Deterioration assessment of buildings using an improved hybrid model updating approach and long-term health monitoring data

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Abstract

In recent years, it has become increasingly important to develop methodologies for reliable deterioration assessment of civil structures over their life-cycle to facilitate maintenance and/or rehabilitation planning processes. Several approaches have been established to address this issue mainly using Bayesian probabilistic model updating techniques with some capability to incorporate uncertainties in the updating process. However, Bayesian model updating techniques are often found to be complex and computationally inefficient as opposed to their deterministic counterparts such as conventional or hybrid techniques of sensitivity based model updating. Nevertheless, the deterministic model updating techniques have not been well developed for sophisticated assessment applications such as deterioration evaluation. To address these issues, this paper presents a novel methodology for deterioration assessment of building structures under serviceability loading conditions, based upon an improved hybrid model updating approach incorporating the use of long-term monitoring data. This is first realised by a simple but effective scheme to simulate the deterioration mechanism in serviceability loading conditions before enhanced with innovative solutions to classify structural elements as well as to handle measurement and updating uncertainties in a meaningful way. The effectiveness of the established methodology is illustrated through a benchmark ten story reinforced concrete building which is equipped with a long-term structural health monitoring system.

Keywords

Deterioration assessment, model updating, building structures, serviceability loading condition, structural health monitoring (SHM) data

1. Introduction

It is blatantly apparent that all the infrastructure systems are vulnerable to progressive deterioration and damage due to various reasons such as cracking, aggressive chemical attacks and other physical damage mechanisms.[1] In the long-term these phenomena can cause detrimental effects to the structures and lead to failure in structural performance under serviceability loading conditions and/or extreme events such as natural disasters (earthquakes, cyclones) and man-made hazards (blasts, vehicle collisions). Hence, it is important to establish procedures to assess the deterioration of the structures over the serviceable life to facilitate the maintenance and/or rehabilitation planning processes in the modern society that encourages sustainable development.[2]

Traditionally, deterioration and damage assessment for engineering maintenance purposes is mostly performed based on data obtained from visual inspection or local non-destructive testing programs. However, these programs are known to be either subjective or time-consuming, as well as very expensive for long-term implementation on civil structures.[3] To overcome these limitations, modern life-cycle assessment concepts have been derived to foster more accurate and systematic approaches for the purpose of not only being able to cope with inherent assessment uncertainties but also enabling life-cycle management processes. One of such approaches is the use of finite element (FE) model updating by means of long-term structural health monitoring (SHM) data.

With the rapid advancements in computer and computer-aided engineering (CAE) technologies, FE modelling techniques have enjoyed their dominance in civil engineering design practice while FE model updating techniques have become an increasingly popular tool for design validation and post-construction assessment of civil structures. Among many methods of classification, most model updating approaches can be broadly categorised as (1) deterministic methods which attempt to develop a single FE model by minimizing the error between the initial FE model and test data, (2) stochastic methods which treat the model updating as a problem of statistical inference or evolutionary optimization.[4] While most deterministic model updating techniques are centralised around the sensitivity method, most popular stochastic methods are based on the Bayesian framework, or machine learning and evolutionary algorithms such as neural network, genetic algorithm and particle swarm optimization.[5-7] Even though the stochastic model updating approach is capable of taking into account uncertainties of both modelling and measurement processes, these methods are often found to be complex, time consuming and computationally costly thereby limiting the applicability to large civil engineering structures.[8, 9] Deterministic methods such as conventional sensitivity based model updating techniques are, on the other hand, considered to be less time consuming, computationally efficient and often found to be successful in real structure applications.[10-17] However, there has been a lack of using the deterministic model updating methods for more sophisticated assessment applications such as life-cycle management and incorporation of long-term SHM data, and consequently there is a real need for further research to be developed in this important direction.

To cater for this need, this paper presents a novel deterioration assessment methodology for building structures under serviceability loading conditions using an improved hybrid model updating approach that has an ability to incorporate relevant deterioration mechanisms as well as tackling the measurement and updating uncertainties. The effectiveness of the established methodology is investigated through a comprehensive case study with a ten-story reinforced concrete building structure located at Queensland University of Technology (QUT), Brisbane Australia.[18] Arguably the first ever long-term SHM testbed in Australia, this modern building complex contains an innovative SHM system operating in a continuous monitoring manner to capture the ambient vibration responses which are then used to estimate modal properties of the structure. The variations of the most relevant modal parameters over the period under investigation are selected as the indicator for deterioration of the structure whilst a special multi-step simulation scheme is derived to search for structural elements that can physically represent the deterioration of the structure. During the assessment process, the uncertainties of the measured responses and confidence levels of the tuning parameters are statistically incorporated via an improved hybrid model updating approach.

The outline of the rest of this paper is as follows. The proposed research methodology is first presented followed by a comprehensive application to the QUT-SHM testbed which includes the description of the test structure, construction of its numerical models, SHM data bank for updating, and data analyses for different stages of hybrid model updating process. Summaries and conclusions for the research are presented in the last section.

2. Methodology

2.1 Numerical deterioration simulation

Expressing deterioration process in mathematical terms often found to be challenging and complex mainly due to the incomplete information about the deterioration mechanisms. However, for practical applications effective models can be established by assuming progressive deterioration of materials and components [2]. According to Biondini and Frangopol[19], both corrosion in steel structures and crushing and cracking in concrete structures can be effectively represented by a progressive reduction of the cross section of the structural elements. In the present paper, this concept will be further extended to be incorporated into a hybrid model updating technique developed earlier by the present authors[20], to assess the deterioration of building structures under serviceability operational loading conditions. Details of this extension and respective implementation are presented in sections 2.2 and 2.3, respectively.

2.2 Hybrid model updating

As mentioned earlier, the main advantage of hybrid model updating over the conventional model updating counterpart is that the former has the ability to incorporate the uncertainties in the test data and to define the confidence levels of the tuning parameters.[20] To incorporate the aforementioned uncertainties in the hybrid model updating process, weighting coefficients are derived using statistical methods or judgement of the analyst and experimentalists.[21] The objective function of the model updating algorithm is a weighted error (E_R) comprised of the differences in the target responses and tuning parameters coupled with weighting matrices in two successive iterations as shown in the Equation 1 below;

$$E_R = \{\Delta R\}^t [C_R] \{\Delta R\} + \{\Delta P\}^t [C_p] \{\Delta P\} \tag{1}$$

ΔR = Variation in the target responses

ΔP = Variation in the tuning parameters

$[C_R]$ = Diagonal weighting matrix in target responses

$[C_P]$ = Diagonal weighting matrix in tuning parameters

(t denotes transpose operator)

The control of the objective function is dependent on the values of C_P and C_R, (inverse of these parameters are the co-variance matrices of the test data and tuning parameters) and the scatter values are used to calculate the co-variance matrices. As expressed in equation 2, scatter value is the ratio of the standard deviation (σ) to the mean value (μ) for a given set of data samples, which is also known as coefficient of variation in statistical terms. Since the tuning parameters are of different order and magnitude scatter values are normalized with respect to the mean values.

$$Scatter = \frac{\sigma}{\mu} \tag{2}$$

The parameters with low scatter will have high C_P values and will only change if majority of the responses have an effect upon the change of those parameters which leads to small parameter changes. Similarly, the parameters with low C_P values which has high scatter values and low confidence levels will result in large parameter changes. For test data with low scatter values (low uncertainty) will steer the parameter changes in the updating process whilst test data with high scatter will only make an impact on the updating process if the responses with low scatter values also change the parameters in a similar way. The iterative procedure used in the automated model updating to obtain the target responses is achieved by commonly employed linear term approximation of Taylor's expansion series and more details are available in Appendix I.

2.3 Deterioration assessment using hybrid model updating

In the proposed methodology, natural frequencies of the first few global modes are used as the indicator for deterioration of the structure and reduction of the cross section of structural elements are used to represent the deterioration of the structure. The main reason for using natural frequencies as the main deterioration indicator is that their precise estimates can be obtained much easier and faster than the other structural properties such as mode shapes, especially when considering the signal quality in ambient vibration monitoring conditions.[22] In addition, it is widely known that changes in modal parameters are often very small for minor damage and this fact further highlights the need for accurate response data.

Construction of response data banks is as follows. First, at least two samples of modal frequency data (one representing the initial state and the other(s) for the current state, or any other subsequent state, of the structure) should be established from the vibration data pool. When selecting the datasets for each sample, it is important to consider a sufficiently long period of time (e.g. one year or at least several months with similar meteorological conditions) so that the samples are deemed to be subjected to similar environmental and operational variations. In this regard, having a long-term monitoring system is advantageous not only to address the aforementioned problem but also to enable to life-cycle management processes. Then the selected samples are statistically analysed to obtain the uncertainty of the measured natural frequencies to incorporate in the deterioration assessment. In this study, commonly used statistical parameters such as mean, standard deviation and statistical scatter were used.

On the modelling side, an initial FE model should be developed based on as-built drawings rather than the design ones to incorporate sufficient detailing; and the modelling should also include appropriate structural conceptualization. The next phase is to update the developed initial FE model through hybrid model updating using uncertain parameters identified by means of sensitivity analysis to represent the initial state of the structure.

In real applications, most often the chosen parameters for the sensitivity analysis are of different types, and hence in those circumstances normalized relative sensitivities are utilised for the sensitivity analysis (Appendix II).

Once the updated model is obtained to represent the initial state of the actual structure, loads are assigned to simulate the serviceability mechanical loading conditions and identify the vulnerable elements to cracking under these loading conditions. In order to identify the structural elements that are likely to undergo cracking in this study, modulus of rupture value of concrete is calculated for each structural element under simulated loading conditions. According to ACI 318-08[23] if an structural element is subjected to a stress exceeding the modulus of rupture of concrete that particular element will crack under the applied load conditions, and the modulus of rupture is calculated using the equation below;

$$f_r = 7.5 \times \sqrt{f_c^{'}} \tag{3}$$

where f_r is the modulus of rupture and $f_c^{'}$ is the compressive strength of concrete (both in psi).

In order to effectively employ the hybrid model updating technique in the deterioration assessment process, it is crucial to appropriately define the scatter values for both test data and tuning parameters. Similar to the model updating of initial state of the structure, scatter values for the test data is derived from statistical analysis of a sample comprises of datasets gathered over a sufficient period of time. The confidence values of the tuning parameters (selected based on the stresses that exceeded the modulus of rupture value of concrete) are derived from the principle that the elements subjected to higher stresses are most likely to undergo cracking and hence, the selected structural elements with higher stresses have low confidence values. These parameters are assigned with high scatter values which allow them to change with more freedom in the updating process. Similarly, the elements with low stress values which are less prone to undergo cracking due to the simulated loading conditions, were assigned with low scatter values to keep the parameter change to a minimum. Hence, the scatter value for the cross section area of a particular element (wall, floor slab or column) has been used as the maximum stress that it has been subjected to under the simulated operational loading conditions.

The stresses of the elements are calculated using the following formula:

$$\sigma = \frac{P}{A} - x_2 \frac{M_3}{i_{33}} - x_3 \frac{M_2}{i_{22}} \tag{4}$$

P is the axial force and M_2 and M_3 are the bending moments in two orthogonal directions. A is the cross sectional area and i_{22} and i_{33} are the moment of inertia in two orthogonal directions whilst x_2 and x_3 are the coordinates of the point where the stress is calculated, measured from the centroid of the section.[24]

Based on the stress distribution of the finite element model and modulus of rupture values, the structural elements that are subjected to cracking under serviceability mechanical loading conditions are identified and cross section of these elements are chosen as the tuning parameters and scatter values are assigned based on the stress values in the model updating procedure. The deterioration of the structure can be assessed by examining the cross section reduction in the chosen structural elements. This procedure can be carried out periodically by repeating the steps at a particular time interval, e.g. 5 years or 10 years. Figure 1 below illustrates the methodology for deterioration assessment of a typical building structure adopted in this study.

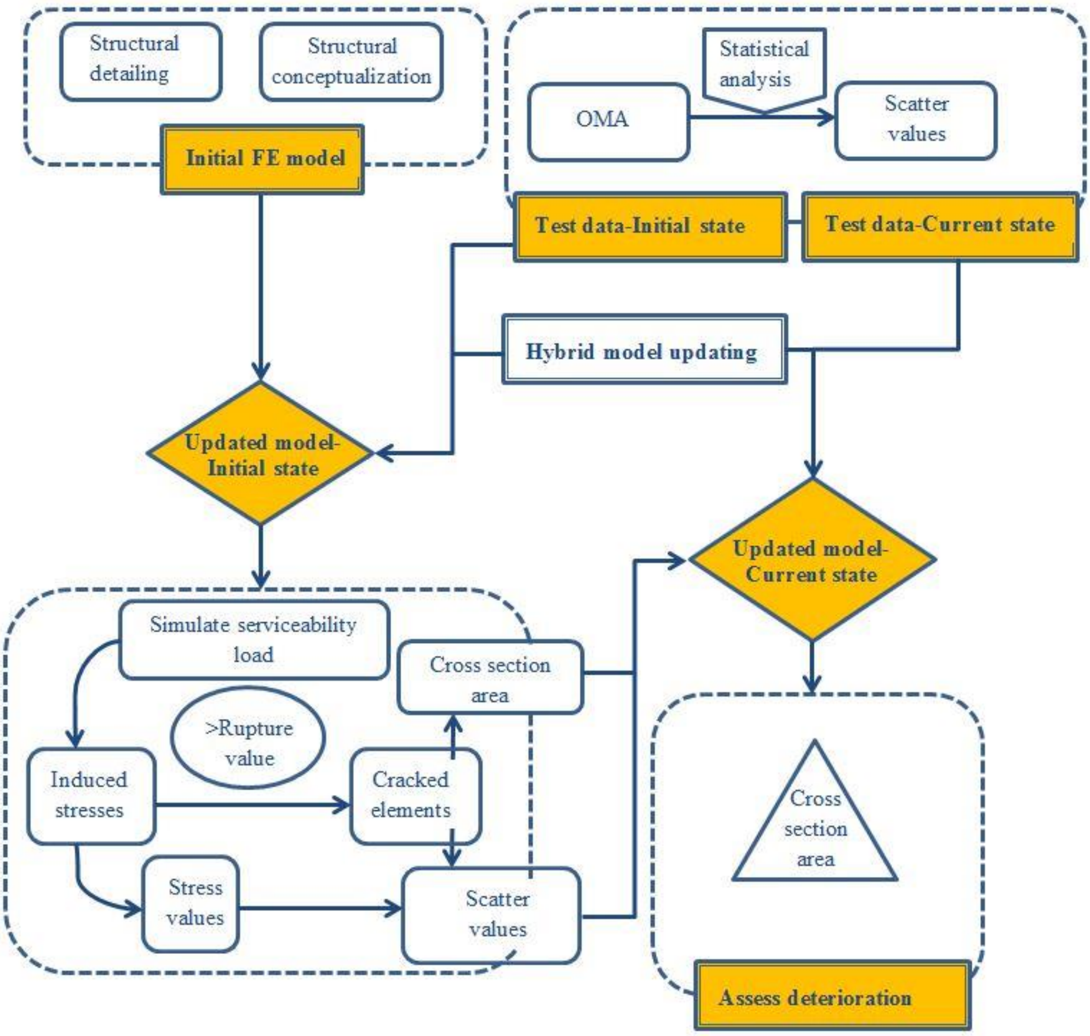

Figure 1 Deterioration assessment process for building structures using hybrid model updating

The application of the proposed methodology for deterioration assessment of the benchmark structure at QUT under serviceability loading conditions is presented in the following sections of the paper.

3. Application to QUT-SHM testbed

3.1 Description of the QUT-SHM testbed

The structure under investigation is the main head quarter building of the Science and Engineering Centre (commonly known as P block) of Gardens Point campus, QUT in the city of Brisbane, Australia. The layout of a typical building floor and instrumentation is shown in

Figure *2*. It is a ten story RC structure with four semi-underground basements, 65 m long, 45m wide and 42m high (measured from the formation level of the building) with story heights varies in the range of 2.7m to 4.5m. The structural system consists of seven two bay moment resisting frames and three shear cores (one at the western side and two at the eastern side) to resist the torsional forces induced by lateral loads. Although the structure is considered to have rather common column and slab layouts, for interior structure detailing it has number of variations with regard to column sizes, orientations and slab thicknesses and openings which need special attention in the development of initial FE models and in the model updating process.[25]

The P block was instrumented with a long-term continuous SHM system employing a software-based synchronization method to capture the ambient vibration response. The instrumentation comprises six analog tri-axial accelerometers and two single-axis accelerometers, which were located in the upper part of the building (as shown in

Figure *2*) which is globally more sensitive to the ambient excitation sources such as wind loads and human activities.

Figure 2 P block building: front corner view (left) and side view with sensor positions (right)

As mentioned earlier, the dynamic characteristics of interest in this study are the natural frequencies of first six global modes of the structure of which first five modes are used in the model updating process and the sixth mode is used only for validation purposes and hence statistical analysis is carried out only for the natural frequencies of first five global modes. To extract these features, an Operational Modal Analysis (OMA) technique named data driven Stochastic Subspace Identification (SSI-data) was used and this was reported in detail in a previous study[18]. Figure *3* illustrates the stabilization diagram of SSI-data analysis and typical views of the input model and the first five global modes. As it is not used in the main analysis stage, the 6^{th} mode view is not included in the below figure but can be found elsewhere[18]. It is worth noting that only the instrumented levels (i.e. 4, 6, 8 and 10) are included in the OMA input model along with the basement where the modal displacement is assumed to be zero under normal operational conditions.

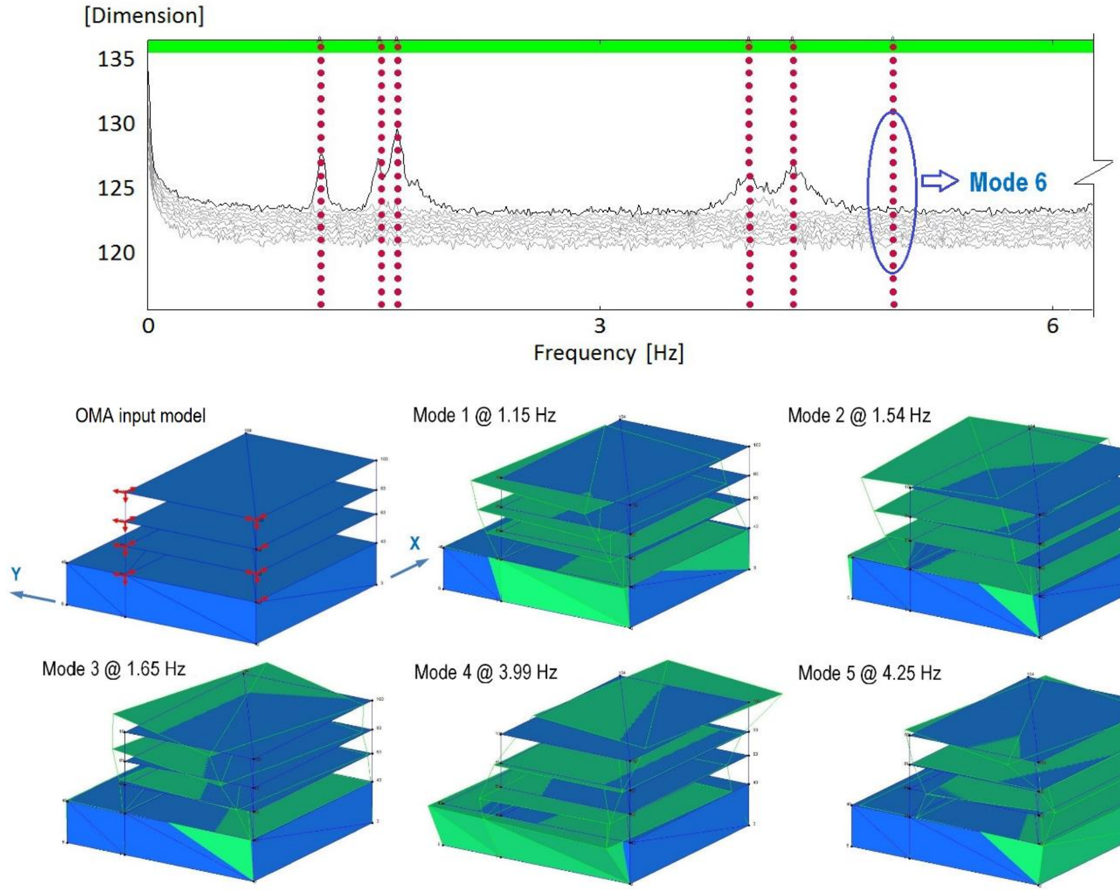

Figure 3 OMA of the building: Stabilization diagram and typical views of input model and the first five modes

Two samples were created by selecting datasets for two different time periods, one immediately after the sensor system development to represent the initial state of the P block and the other from the latest available data-sets to depict the current state of the building. To account for the environmental and operational variations, several tens of datasets were chosen to cover a sufficiently long period of time as well as all the functional times of the building. Over the period of this study, the building has not deemed to be undergone any refurbishments that may cause a significant change in the occupancy mass. Hence, it is safe to assume that the dead weight component of the occupancy mass for the building is constant throughout the period under investigation. The mean values, standard deviations and scatter values of the natural frequencies of the first five global modes for the two samples are tabulated in Table *1* and the box plots diagrams for the first five modes are provided in Figure *4*.

Table 1 Statistics of initial state sample versus current state sample

Mode	Mean (Hz)	Standard Deviation	Scatter Values

	Initial	Current	Initial	Current	Initial	Current
1	1.150	1.140	0.005	0.005	0.473	0.440
2	1.542	1.520	0.018	0.016	1.161	1.046
3	1.660	1.652	0.005	0.007	0.330	0.439
4	3.989	3.933	0.015	0.019	0.371	0.494
5	4.268	4.244	0.021	0.014	0.491	0.319

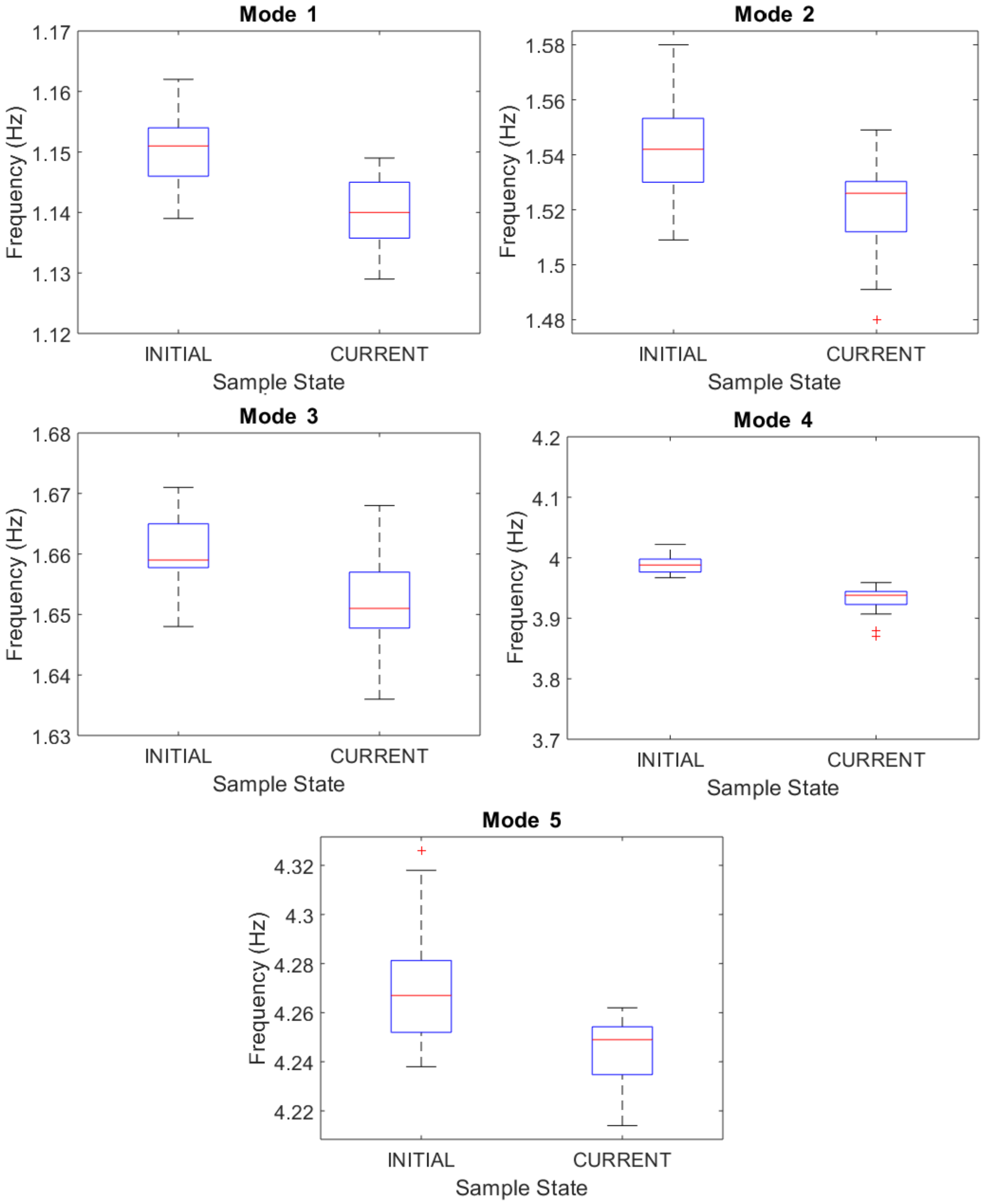

Figure 4 Box-plot diagrams of initial state sample versus current state sample

By analysing the statistical parameters in Table *1* and Figure *4*, a small but distinct reduction can be seen in the natural frequencies for the first five global modes for the current state compared to the initial state (reflected through mean values in the table and red line in the boxplot diagram). Hence, this reduction in natural frequency is exploited in the structural deterioration assessment of the building through hybrid model updating techniques in the following sections of the paper.

On the modelling aspect, initial FE models and it is important to include appropriate detailing and choose feasible conceptualization techniques since the level of structural detailing and/or structural conceptualization (such as fixities of structural elements) of the initial FE model might have a considerable effect on the outcome of the sensitivity based automated model updating[26] and hence affect the deterioration assessment. An extensive study has been conducted on the P block structure to study these phenomena and to select sufficiently detailed and suitably conceptualized initial FE model for the model updating process.[27, 28] Only selected information is presented in this paper to serve the purpose of completeness and to highlight the importance of initial FE modelling in the context of structural deterioration assessment.

First, a simple FE model developed based purely on the design drawings was trialled but the error in the natural frequencies between the FE model and the experiment were close to 50% which is by no means acceptable for model updating. Hence, a detailed 3D FE modelling exercise was undertaken using the commercial software package SAP2000. As-built drawings and documentation were used to take into account all the changes that occurred in every building floor level and bearing component during the construction stage. Upon checking with actual concrete sample test results, standard material properties of three designated concrete grades (32, 40 and 50 MPa) as specified by the Australian standard AS3600-2009 for concrete structures[29] were used to assign into the 3D frame model. Young's modulus values were taken as 30100, 32800, 34800 MPa, respectively while Poisson ratio of 0.2 were assigned for all concrete grades. Mass density was chosen as 2500 kg/m^3 to take into account the mass of reinforcement besides concrete. In addition, some special considerations taken during the initial modelling include: (1) detailed modelling of shear cores (openings and thin walls), (2) assigned floor diaphragms to maintain the rigid behaviour, (3) non-structural components are not included since the initial investigations revealed that effect of stiffness and mass of these components has little impact on the global behaviour of the overall system and (4) average slab thicknesses are used for the floor slabs since the structure has complicated internal slab thickness variations and the simplification is addressed in the model updating for initial state.

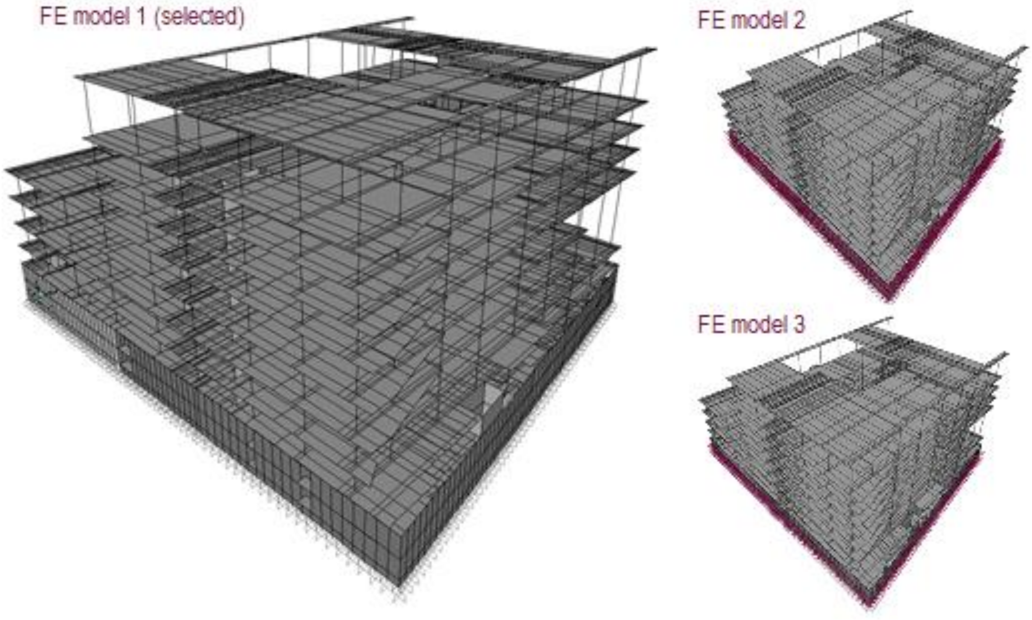

Figure 5 Three FE models with different fixities for basement walls

Apart from using sufficient detailing, to identify the most appropriate structural conceptualization for the initial FE models in order to facilitate effective model updating, three FE models were developed based on the fixity of the underground basement levels (Figure 5) for comparison with the OMA results. No fixities and full fixities for all basement levels were considered in the FE model 1 and FE model 2 respectively; where as in FE model 3 full fixity is considered for basement levels up to level 3. FE model 1 provided the best match with the OMA results, hence it was chosen as the initial model for the deterioration assessment case study under ambient vibration conditions. The natural frequencies of the first six lateral modes were used for the correlation analysis and the results for the selected initial FE model are tabulated in Table *2*. For illustration purposes, the FE model and its first five modes are shown in Figure 6.

Table 2 Comparison of natural frequencies between the selected FE model and OMA results

Mode No	Mode Shape	Natural Frequency		Error
		Initial FE model	OMA	
1	1st translational – X direction	0.990 Hz	1.147 Hz	-13.69%
2	1st translational – Y direction	1.452 Hz	1.544 Hz	-5.96%
3	1st torsional	1.678 Hz	1.653 Hz	1.51%
4	2nd translational – X direction	3.680 Hz	3.989 Hz	-7.75%
5	2nd torsional	4.972 Hz	4.254 Hz	16.88%
6	2ndtranslational – Y direction	5.220 Hz	4.912 Hz	6.27%

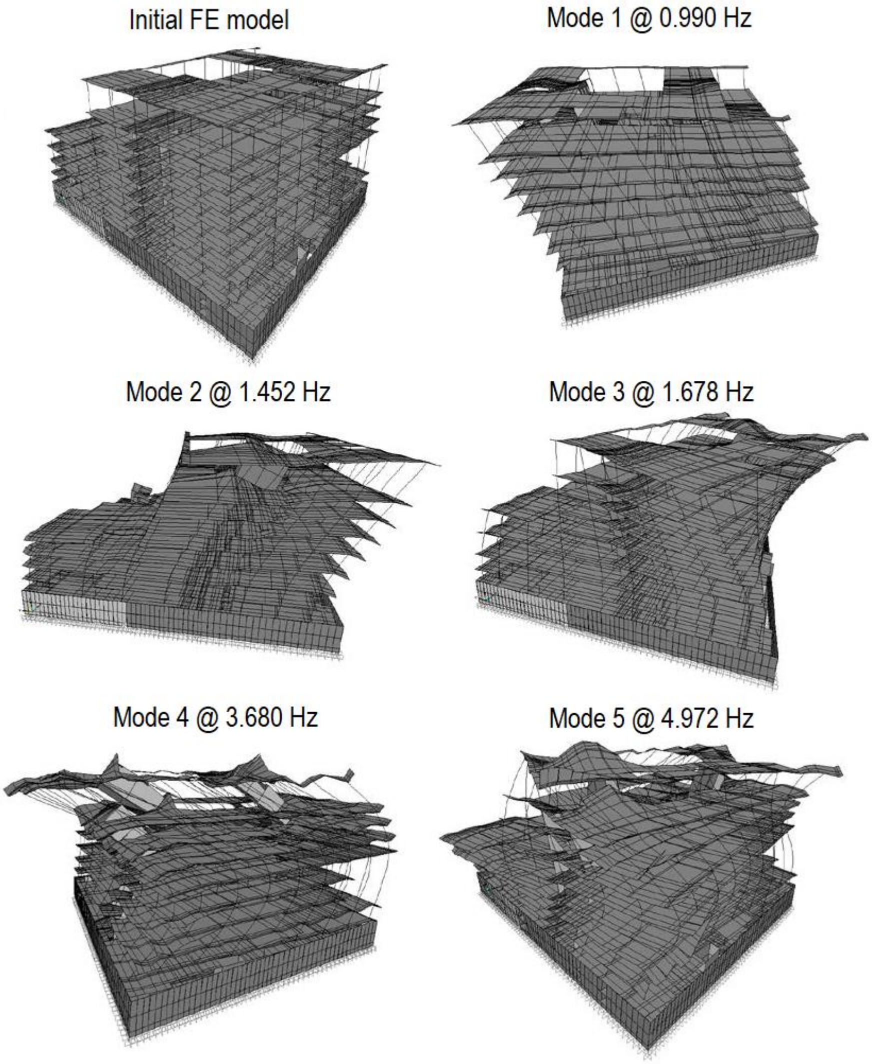

Figure 6 Initial FE model and its first five modes

Compared to the FE model used in design stage, the developed initial FE model in this study shows good correlation with OMA in-terms of natural frequencies. However, still the natural frequency error is substantial to use in the FE model to represent the actual structure, hence model updating need to be carried out to minimise the discrepancies to an acceptable limit.

3.2 Hybrid model updating : Initial state of the structure

This section describes the model updating work carried out to reduce the error in natural frequencies of the developed initial FE model using hybrid model updating techniques in the initial state of the structure. The first part of the section explains the sensitivity analysis process carried out to identify the uncertain tuning parameters in the updating process and hybrid model updating procedure adopted in this study whilst latter part outlines the model updating results.

3.2.1 Sensitivity Analysis and Model Updating Procedure

Selection of correct number of responses and appropriate tuning parameters is vital for a successful automated sensitivity based model updating.[30] Since, only natural frequencies are used in the deterioration assessment process and only the data for 6 modes of the real structure are available through OMA, the natural frequencies of the first five modes were used in the hybrid model updating process and natural frequency of the 6th mode is used to validate the updated model. To choose the appropriate tuning parameters which are uncertain in the FE model, in order to facilitate physically meaningful updated parameters yet most sensitive to the selected parameters, a sensitivity analysis is carried out prior to the model updating process. Normalized sensitivity analysis is utilized in this study since the tuning parameters are in different order and magnitude (More details about normalized sensitivity analysis are available in Appendix II).

The uncertain parameters in the FE model that can be systematically coped in an automatic model updating process were used in the sensitivity analysis. The uncertain parameters included in the sensitivity analysis are Young's modulus and mass density of all local elements (9400 local elements each), cross sectional area, torsional stiffness, bending moment of inertia about Y direction and Z direction of all columns (1400 local elements each) and shell thickness of floor slabs (5680 local elements). Hence, the total parameter space used for the sensitivity analysis was 30080 local parameters. The outcome of the sensitivity analysis revealed that the highest sensitive parameter for all the target responses is the shell thickness of floor slabs and Young's modulus of concrete, hence these local elements are chosen as the updating parameters to obtain the FE model to represent the initial state. Once the tuning parameters are selected, it is the common practice to group and define upper/lower bounds for the selected parameters to make the model updating more realistic and meaningful. However, in this study the parameter sets were defined only for Young's modulus (E) of concrete, because as stated earlier, average slab thicknesses are used in the initial FE model and slab thicknesses vary significantly in small portions in the actual structure, not defining parameter sets for shell thickness is justifiable. For the E value of concrete, parameter sets were defined based on individual columns (for frame elements) and individual walls and slabs in each level (for shell elements). Further, 10% change from the original value has been used as the upper/lower bound for the E value of concrete and a 30% value has been used for slab thickness that has a higher uncertainty in the initial FE model.

Then the model updating is carried out using the hybrid approach utilizing the scatter values to represent the uncertainty in test data and confidence values in tuning parameters. The scatter values for the test data obtained through statistical analysis of data-sets are presented in the section 3.1. The values corresponding to the initial state were used in the process of developing updated models for the initial state of the building. Since there is no actual testing data available for the derivation of scatter values for the tuning parameters, these values have been estimated based on codified recommendation and engineering judgement. For example, according to Australian standard for concrete structures[29] the E value of concrete can have a scatter up to 20% from the design values, hence 20% value was chosen as the scatter for the tuning parameter E. Since the shell thickness has a relatively high scatter for this particular case study a scatter value of 30% was used in this study.

3.2.2 Model updating results

The correlation function (C_f), weighted relative difference between natural frequencies, is used as the optimization algorithm to minimize the the weighted error E_R and hence to improve the response prediction of the FE model.

$$C_f = [\frac{1}{C_R}\sum_{i=1}^{N} C_{R_i} \frac{\Delta f_i}{f_i}] \tag{5}$$

Where $C_R = \sum_{i=1}^{N} C_{R_i}$; C_{R_i} are weighting values of responses; N is the total number of target responses (natural frequencies) considered; Δf_i and f_i are the frequency error and target frequency respectively. The stopping criteria set for the optimization algorithm are as follows;

- Minimum residue value - 0.1%
- Minimum improvement between two consecutive iterations – 0.01%
- Maximum number of iterations – 100

The established minimum residue value of 0.1% was achieved after 16 iterations. As stated earlier, only the natural frequencies of the first five global modes were selected as the target responses and natural frequency of the 6th mode is used to check the prediction ability of the updated FE model beyond the active frequency range. Table 3 summarises the OMA frequencies and the FE model frequencies both before and after updating process for the first six global modes. The results clearly show a significant improvement in the natural frequencies, especially in the active frequency range where the maximum error has reduced to 0.19%. Naturally frequency of the sixth mode which was in the passive range and used to validate the updated model also shows good improvement with a reduction in the error from 6.27% to 1.05% which enhanced the reliability of the updated model.

Table 3 Frequencies of initial model and updated model against OMA results - initial state

Mode Number	OMA Frequency	Initial FE model		Updated FE model –Initial State	
		Frequency	Error	Frequency	Error
1	1.147 Hz	0.990 Hz	-13.69%	1.146 Hz	-0.09%

2	1.544 Hz	1.452 Hz	-5.96%	1.547 Hz	0.19%
3	1.653 Hz	1.678 Hz	1.51%	1.654 Hz	0.06%
4	3.989 Hz	3.680 Hz	-7.75%	3.985 Hz	-0.10%
5	4.254 Hz	4.972 Hz	16.88%	4.254 Hz	0.00%
6	**4.912 Hz**	**5.220 Hz**	**6.27%**	**4.964 Hz**	**1.05%**

The above updated model utilising the test data sample obtained during the early stage of the sensor development (just after the construction) has been used to represent the initial state of the structure. The following section describes the deterioration assessment process utilising the updated model in this section, hybrid model updating technique, test data sample obtained recently and using tuning parameters to express deterioration of the structure.

3.3 Hybrid model updating : Current state of the structure & Deterioration Assessment

This section of the paper presents the identification of structural elements that are subjected to cracking under serviceability loading conditions and the hybrid model updating carried out to obtain the FE model to represent the current state of the structure using cross section area of the identified structural elements with appropriate scatter values derived based on stress values of individual structural elements.

To determine the structural elements that will undergo cracking, investigations were carried out on the initial state FE model by simulating serviceability operational loading conditions such as dead loads, live loads and wind loads based on the Australian/New Zealand code for wind actions[31] since the structure is located in Brisbane, Queensland, Australia. Similar to the initial state model updating scatter values for the test data were obtained from statistical analysis of a data-set sample (Section 4) whilst the scatter values for the tuning parameters (cross section area) are the corresponding stress values of the structural elements. The stress distribution of the shell elements and columns under serviceability loading conditions are illustrated in Figure 7 respectively.

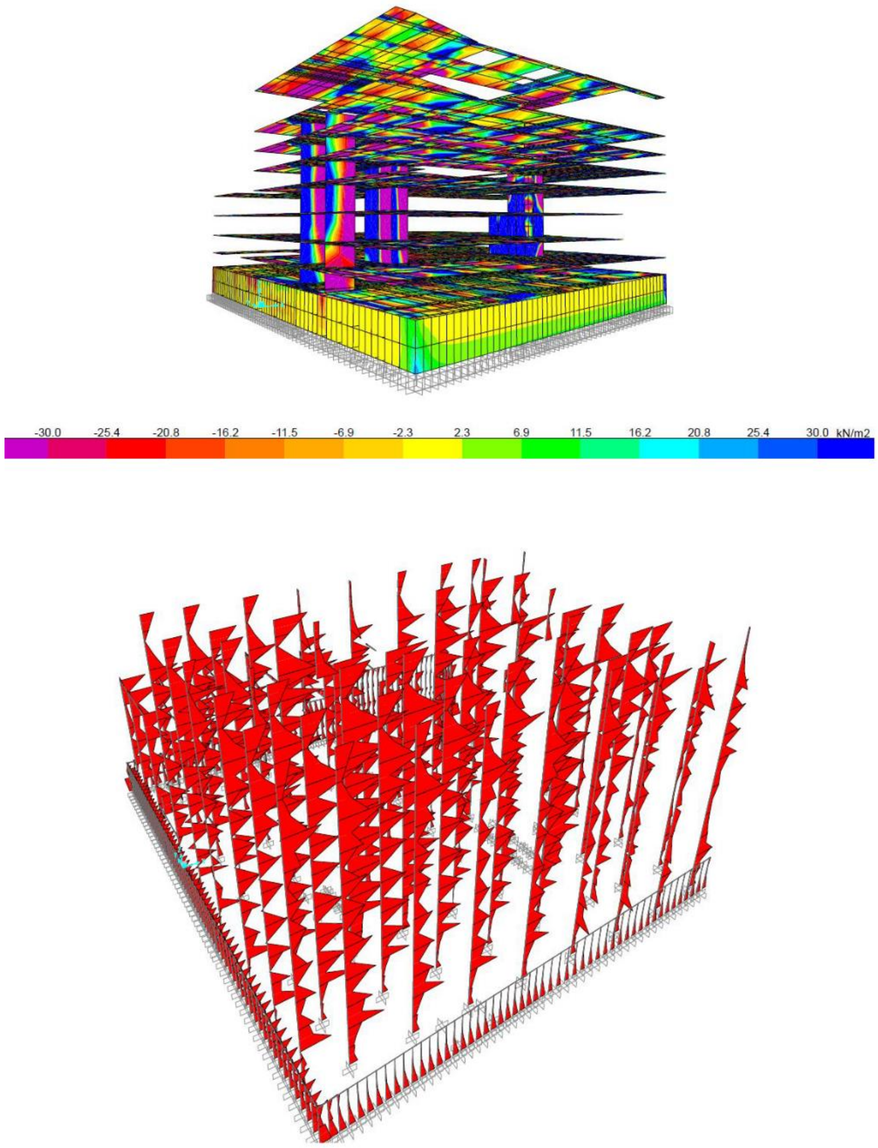

Figure 7 Stress distributions of shell elements (upper) and columns (lower)

Based on the stress distribution of the finite element model and modulus of rupture values, the structural elements that are subjected to cracking under serviceability loading conditions were identified. Then, the cross sections of these elements (397 column elements, 498 wall elements and 226 slab elements) are chosen as the tuning parameters in the model updating procedure. Confidence values for the chosen structural elements were assigned based on the stress values and upper bound of the tuning parameter is set to 0% since the deterioration process is represented as a reduction in the cross section area. Further, since the structure is relatively new and there are no visible cracks the deterioration of the structure is small and to account for that small value (0.40%) has been used as the lower bound for the tuning parameters.

The same stopping criteria used in the model updating process for the initial state was used in the current state updating and the updating process has stopped after 47 iterations due to the minimum improvement between two consecutive iterations fallen below the set-up value of 0.01%. Similar to the earlier case, only the natural frequencies of first five modes were selected in the model updating process and sixth mode was used to validate the updated model. OMA frequencies and the FE model frequencies both before and after the model updating process for the first six natural modes are tabulated in Table *4*. The model updating results show a good agreement with the OMA frequencies for the current state with a maximum error in the frequency for active range dropped down to 0.20% and the validity of the updated model is proven by the good agreement of the natural frequency of the sixth mode which was in the passive range.

Table 4 Frequencies of initial state and current state updated models versus OMA results of current state

Mode Number	OMA Frequency – Current State	Updated FE model – Initial State		Updated FE model –Current State	
		Frequency	Error	Frequency	Error
1	1.139	1.146 Hz	0.61%	1.138 Hz	-0.09%
2	1.528	1.547 Hz	1.24%	1.531 Hz	0.20%
3	1.650	1.654 Hz	0.24%	1.649 Hz	-0.06%
4	3.933	3.985 Hz	1.3%	3.935 Hz	-0.05%
5	4.243	4.254 Hz	0.26%	4.242 Hz	-0.02%
6	**4.818 Hz**	**4.964 Hz**	**3.03%**	**4.835 Hz**	**0.35%**

4 Conclusions

This paper has presented a novel methodology for deterioration assessment of building structures under serviceability operational loading conditions based on an improved hybrid sensitivity based model updating approach assisted by the use of long-term SHM data. This was realised by a simple yet effective scheme to simulate progressive deterioration for new-built structures; as well as innovative methods to effectively manage measurement, modelling and updating uncertainties. By statically analysing measured modal data as well as ranking the structural elements according to their vulnerability to cracking, the developed procedure is able to classify the levels of uncertainties and confidence for the tuning parameter and response. Based on these, appropriate weighting coefficients and upper/lower bounds are then assigned to ensure that all changes taken place in the numerical model are physically and structurally meaningful. The efficacy of the established methodology is studied through a case study of a ten story benchmark structure located at Queensland University of Technology (QUT) premises equipped with a long-term SHM system. The results showed that the established methodology is successful in providing an alternative deterministic approach which is computationally efficient compared to the existing probabilistic deterioration assessment processes. A long-term SHM system such as the one of QUT-SHM testbed is very helpful in providing representative datasets not just for global anomaly detection exercises as demonstrated earlier[32] but also for continually tracking the deterioration status of the structure from an onset as studied herein. The proposed methodology can be further developed by incorporating degradation due to chemical attacks which have an effect on the deterioration of concrete structures in the long-term and these developments will be reported elsewhere in future.

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APPENDIX I – Hybrid model updating algorithm

$$E_R = \{\Delta R\}^t [C_R] \{\Delta R\} + \{\Delta P\}^t [C_p] \{\Delta P\} \tag{6}$$

ΔR = Difference of the responses

ΔP = Difference of the parameters

$\left[C_R\right]$ = Diagonal weighting matrix for responses

$\left[C_P\right]$ = Diagonal weighting matrix for parameters

The linear term of Taylor's expansion series is used to approximate the target response vector $\mathrm{R_e}$ using the vectors $\mathrm{R_0}$ (original response vector), $\mathrm{P_0}$ (original parameter vector) and $\mathrm{P_u}$ (updated parameter vector).

$$\mathrm{R_e} \approx \mathrm{R_0} + \mathrm{S}(\mathrm{P_u} - \mathrm{P_0}) \tag{7}$$

Hence, using the above linear relationship between target responses and tuning parameters, parameter difference $\Delta\mathrm{P}$ can be expressed as follows;

$$\Delta\mathrm{P} = \mathrm{P_u} - \mathrm{P_0} = \mathrm{G}(\mathrm{R_e} - \mathrm{R_0}) \tag{8}$$

$\left[\mathrm{G}\right]$ = Gain matrix

Matrix G is derived in such a way to minimise the error function and when there are more responses than parameters it is calculated as;

$$\left[\mathrm{G}\right] = \left(\left[\mathrm{C_p}\right] + \left[\mathrm{S_n}\right]^t \left[\mathrm{C_R}\right]\left[\mathrm{S_n}\right]\right)^{-1} \left[\mathrm{S_n}\right]^t \left[\mathrm{C_R}\right] \tag{9}$$

And when there are more parameters than responses matrix G is calculated as;

$$[\mathrm{G}] = ([\mathrm{C_p}])^{-1}[\mathrm{S_n}]^t([\mathrm{C_R}]^{-1} + [\mathrm{S_n}]([\mathrm{C_P}])^{-1}[\mathrm{S_n}]^t)^{-1} \tag{10}$$

$\left[\mathrm{S_n}\right]$ = normalized relative sensitivity matrix

Updated parameter vector can be obtained through a re-arranged equation 7 and the new response vector corresponding to the new updating parameter P_u is calculated from the modal analysis.

$$\left\{\mathrm{P_u}\right\} = \left\{\mathrm{P_o}\right\} + \left[\mathrm{G}\right]\left\{-\Delta\mathrm{R}\right\} \tag{11}$$

The resulting response vector and the updated parameters will be the starting vectors $\mathrm{R_0}$ and $\mathrm{P_0}$ for the next iteration. This iteration process is carried out until the error function is minimized to a pre-determined tolerance.

APPENDIX II – Normalized sensitivity analysis

The relative sensitivity matrix $\left[\mathrm{S_r}\right]$ is a rectangular matrix of order $m \times n$ where *m* and *n* are the number of target responses and parameters, respectively.

$$[S_r] = [S_{ij}] = \left[\frac{\delta R_i}{\delta P_j}\right][P_{jj}] \tag{12}$$

S_{ij} is the sensitivity of the target response R_i due to the change in tuning parameter value P_j and the operator δ represents the change in the variable while $[P_{jj}]$ is the diagonal square matrix holding the tuning parameter values. The forward finite difference approach has been implemented to compute the derivatives in equation 2.

$$\frac{\delta R_i}{\delta P_j} = \frac{R_i(P_j + \Delta P_j) - R_i(P_j)}{\Delta P_j} \tag{13}$$

$R_i(P_j)$ is the i[th] response value for the parameter value P_j and $R_i(P_j + \Delta P_j)$ is the response of the i[th] response value when the parameter value changes by ΔP_j. Then the sensitivity matrix is normalized with respective to the response value as shown in equation 4.

$$[S_n] = [R_i]^{-1}[S_r] = [R_i]^{-1}\left[\frac{\delta R_i}{\delta P_j}\right][P_j] \tag{14}$$

$[S_n]$ = Normalized relative sensitivity matrix;

$[R_i]$ = A diagonal, square matrix holding the response value