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BAYESIAN MODEL UPDATING OF A PASSIVELY CONTROLLED BUILDING USING EARTHQUAKE MEASUREMENTS

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Abstract

Model updating of large-scale, sparsely-instrumented civil engineering structure is often ill-conditioned and can be computationally challenging when high-fidelity finite element models are utilized. In this study, the model updating of a passively controlled building is examined, carried out by adopting an efficient Bayesian model updating approach and using earthquake measurements. The building is located at Tohoku Institute of Technology and is equipped with a structural health monitoring system that measures its seismic response, including accelerations of a few monitored floors and displacement and force of a few monitored oil dampers. To alleviate the computational burden, a computationally efficient finite element (FE) model, simplified from a high-fidelity FE model of the building, is utilized as the initial model to be updated. Subsequently, a modal sensitivity analysis is performed for the selection of significant model parameters, in which a derivative-based sensitivity index is utilized to rank the importance of different parameter candidates. Then, a time-domain Bayesian model updating approach based on a stochastic simulation algorithm is adopted to estimate the selected model parameters using earthquake measurements. The parameter estimation uncertainty is qualified in the form of probability distribution (the posterior distribution), which contains useful information about the reliability of the updated parameter values, as well as the correlation in the way they affect the monitored responses. Finally, a relatively large earthquake event is selected to demonstrate the effectiveness of the proposed approach for the model updating of this building, comparing measured and predicted responses, the latter established using the updated FE model.

Keywords: Bayesian model updating, modal sensitivity analysis, building structure, earthquake measurement

1. Introduction and description of the investigated building

Model updating methods are commonly used in structure dynamics to calibrate physically based models, such as finite element models, to better represent real-world structures [1,2]. The updated models can be then utilized confidently in many practical applications such as response prediction, damage diagnosis and safety assessment [3,4]. Model updating is intrinsically an inverse problem that identifies unknown (i.e, uncertain) model parameters from observed structural response data. Many model updating methods have been proposed in the literature and may be generally classified into two categories: deterministic methods [5,6] or probabilistic methods [7,8]. The former identifies an optimal point estimate of the model parameters, while the latter can provide more diverse, probabilistic information about the parameter estimates, such as statistical moments or probability distributions.

In real world settings, large-scale civil engineering structures are often sparsely instrumented, while their dynamic behavior is usually characterized by high-fidelity, finite element models with many parameters. As a result, model updating of such kind of structures is intrinsically ill-conditioned and, very frequently, computationally challenging [9,10]. Ideally, the model updating should be conducted in a probabilistic manner to account for the effects of both the unavoidable modelling errors and the measurement noise, on the parameter estimation [11,12,13]. Of particular importance among the probabilistic methods is Bayesian-inference, also frequently referred to Bayesian model updating approach [8]. This approach has recently received increasing attention in system identification, mainly because of its ability to provide not only the optimal estimates of model parameters but also their associated estimation uncertainty quantified in the form of probability distributions. These probability distributions, called in this setting the posterior distributions, contain valuable information about the reliability of the updated model parameter values, as well as their possible correlation in the way they affect the monitored responses, as identified through the updating process. This study focuses on the application of such a Bayesian inference approach to the model updating of a real-world passively-controlled building structure using earthquake measurements.

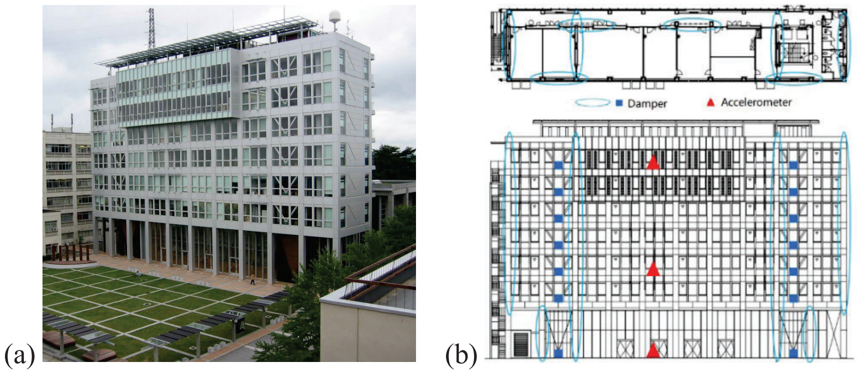
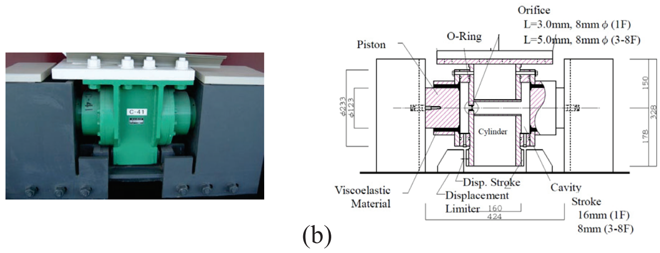


Fig. 1 – Building information: (a) front view; (b) distributions of accelerometers and oil dampers

The investigated structure, shown in the Fig. 1, is located in Sendai, Japan and is the administration building of Tohoku Institute of Technology. It was constructed in 2003 and is steel framed with precast concrete slabs. The plan dimension is 48m by 9.6m while the total height is 34.2 m with eight stories above the ground. The story height is 3.8m except the first floor, which has a height of 8m due to the fact that the first two stories merge for a large public place. The building was designed according to the Japanese Earthquake Resistance code for School Buildings. For enhancing the capability of seismic-energy dissipation, a total of 56 oil dampers of two types were installed additionally in building: 4 dampers in each direction for each story. The details of the installed oil dampers are shown in Fig. 2. The piston of each oil damper is fixed with a U-type abutment on the floor and the central cylinder is attached to a V-type brace, as also indicated in Fig. 1(b).



(a) (b)

Fig. 2 – Damper details: (a) front view; (b) configurations

A structural monitoring system has been installed in the building to study its dynamic behavior, as well as the on-site performance of the oil dampers during earthquakes. The accelerations along the longitudinal and transverse directions of the building are recorded using two-directional accelerometers. Three accelerometers are placed near the central locations of the 1st, 4th, and 8th floors, as shown in the Fig. 1(b), for monitoring the translational motions during earthquakes. In addition, 4 oil dampers placed on the 1st and 8th floors along the two horizontal directions are selected to be monitored. The force and displacement response of the selected oil dampers are measured by using load cells with strain gauges and displacement transducers, respectively. Fig. 3 and Fig. 4, respectively, show the monitored floor acceleration and the monitored damper response along the longitudinal direction of the building during a large earthquake (M_w 7.0) on May 26, 2003. This set of earthquake measurements will be utilized in this study to demonstrate the model updating process for this building.

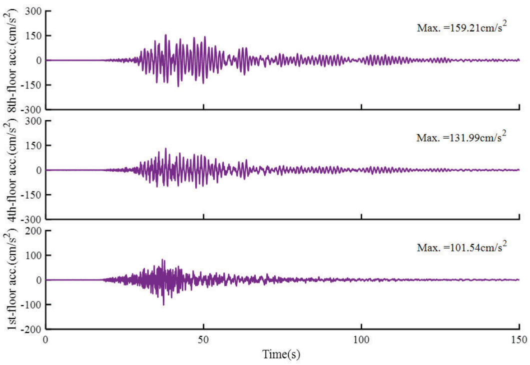


Fig. 3 – Acceleration of monitored floors during a large earthquake on May 26, 2003

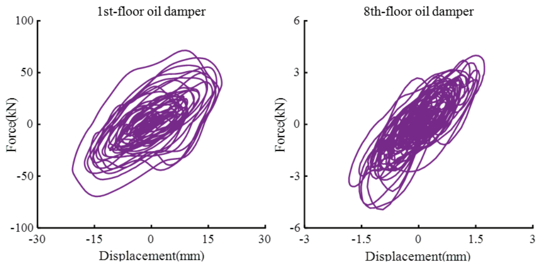


Fig. 4 – Force-displacement hysteresis curves of monitored dampers during the same earthquake shown in Fig. 3

The remaining of this paper is organized as follows: in section 2, the FE modeling of the building based on its design blueprints is introduced, including discussions related to simplifying assumptions adopted during the FE model development. Then, a modal sensitivity analysis is conducted for the model parameter selection in Section 3. Section 4 presents an efficient Bayesian model updating approach to estimate the selected model parameters using earthquake measurements, and further discussed results from the model updating.

2. Finite element modelling of the building

The planar equation of motion of the building subjected to earthquake excitation can be expressed by

$$\mathbf{M}\ddot{\mathbf{x}} + \mathbf{C}\dot{\mathbf{x}} + \mathbf{K}\mathbf{x} + \mathbf{f}_d\left(\mathbf{x}, \dot{\mathbf{x}}\right) = \mathbf{M}\mathbf{I}\ddot{x}_g \tag{1}$$

where **M** and **K** are the $n \times n$ mass and stiffness matrices of building, respectively, **C** is the $n \times n$ inherent structural damping matrix, modelled by using the linear viscous damping model, $\mathbf{x}$ is the n-dimensional vector of displacement relative to the building base, $\mathbf{f}_d\left(\mathbf{x}, \dot{\mathbf{x}}\right)$ is the n-dimensional force vector of resultant forces from the oil dampers, $\mathbf{I} \in \mathbb{R}^n$ is the earthquake influence coefficient vector and $\ddot{x}_g \in \mathbb{R}$ is the input acceleration, corresponding in this case to the acceleration of the ground floor of the building.

For the estimation of the mass and stiffness matrices of the building, a high-fidelity finite element model, as shown in Fig.5, was created in the SAP2000 environment based on the structural drawings of building. The structure is assumed to be fixed at the ground floor without considering any soil-structure interaction effects. The connections between steel columns and beams are fully constrained. The floor slabs are modelled by shell elements for accurate mass distribution. The oil dampers are modelled as by a nonlinear Maxwell model that consists of a linear spring element connected in series with a nonlinear viscous dashpot element. The damper parameters were independently identified from the seismic measurements and are directly utilized in the remainder of this study.

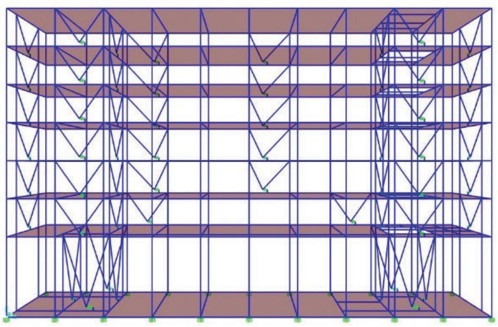
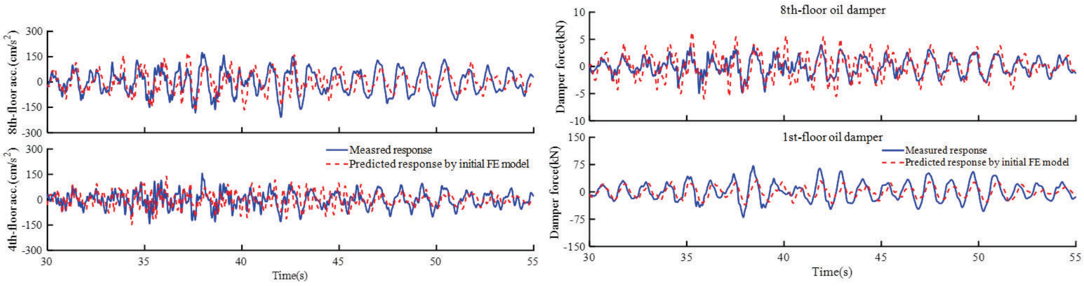


Fig. 5 – A high-fidelity finite element model of the building

Since only the translational motion of floors is monitored, emphasis is placed here on updating the corresponding translational modes, specific the one along the longitudinal direction. As such, the high-fidelity FE model is reduced to a computationally more efficient planar/2-D FE model, that can be ultimately represented by Eq. (1), as long as appropriate parameters are identified for the different matrices and forcing vectors. To further alleviate the computational burden, assumptions common for building structure are also adopted, such as concentrating the mass of structural components at the floor levels and neglecting the mass of nodes in the vertical direction.

The resulting planar FE model has 7 translational, dynamic (i.e., with mass) Degrees of Freedoms (DoFs) and 279 (zero-mass) rotational DoFs for the beam-column joints. This model is referred to as the initial FE model to be updated. Mass and stiffness matrices pertaining to the dynamic DoFs are obtained through static condensation of the initial FE model and are the ones that will be used in the dynamic time-history analysis of the building according to Eq (1).

Fig. 6 presents the comparison between the measured response and the corresponding predicted response by the initial FE model, including acceleration of monitored floors and force of monitored oil dampers. In this time-history analysis, the inherent damping matrix is determined by adopting a damping ratio of 2% for the first three modes and 10% for the other modes. A time-segment, 30s~55s, of the strong shaking phase of building is only shown in this figure. It is clearly evident that a large discrepancy is observed between the actual measurements and the model predictions. This indicates considerable modeling errors for the initial FE model, and clearly motivates the need to update it used measured responses.



(a) Acceleration of monitored floors (b) Force of monitored dampers

Fig. 6 – Comparison between measured and predicted response of the initial FE model

3. Modal sensitivity analysis and parameter selection

A common but crucial issue in model updating is the selection of the parameters to be updated between all-possible parameter candidates in an initial FE model. To help this selection a sensitivity analysis is typically performed, identifying the significant parameters while ruling out insignificant parameters for the measured response quantities according to some sensitivity index [2,6]. This approach can both reduce the computational complexities and avoid ill-posedness features of model updating for complex large-scale structures with incomplete measured response data, which is the case for the investigated building.

The initial FE model has 506 nodes, 94 shell elements, and 920 frame elements. Generally speaking, many parameters of those elements, such as mass density and elastic modulus of materials, or constrains of nodes, may be considered as parameter candidates for the model updating. In this study, the mass of all structural components and the elastic modulus of steel columns are first considered. To reduce the number size, these parameters are grouped by floors, rather than by element types, which results in 7 mass density parameters (denoted by $\boldsymbol{\theta}_m$) and 7 elastic modulus parameters (denoted by $\boldsymbol{\theta}_E$). In addition, the dominate submatrix of the stiffness matrix, associated only with the translational, dynamic DoFs, is also considered to be updated. This submatrix is the tri-diagonal matrix representing a shear-type model of the building and is ultimately parameterized though the story stiffness parameters. This introduces an additional 7 candidate parameters, denoted herein by $\boldsymbol{\theta}_k$).

A modal sensitivity analysis [6] was conducted to quantify and rank the importance of the parameter candidates discussed above. Specifically, the first-order partial derivatives of modal outputs with respect to model parameter inputs are utilized as sensitivity index. Modal outputs of two types, natural frequencies and mode shape ratios, are considered as the target output for the sensitivity analysis. Specifically, the mode shape ratios are defined only for the two upper floors for which measurements are available, since information for the ratios for other floors are not observable from the available data. The first-order partial derivatives were caculated at the prameter design point/value by using finite diference approximation, for example for the natural frequency $\partial\omega(\theta)/\partial\theta \approx \Delta\omega(\theta)/\Delta\theta$, where $\Delta\theta$ and $\Delta\omega(\theta)$ are the variations of a parameter candidate and a natural frequency, respectively. A small variation of ±5% design value is considered for the parameter candidates to perform the sensitivity analysis.

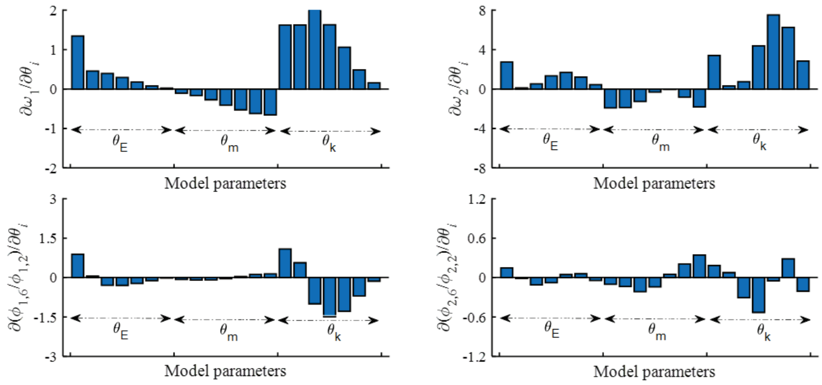


Fig. 7 – Modal sensitivity analysis of selected parameters of the initial FE models

Fig. 7 presents the caculated partial deratives of the first two modes, where the parameters of same type (from left end to right end) are ordered by floor number (from first floor to top floor). The sign of partial derivatives shows the global relations between the variations of modal output and candidate parameters. As expected, the mass parameters $\boldsymbol{\theta}_m$ and the stiffness-related parameters $\boldsymbol{\theta}_E$ and $\boldsymbol{\theta}_k$, respectively, have positive and negative relations, respectively, with the first two nature frequencies. Findings and insights on the results are the following:

(1) The mass parameters have an increasing trend of importance, as floor orders increase, for the first natural frequency. The second frequency is insensitive to the mass of both the fourth floor and the fifth floor. For the mode shape ratios, the mass density is insignificant for the first mode, but significant for the second mode.

(2) The elastic modulus parameters have a decreasing trend of influence on the first natural frequency, compared to the mass parameters. Of particular importance among the parameters is the elastic modulus of the first floor, to which almost all of frequencies and modal shape ratios are sensitive, except for the second modal shape ratio. Elastic modulus of other floors is less important for modal shape ratios for both the first two modes.

(3) The story stiffness parameters are the most significant parameters among all of parameters candidates for both the first two modes. Almost all of story stiffness parameters significantly affect the first two natural frequencies, except for the second and the third stiffness parameters which are quite important for the first natural frequency, but become insignificant for the second one. Regarding the mode shapes ratios, the story stiffness parameters also show greater importance compared to any other type of parameters.

Considering both their physical explanations and the significance for the examined modal outputs, the story stiffness parameters are only selected as the updating parameters. To further alleviate the ill-pondeness of the updating problem, these parameters are further grouped as $\boldsymbol{\theta}_k = [\theta_{k,1}, \theta_{k,2}, \theta_{k,3}]^T$, in which $\theta_{k,1}$, $\theta_{k,2}$, and $\theta_{k,3}$ are, respectively, the stiffness parameters of the first two floors, the following two floors, and the upper three floors. Herein these parameters are quantified as the ratios of the variation of story stiffness assigned to the stiffness submatrices with respect to the design values. So value of 0 corresponds to the original (design) parameters and value of 0.2 to a 20% difference in the parameter values with respect to the design values.

Finally, the inherent damping of the structure, here ultimately parameterized though modal damping ratios, is considered as characteristic to be updated, as it is widely acknowledged to have a significant influence on the structural dynamic response. Note that since the adopted sensitivity analysis focused on modal properties of the undamped structure, it cannot reveal anything about the importance of these damping ratios. Instead, the decisions made here follow general structural dynamics observations. Specifically, the damping ratios for the first three modes, denoted by $\boldsymbol{\theta}_{\xi} = [\xi_1, \xi_2, \xi_3]^T$, are selected as uncertain parameters to be updated, while the damping ratios of the remaining, higher modes, considered of low importance, are constrained to their preset design values discussed earlier.

4. Bayesian model updating of the building

4.1 Bayesian formulation

The idea of Bayesian inference for model updating [8,12] is expressed through Bayes' theorem as

$$p(\boldsymbol{\theta}|\mathbf{D}) = c^{-1} p(\mathbf{D}|\boldsymbol{\theta}) p(\boldsymbol{\theta}) \tag{2}$$

where $\boldsymbol{\theta}$ is the vector of parameters to be updated, including the model parameters and the parameters that characterize the model prediction errors, $p(\boldsymbol{\theta})$ is the prior probability density function (PDF), $p(\boldsymbol{\theta}|\mathbf{D})$ is the posterior PDF for $\boldsymbol{\theta}$, $p(\mathbf{D}|\boldsymbol{\theta})$ is the likelihood function for the data $\mathbf{D}$ (corresponding to input/output data or output-only data) and c is a normalization constant that makes the integral of the posterior PDF over the parameter space equals to unity and, ultimately represents the evidence for the data $\mathbf{D}$. The prior PDF is usually determined based on user's empirical knowledge and Bayes' theorem updates this prior knowledge through the available data to provide the posterior PDF $p(\boldsymbol{\theta}|\mathbf{D})$.

As described in the introduction, the acceleration measurements of floors are utilized for the model updating, corresponding to acceleration response of the first floor (used as input data) and accelerations response of other two upper monitored floors (used as output data). Under assumptions of zero-mean independent Gaussian variables for the model prediction errors [10], the likelihood function can be expressed by

$$p\left(\mathbf{D}|\boldsymbol{\theta}\right) = \prod_{i=1}^{2} \frac{1}{\left(2\pi\sigma_i^2\right)^{N_d/2}} \exp\left(-\sum_{j=1}^{N_d} \frac{1}{2\sigma_i^2} \left(\hat{\ddot{x}}_i(t_j) - \ddot{x}_i(\boldsymbol{\theta}_k, \boldsymbol{\theta}_{\xi}, t_j) \right)^2 \right) \tag{3}$$

where σ_i^2 is the unknown variance of the model prediction error for the ith measured output quantity, $\hat{\ddot{x}}_i(t_j)$ and $\ddot{x}_i(\boldsymbol{\theta}_k, \boldsymbol{\theta}_{\xi}, t_j)$ are, respectively, the measured and predicted accelerations of monitored floors at time point t_j, N_d is the length of discrete time history data. For the latter 1000 data points for each channel of the output measurements are uniformly selected from the time-segment of 30s~55s, as shown in Fig. 6(a). Subscript i is utilized herein to distinguish between the different measured responses.

The vector of parameter to be updated through the Bayesian inference scheme, includes the story stiffness parameters and damping ratios, as well as the unknown variances for the prediction errors, and is dented by $\boldsymbol{\theta} = [\theta_{k,1}, \theta_{k,2}, \theta_{k,3}, \xi_1, \xi_2, \xi_3, \sigma_1, \sigma_2]^T$. The prior PDF for the updating parameters is assumed as follows: all story stiffness parameters are independently and uniformly distributed over [-0.2 1], all damping ratios are independently and uniformly distributed over [0 0.1], and the variance $\sigma_i^2, i = 1,2$ is uniformly distributed over $[0\ 1]\sigma_{acc,i}^2$, in which $\sigma_{acc,i}$ is the root-mean-square value of the acceleration data.

In order to obtain samples from the posterior PDF, the TMCMC algorithm [14,15] is adopted in this study, though should be pointed out that any other algorithm could had been used instead. TMCM is a modified version of an adaptive Metropolis-Hasting method proposed by Beck and Au

[16] and is capable of sampling from the posterior PDFs with unknown and complex distribution shapes, such as extremely peaked or multimodal. Rather than directly sampling from the posterior PDF, the TMCMC algorithm adopts a sequential sampling strategy through a sequence of (non-normalized) intermediate PDFs that converge to the target posterior PDF. The construction of intermediate PDFs is achieved by

$$\pi_i(\boldsymbol{\theta}) \propto p(\mathbf{D}|\boldsymbol{\theta})^{\alpha_i}\, p(\boldsymbol{\theta}) \qquad i = 0,\cdots,n_\alpha \tag{4}$$

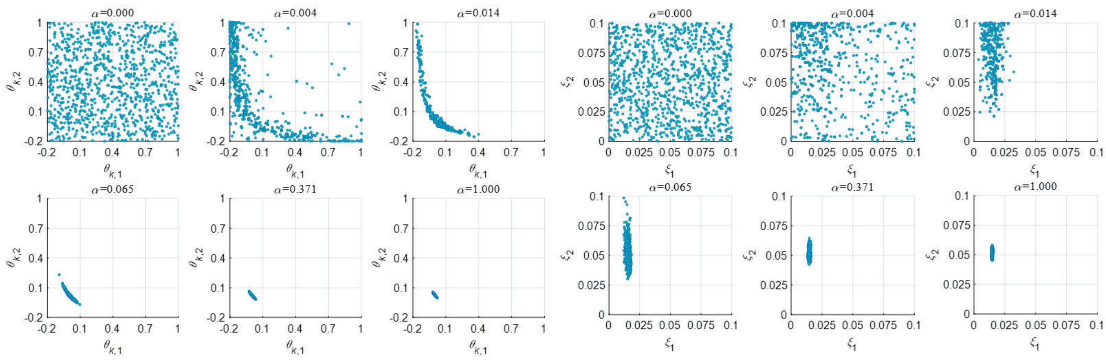
where α_i is the tempering coefficient, ranging from 0 to 1, $0 = \alpha_0 < \alpha_1 < \cdots < \alpha_{n_\alpha} = 1$, n_α is the number of intermediate PDFs. At the stat stage (i=0), $\pi_i(\boldsymbol{\theta})$ is proportional to the prior PDF, and at the last stage (i=1), $\pi_i(\boldsymbol{\theta})$ is proportional to the target posterior PDF. In this algorithm, the samples of the prior PDF are treated as initial seeds and gradually evolve to the desired posterior samples through several step-by-step transitions between the adjacent intermediate PDFs. These evolution transitions are achieved by using the resampling technique with a certain constrain on the changes between two adjacent intermediate PDFs. Implementation details of the TMCMC algorithm are omitted here. The interested reader is referred to publications [14,15] for a detailed description.

4.2 Results for model updating and discussions

TMCMC is applied to obtain samples from the selected parameters of the initial FE model using the earthquake measurements, following description of Eq. (2). Fig. 8 presents the generated 1000 samples by TMCMC for six selected intermediate PDFs, in which samples of the first two story stiffness and the first two damping ratios are only presented. Results in the figure illustrate how the samples in the parameters space converge to the high-probability regions for the posterior PDF as the tempering parameter α_i increases. Moreover, an obvious correlation between the first two story-stiffness parameters is observed across the whole evolution process, which indicates some connections for these two parameters in the way they affect the predicted response. No such correlation is observed for the first two damping ratios. The posterior samples obtained from TMCMC for the story stiffness parameters and the damping ratios are presented in Fig. 9. Both frequency histograms and scatter plots of the posterior samples are given. The location of the maximum a posteriori (MAP) parameter $\boldsymbol{\theta}_{MAP}$, the one corresponding to the mode (peak) of the posterior PDF

$$\boldsymbol{\theta}_{MAP} = \arg\max_{\boldsymbol{\theta}\in\Theta} p(\boldsymbol{\theta}|\mathbf{D}) \tag{5}$$

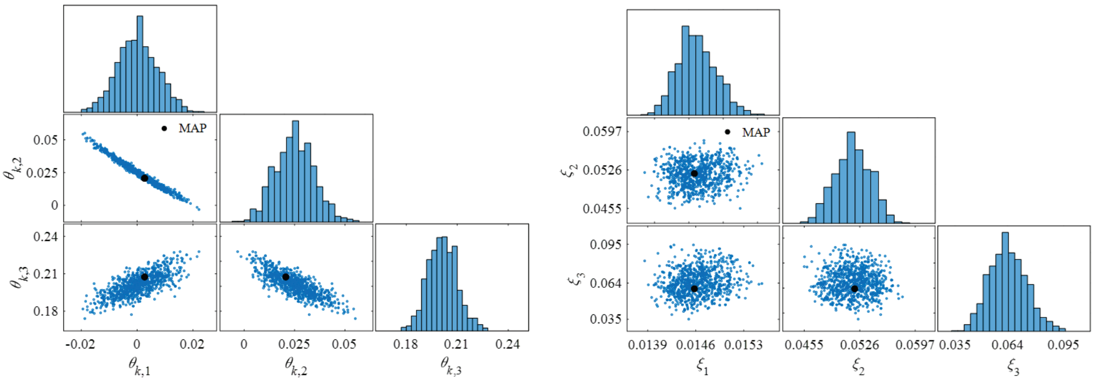
is also shown in this figure.



(a) Story stiffness parameters (b) Damping ratios

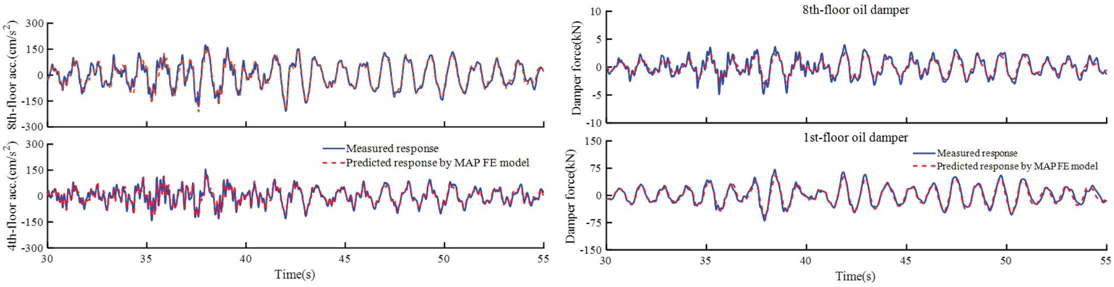
Fig. 8 – Evolution of samples from TMCMC algorithm for selected stages

The effectiveness of the Bayesian inference scheme is next validated. For this reason, the FE model corresponding to the maximum a posteriori (MAP) estimate of the updated parameters, also shown in Fig. 9, is utilized to predict the structural responses of the building during the selected earthquake, Fig. 10 presents the measured and predicted response during the strong shaking phase, corresponding to both the acceleration of monitored floors and the force history of monitored oil dampers. It can be seen from Fig. 10 that the MAP predictions are in good agreement with the actual seismic measurements, which shows the effectiveness of the proposed updating approach for this building.



(a) Story stiffness parameters (b) Damping ratios

Fig. 9 – Posterior distribution of story stiffness parameters and damping ratios



(a) Acceleration of monitored floors (b) Force of monitored dampers

Fig. 10 – Comparison between measured and predicted response of the MAP FE model

It is worth pointing out that the MAP estimates of the updated parameters is only a deterministic point estimate. An important benefit of the Bayesian inference scheme is its ability to quantify the estimation uncertainty of these parameters in the form of the posterior PDF. As it can be seen in Fig. 9 the posterior samples of each parameters exhibit a single mode, which may be approximated by a truncated Gaussian distribution. Table 1 shows the calculated mean values and standard deviations of the posterior samples. It is evident from the results in Table 1 that the calculated standard deviations, utilized for representing the estimation uncertainty, of the story stiffness parameters is not negligible, indicating a substantial variability. For the damping ratios, standard deviation increased for higher modes. This should be attributed also to the deterioration in the signal-to-noise ratios for the higher frequencies corresponding to these higher modes.

Table 1 – Means and standard deviations of the posterior samples

	$\theta_{k,1}$	$\theta_{k,2}$	$\theta_{k,3}$	ξ_1	ξ_2	ξ_3
Mean	0.0002	0.0251	0.2013	0.0146	0.0517	0.0643
Std	0.0071	0.0096	0.0088	0.0003	0.0023	0.0102

The updated story stiffness parameters indicate that the initial FE model underestimates the story stiffness of the building by up to about 20%, possibly attributed to the neglected stiffness contributions from the nonstructural components. In addition, an increasing trend can also be found in the calculated mean values as the parameter as the floor number increases, as shown in Table 1. The observed stiffness reduction may be due to many sources, such as the loosening of the connections between structural and nonstructural components, and may be amplitude dependent.

Finally, to quantify the correlation between the updated model parameter values, evident in Fig. 9, the Spearman's rank correlation coefficients between each pair of those parameters are calculated

$$\boldsymbol{\rho}_{\boldsymbol{\theta}_k,\boldsymbol{\theta}_\xi} = \begin{array}{c} \theta_{k,1} \\ \theta_{k,2} \\ \theta_{k,3} \\ \xi_1 \\ \xi_2 \\ \xi_3 \end{array} \begin{bmatrix} 1.00 & -0.99 & 0.72 & 0.26 & 0.48 & 0.04 \\ -0.99 & 1.00 & -0.80 & -0.25 & -0.49 & -0.02 \\ 0.72 & -0.80 & 1.00 & 0.14 & 0.43 & -0.08 \\ 0.26 & -0.25 & 0.14 & 1.00 & -0.09 & 0.19 \\ 0.48 & -0.49 & 0.43 & -0.09 & 1.00 & -0.01 \\ 0.04 & -0.02 & -0.08 & 0.19 & -0.01 & 1.00 \end{bmatrix} \quad (6)$$
$$\begin{array}{cccccc} \theta_{k,1} & \theta_{k,2} & \theta_{k,3} & \xi_1 & \xi_2 & \xi_3 \end{array}$$

Very strong correlation is observed between the stiffness parameters. This is expected since trade-off between these parameters may result to same modal characteristics, and therefore similar response. The pairs of stiffness parameters $\theta_{k,1}$ and $\theta_{k,2}$, and $\theta_{k,2}$ and $\theta_{k,3}$ have negative coefficients, indicating that an increase in one parameter needs to be compensated with a decrease in the value of the other. This is an anticipated trade-off for the stiffness between adjacent stories. On the other hand the pair of $\theta_{k,1}$ and $\theta_{k,3}$ has positive coefficients, which indicates an increase in $\theta_{k,1}$ needs to be accommodated by an increase in the value of $\theta_{k,3}$. This behavior probably stems from the negative correlation each of them has to their adjacent story stiffness $\theta_{k,2}$, which results to a positive correlation between them. It is interesting to note that, $\theta_{k,1}$ and $\theta_{k,2}$ have correlation coefficient nearly to 1 (in absolute value), which means an almost perfect correlation. Correlation coefficients between pairs of damping ratios are very small, indicating a very weak correlation across the different modes with respect to damping characteristics.

5. Conclusions

This study overviewed the model updating of a real-world, passively controlled building structure. This updating was carried out by adopting an efficient Bayesian model updating approach and using earthquake measurements. To reduce the computation cost associated with the model updating, a simpler FE model accommodating high computational efficiency was utilized. To further improve efficiency by reducing the number of parameters to be updated and to further avoid ill-posed issues for the updating (corresponding to an inversion problem), a modal sensitivity analysis was first leveraged to identify significant model parameters, Then, a stochastic simulation based Bayesian model updating approach was adopted to obtain sampled from the selected model parameters using the recorded structural response under earthquake excitation. The updating results show the story stiffness of the initial FE model is underestimated by an order of up to 20%, which may be caused by the omitted contributions from the non-structural components. The updated structure was shown to provide a good match with respect to both acceleration and oil-damper force/displacement relationships, improving substantially over the poor match the original FE model was facilitating.

6. Acknowledgements

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