonlin.*Optimisation funtion *lsqnonlin* is one of the Least Square Optimisaton method where it is a standard approach used in regression analysis to the approximate solution of over-determined systems. For instance, set of equations which have more equations compared to unknown. In this study, nonlinear system of equations $F(x)$ is utilized where there are n equations and n are need to be optimized. In least squares function, a function $f(x)$ minimized is composed of sum of squares.

$$F(x) = \begin{bmatrix} f_1(x) \\ f_2(x) \\ f_3(x) \end{bmatrix} \tag{3}$$

$$\min_{x \in \Re^n} f(x) = \frac{1}{2}\| F(x) \|_2^2 = \frac{1}{2}\sum_i F_i(x)^2 \tag{4}$$

fmincon. Optimisation function *fmincon* is categorised as Sequential Quadratic Programming of Constrained Optimization. It is an iterative method used to solve nonlinear optimization consists of sequence of optimization sub-problems, whereby each of it optimizes a quadratic model of the objective function to a linearization of the constraint. For each major iteration made, Hessian of the Lagrangian function made an approximation by using a quasi-Newton updating. Generally, the formulation of quadratic approximation of the Lagrangian function is expressed in Equation (5).

$$L(x,\lambda) = f(x) + \sum_{i=1}^{m} \lambda_i \cdot g_i(x) \tag{5}$$

fgoalattain.Optimisation function *fgoalattain* is categorised as Goal Attainment Method of Multiobjective Optimisation. Although this study focuses on one objective function, multiobjective optimization is still applicable and valid for the optimization procedure. Equation (6) indicates a set of design goals which relates with Equation (7) indicating a set of objectives. The relationship between these equations is where it allows the goals of the optimization to be under-achieved or over-achieved which provide the convenience to designer to relatively approximate about the initial design goals.

$$F^* = \{F_1^*, F_2^*, \ldots, F_m^*\} \quad (6)$$

$$F(x) = \{F_1(x), F_2(x), \ldots, F_m(x)\} \quad (7)$$

$$F_i(x) - w_i\gamma \le F_i^* \qquad i = 1, \ldots, m \quad (8)$$

Result Quantification

The result from optimisation is a vector of E where this vector is then used in locating and quantifying damage. This study employed Stiffness Reduction Factor (SRF) and Mean Squared Error (MSE) for computation of stiffness changes. The ratio for SRF lies in the range of 0 to 1 where the higher the SRF indicate to more severe damage. For MSE, the lesser value indicate minimal error exist between the obtained and targetted result. Equation (9) and (10) indicates SRF and MSE respectively.

$$SRF = 1 - \frac{E\prime}{E} \quad (9)$$

$$MSE = \sum \frac{(E' - E'')^2}{n} \quad (10)$$

Results and Discussion

Table 3 below shows different cases used in this study for the implementation of modal updating parameters selected whereas Table 4 shows the domain frequencies of undamaged and damaged beam model.

Table 3: Damage Cases

Damage Cases	Element Number	*E* reduction
1	3	0.3 x E_o
2	6	0.45 x E_o
3	3	0.3 x E_o
	8	0.6 x E_o
	13	0.4 x E_o
4	2	0.2 x E_o
	6	0.35 x E_o
	14	0.55 x E_o

Table 4 : Domain frequencies of undamaged and damaged beam model

Frequencies/Damage Cases	Undamaged	Case 1	Case 2	Case 3	Case 4
λ_1	9.009	8.944	8.624	8.102	8.672
λ_2	35.99	35.25	35.03	34.13	34.16
λ_3	80.79	78.74	80.3	70.23	75.88

Effect of Different Algorithms in Modal Updating for Damage Detectability

As mentioned previously, modal updating procedure is divided into two main procedure. The first main procedure involving the effect of employment of three types of algorithm consist of *lsqnonlin*, *fmincon and fgoalattain* utilising only default setting is discussed in this section. In predicting damage(s) for all the four damage cases, accuracy of location and intensities of damage as well as time history are important for damage detection. Table 5 shows the MSE for the damage cases at default setting of three types of algorithms.

Table 5: MSE values at default $(1e - 6)$ setting

MSE / Algorithm	Case 1	Case 2	Case 3	Case 4
lsqnonlin	0.0614	0.1382	0.4164	0.3174
fmincon	0.0291	0.1381	0.4162	0.2252
fgoalattain	0.0042	0.0087	0.0244	0.0234

Based on Table 5, the least values of MSE for all four cases obtained by using *fgoalattain* algorithm with values of 0.0042, 0.0087, 0.0244 and 0.0234 for Case 1, Case 2, Case 3 and Case 4 respectively. In general, all algorithms displayed small values of MSE at single damage cases compared to multiple damage cases. This is due to the severity of damages experienced by single damage is less compared to multiple damage case which experienced greater intensities of damages.

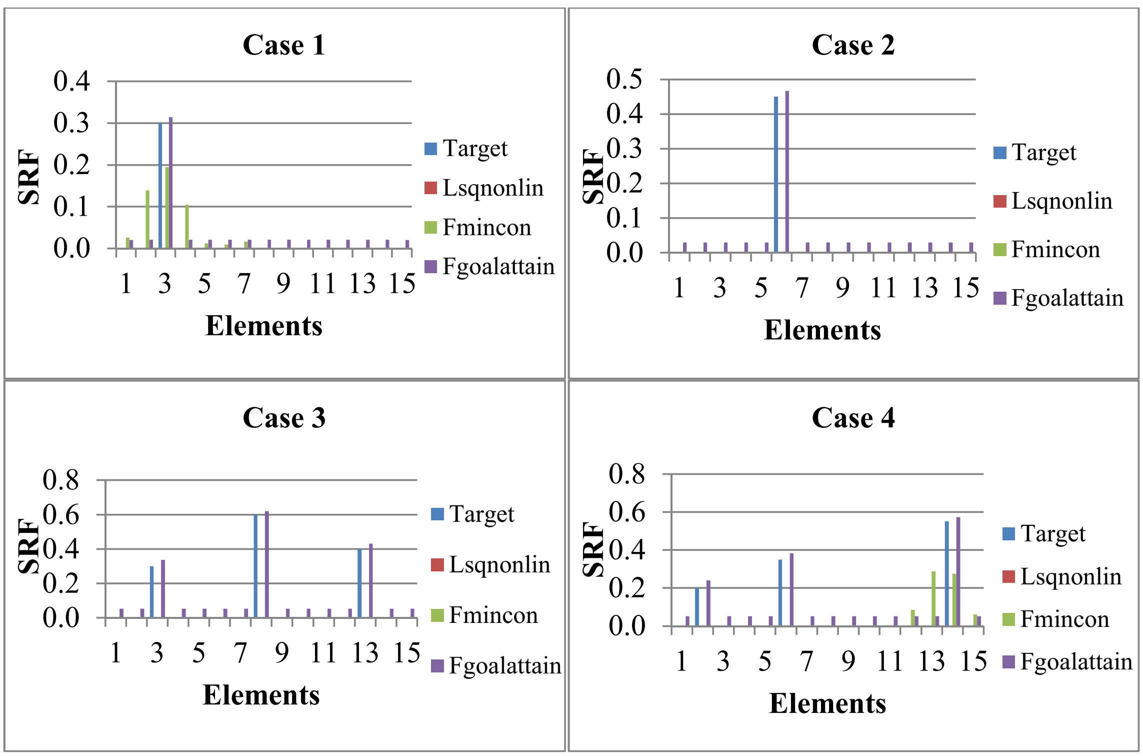


Figure 3: SRF at default $(1e - 6)$ setting

Based on Figure 3, generally, by using *fgoalattain* algorithm, it is able to provide the nearest difference of SRF values in comparison with the targetted SRF for all damage cases. The least favourable algorithm for the damage detection at default setting is *lsqnonlin* as the SRF values are too far from the targetted values. For *fmincon* algorithm, the SRF values diplayed are not in steady form where it appears at Case 1 and Case 4 but not in Case 2 and Case 3. Thus, in providing better damage detection applicability, the second part of this study is regarding the implementation of variation of tolerances in order to obtain higher precision of damage location and intensities.

Effect of Different Tolerances in Modal Updating Algorithms for Damage Detectability

In conducting modal updating, selection of algorithms will determine the arrangement of settings in modal updating procedure. Optimization options are varied according to the needs and algorithm chosed. Lies under optimization option, termination criteria are used to define where the updating procedure should stop. Thus, in order to enhance the capability of modal updating to acquire higher precision of damage detection, optimization option parameters comprised of *MaxFunEvals* (Maximum Function Evaluation) and tolerances are modified and increased. This part employed maximum function evaluation valued of 1500 for each updating procedure. In term of tolerances, they are varied in three more additional types comprised of $1e-10$, $1e-15$ and $1e-20$. These tolerances referred to *TolFun*, *TolCon* and *TolX* which indicate termination tolerance on the function, constraint violation and parameter estimates respectively. Table 6 shows the MSE of *lsqnonlin*, *fmincon* and *fgoalattain* for all four damage cases utilizing variation of tolerances whereas Figure 4 shows the graphical illustration of combined MSEs.

Table 6: MSE values at variation of tolerances

MSE / Algorithm	Tolerances	Case 1	Case 2	Case 3	Case 4
lsqnonlin	Default	0.0614	0.1382	0.4164	0.3174
	$1e-10$	0.0281	0.0422	0.1314	0.1257
	$1e-15$	0.0089	0.0167	0.0582	0.0894
	$1e-20$	0.0089	0.0167	0.0582	0.0894
fmincon	Default	0.0291	0.1381	0.4162	0.2252
	$1e-10$	0.0164	0.0383	0.0661	0.0422
	$1e-15$	0.0164	0.0301	0.0628	0.0422
	$1e-20$	0.0164	0.0301	0.0628	0.0422
fgoalattain	Default	0.0042	0.0087	0.0244	0.0234
	$1e-10$	0.0042	0.0087	0.0244	0.0234
	$1e-15$	0.0042	0.0087	0.0244	0.0234
	$1e-20$	0.0042	0.0087	0.0244	0.0234

Based on Table 6, MSE values of increased value of tolerances is less compared to MSE values at default ($1e-6$). The same trend is observed for all four damage cases for each type of algorithm except for *fgoalattain* algorithm where the MSE values remain the same although the tolerances are changed. For *lsqnonlin* algorithm, MSE values for all cases at $1e-15$ and $1e-20$ are similar at respective case. For instance, Case 1 displays MSE of 0.0089 at $1e-15$ and $1e-20$ similarly and same goes to Case 2 where it displays MSE of 0.0167 at $1e-15$ and $1e-20$ similarly. The same trend is observed for *fmincon* algorithm. However, the difference is that MSE values for all cases are similar at the last consecutive tolerances for respective case except for Case 2 and Case 3. At these two cases, only the last two consecutive tolerances displays the same values, as similar trend with *lsqnonlin* algorithm. In general, similarly observed in Table 6, all algorithms displayed less values of MSE at single damage cases compared to multiple damage cases due to the severity of damages experienced by single damage is less compared to multiple damage case. Figure 4 illustrates the difference of the MSEs in clearer view. In terms of SRF, Figure 5, 6 and 7 shows the SRF values for all four damage cases for algorithm *lsqnonlin*, *fmincon* and *fgoalattain* respectively.

Based on Figure 5 to 7, each of the SRF values at different tolerances are compared to the targetted value of SRF as the reference line. Based on Figure 5, the updating model utilizing *lsqnonlin* is able to identify the damage location for tolerance $1e-10$, $1e-15$ and $1e-20$. The SRF values at the last two consecutive tolerances display the exact value for each cases applied. For the accuracy level, $1e-15$ and $1e-20$ are able to provide better damage detection compared to $1e-10$. However, application of termination criteria at default setting does not provide any accuracy of damage identification for all the damage cases for *lsqnonlin* algorithm. This trend also implies for *fmincon* algorithm. The difference is that, for Case 1, SRF values at default tolerance did appear, but it is not accurate for the damage detection. For *fgoalttain* algorithm, the trend is not similar with the previous two algorithms. The SRF values at tolerance $1e-10$, $1e-15$ and $1e-20$ display the exact value although the tolerances are varied for each damage cases. The level of accuracy for damage detection for *fgoalattain* algorithm is very near to the targetted SRF value(s). From all the results obtained, there is small false damage identification at undamage element and the accuracy of the damage localisation is also increased. However, errors are still exist although termination criteria increment is considered in updating procedures. Besides, due to the increment of tolerances and maximum function evaluation, longer time is required to complete the iteration process. Thus, for better damage localisation, it is recommended to incorporate frequency as a another objective function in updating procedure.

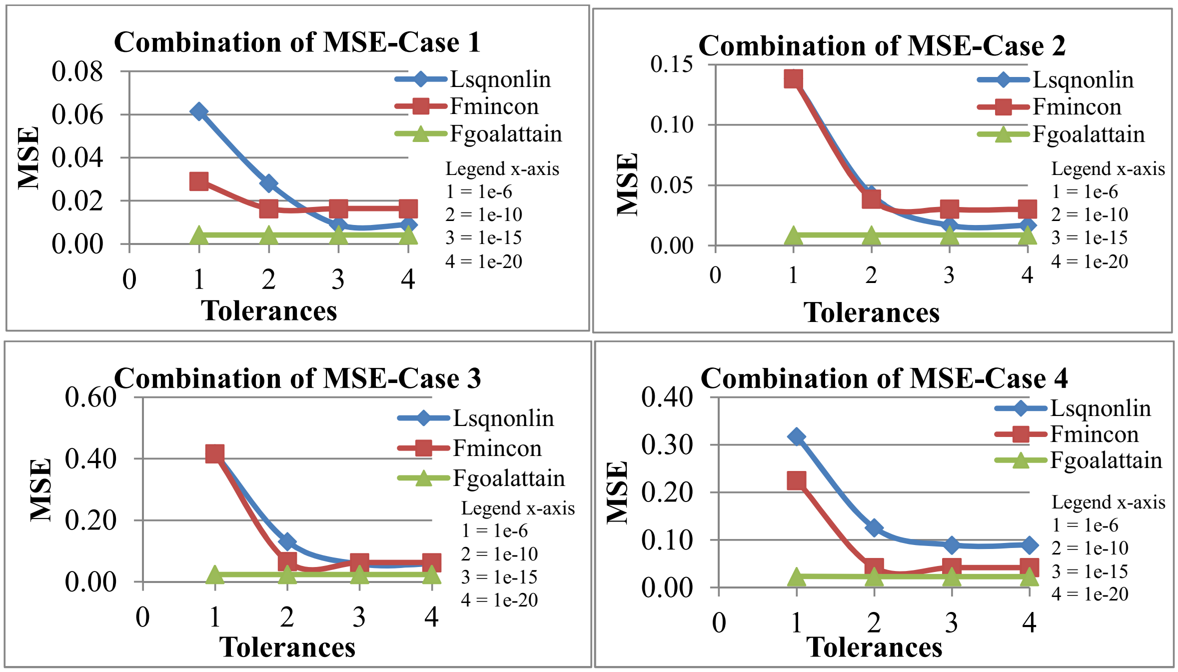


Figure 4: MSE for combined algorithms and tolerances at respective four damage cases

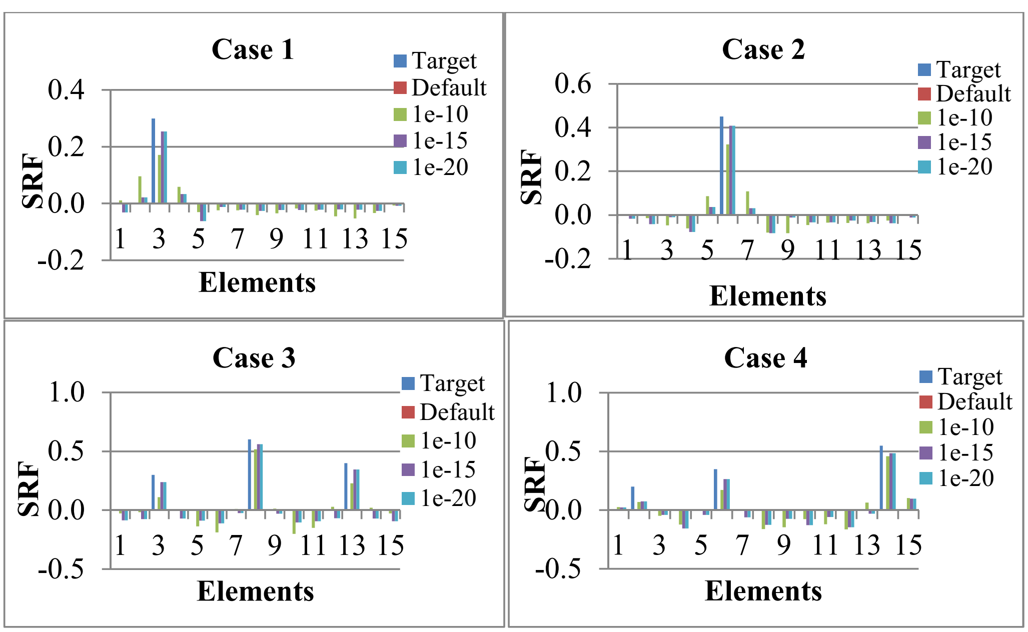


Figure 5: SRF for *lsqnonlin* algorithm at different tolerances for four damage cases

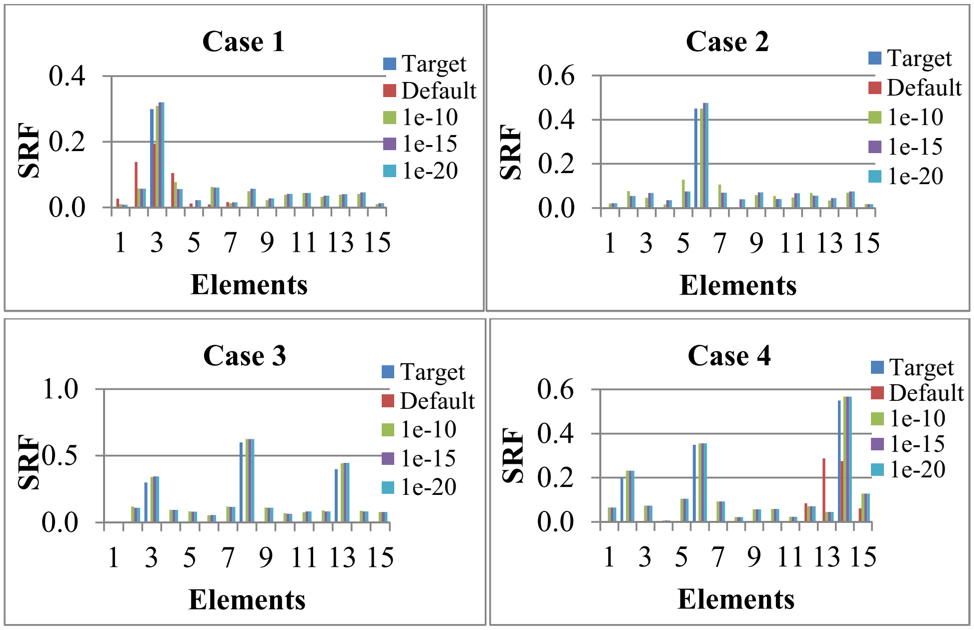


Figure 6: SRF for *fmincon* algorithm at different tolerances for four damage cases

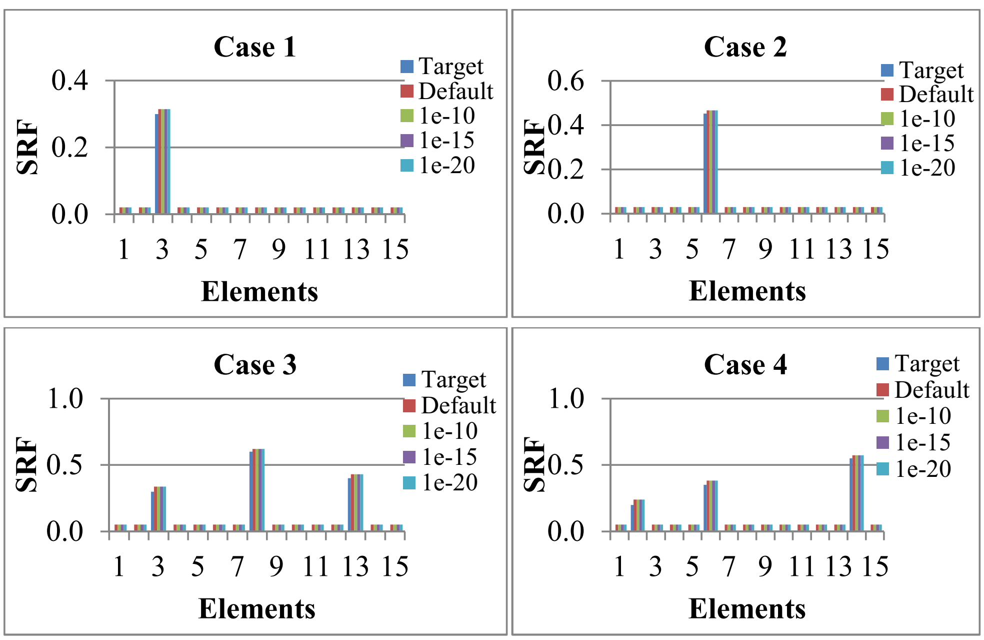


Figure 7: SRF for *fgoalattain* algorithm at different tolerances for four damage cases

Conclusion

This study involves modal updating procedure in two main parts where the first part involves damage detection utilising three algorithms at default setting whereas the second part provide the extension to the first part by utilising variation of tolerances. The algorithms are *lsqnonlin*, *fmincon* and *fgoalattain* whereas the tolerances are consists of $1e-10$, $1e-10$, $1e-15$ and $1e-20$. From the sensitivity analysis conducted, it can be conclude that *fgoalattain* algorithm provide higher accuracy of damage detection by observing the damage intensities and locations. Generally, *fmincon* algorithm is able to provide better damage detection ability when the tolerances are increased compared to *lsqnonlin* algorithm. Another conclusion can be drawn from the sensitivity analysis is that, the tolerances values affected the damage identification ability. The higher the value of tolerance, the better the damage identification is. As this study only employ numerical model for results verification, it is suggested to conduct experimental work in order to provide practicality in real cases. For better damage localisation, it is suggested to incorporate frequncy as another objective function instead of using only mode shape as single objective function. In general, different efficiency of algorithm and tolerances is case dependent where different cases provide different output performance. Objectives of this study are achieved successfully.

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