ABSTRACT
A full-scale seven-story reinforced concrete shear wall building structure was tested on the UCSD-NEES shake table in the period October 2005 - January 2006. The shake table tests were designed so as to damage the building progressively through several historical seismic motions reproduced on the shake table. A sensitivity-based finite element (FE) model updating method was used to identify damage in the building. The estimation uncertainty in the damage identification results was observed to be significant, which motivated the authors to perform, through numerical simulation, an uncertainty analysis on a set of damage identification results. This study investigates systematically the performance of FE model updating for damage identification. The damaged structure is simulated numerically through a change in stiffness in selected regions of a FE model of the shear wall test structure. The uncertainty of the identified damage (location and extent) due to variability of five input factors is quantified through effect screening. These five input factors are: (1-3) level of uncertainty in the (identified) modal parameters of each of the first three longitudinal modes, (4) spatial density of measurements (number of sensors), and (5) mesh size in the FE model used in the FE model updating procedure (modeling error). A full factorial design of experiments is considered for these five input factors. The results of this investigation demonstrate that the level of confidence in the damage identification results obtained through FE model updating, is a function of not only the level of uncertainty in the identified modal parameters, but also choices made in the design of experiments (e.g., spatial density of measurements) and modeling errors (e.g., mesh size).

Introduction
In recent years, structural health monitoring has received increasing attention in the civil engineering research community with the objective to identify structural damage at the earliest possible stage and evaluate the remaining useful life (damage prognosis) of structures. Vibration-based, non-destructive damage identification is based on changes in dynamic characteristics (e.g., modal parameters) of a structure. Experimental modal analysis (EMA) has been used as a technology for identifying modal parameters of a structure based on its measured vibration data. It should be emphasized that the success of damage identification based on EMA depends strongly on the accuracy and completeness of the identified structural dynamic properties. Extensive literature reviews on vibration-based damage identification are provided by Doebling et al. [1, 2] and Sohn et al. [3].

Damage identification consists of (1) detecting the occurrence of damage, (2) localizing the damage zones, and (3) estimating the extent of damage. Numerous vibration-based methods have been proposed to achieve these goals. Salawu [4] presented a review on the use of changes in natural frequencies for damage detection only. However, it is in general impossible to localize damage (i.e., obtain spatial information on the structural damage) from changes in natural frequencies only. Pandey et al. [5] introduced the concept of using curvature mode shapes for damage localization. In their study, by using a cantilever and a simply supported analytical beam model, they demonstrated the effectiveness of employing changes in curvature mode shapes as damage indicator for detecting and localizing damage. Other methods for damage localizations include strain-energy based methods [6] and the direct stiffness calculation method [7]. A class of sophisticated methods consists of applying sensitivity-based finite element (FE) model updating for damage identification [8]. These methods update the physical parameters of a FE model of the structure by minimizing an objective function expressing the discrepancy between numerically predicted and experimentally identified features that are sensitive to damage such as natural frequencies and mode shapes. Optimum solutions of the problem are reached through sensitivity-based optimization algorithms. Recently, sensitivity-based FE model updating techniques have been applied successfully for condition assessment of structures [9].
A full-scale seven-story reinforced concrete (R/C) shear wall building slice was tested on the UCSD-NEES shake table in the period October 2005 - January 2006. The shake table tests were designed so as to damage the building progressively through several historical seismic motions reproduced on the shake table. A sensitivity-based FE model updating approach was used to identify damage at each of several damage states of the building based on its identified modal parameters. The estimation uncertainty in both the system identification and damage identification results was observed to be significant [10-13]. This motivated the authors to perform (through numerical simulation) an uncertainty analysis on these system and damage identification results. In an earlier study [14], the authors investigated the performance of three different output-only system identification methods, used for experimental modal analysis of the shear wall building, as a function of the uncertainty/variability in the following input factors: (1) amplitude of input excitation, (2) spatial density of measurements, (3) measurement noise, and (4) length of response data used in the identification process. This paper, which is an extension of the above mentioned study, investigates the performance of damage identification using FE model updating based on the identified modal parameters of the first three longitudinal vibration modes. In this study, the identified modal parameters of the damaged structure are generated numerically using a three-dimensional FE model of the test structure with different levels of damage simulated (numerically) along the height of the structure. The uncertainty of the identified damage (location and extent) is quantified through analysis-of-variance (ANOVA) due to variability of the following input factors: (1-3) level of uncertainty in the (identified) modal parameters of the first three longitudinal modes (M1, M2, M3), (4) spatial density of measurements (number of sensors) (S), and (5) mesh size in the FE model used for damage identification (modeling error) (E). A full factorial design of experiments is considered for these five input factors.

**Finite Element Model of the Test Structure**

The full-scale seven-story R/C building slice tested on the UCSD-NEES shake table consists of a main wall (web wall), a back wall perpendicular to the main wall (flange wall) for lateral stability, concrete slabs at each floor level, an auxiliary post-tensioned column to provide torsional stability, and four gravity columns to transfer the weight of the slabs to the shake table. Figure 1 shows a picture of the test structure, a drawing of its elevation, and a rendering of its FE model with fine mesh (one of the two FE models used in this study). Also, a plan view of the structure is presented in Figure 2. Details about construction drawings, material test data, and other information on the set-up and conducting of the experiments are available in [15].

![Test structure](image)

![Elevation dimensions](image)

![Finite element model](image)

Figure 1. R/C shear wall building slice

A three dimensional linear elastic FE model of the test structure was developed using a general-purpose FE structural analysis program, FEDEASLab [16]. A four-node linear flat shell element (with four Gauss integration points) borrowed from the FE literature was implemented in FEDEASLab in order to model the web wall, back wall, and concrete slabs [12]. In the FE model of the test building, the gravity columns and braces connecting the post-tensioned column to the building slabs are modeled using truss elements. The inertia properties of the test
structure are discretized into lumped translational masses at each node of the FE model. In this study, two FE models of the building with different mesh sizes (i.e., numbers of elements) are used in the FE model updating process in order to investigate the effects of mesh size (modeling error) on the damage identification results. The FE model with fine mesh is also used for generating the modal parameters of the damaged structure with damage simulated as change in material stiffness (effective moduli of elasticity) distributed over the finite elements of the web wall. Table 1 reports the measured moduli of elasticity (through concrete cylinder tests) at various heights (stories) of the test structure, which are used in both FE models representing the test structure in its undamaged/baseline state.

<table>
<thead>
<tr>
<th>Concrete Components</th>
<th>Measured Modulus of Elasticity (GPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st story</td>
<td>24.47</td>
</tr>
<tr>
<td>2nd story</td>
<td>26.00</td>
</tr>
<tr>
<td>3rd story</td>
<td>34.84</td>
</tr>
<tr>
<td>4th story</td>
<td>30.20</td>
</tr>
<tr>
<td>5th story</td>
<td>28.90</td>
</tr>
<tr>
<td>6th story</td>
<td>32.14</td>
</tr>
<tr>
<td>7th story</td>
<td>33.54</td>
</tr>
</tbody>
</table>

The natural frequencies and mode shapes of the first three longitudinal modes are used in the damage identification process. Figure 3 shows the modal parameters of the first three longitudinal modes computed from the fine mesh FE model representing the building in its undamaged state. These mode shapes and natural frequencies are in relatively good agreement with their counterparts identified experimentally based on ambient measurement data recorded on the undamaged test structure [10, 11].

Description of Input Factors Studied and Design of Experiments

As already mentioned, the objective of this study is to analyze and quantify the uncertainty of the identified damage obtained using a FE model updating strategy due to the variability of five input factors: (1-3) level of uncertainty in the (identified) modal parameters of each of the first three longitudinal modes (M1, M2, M3), (4) spatial density of measurements (number of sensors) (S), and (5) mesh size in the FE model used for damage identification (a type of modeling error) (E). A number of other factors could be considered such as modeling assumptions (e.g., type of finite elements), number of updating parameters (number of sub-structures), type and number of residuals and their weights used in the objective function. This study is restricted to the above mentioned 5 factors which are selected based on previous experience and expert opinion [10-14]. This section briefly describes each of the input factors considered in this study and the design of experiments considered.
Uncertainty in Modal Parameters

In practice, the main source of uncertainty in damage identification results arises from the uncertainty in the estimates of modal parameters that are used in the damage identification process. In a previous study by the authors [14], it was observed that the estimation uncertainty of the modal parameters identified using three state-of-the-art output-only system identification methods (i.e., Natural Excitation Technique combined with Eigensystem Realization Algorithm, Data-driven Stochastic Subspace identification, and Enhanced Frequency Domain Decomposition) depend significantly on the variability of various input factors such as amplitude of excitation (i.e., level of nonlinearity in the response), level of measurement noise, and length of measured data used for system identification. In this study, the modal parameters of the first three longitudinal vibration modes are used in the damage identification process. Two levels of uncertainty, namely 0.5% and 1.0% coefficient-of-variation (COV), are considered for the natural frequencies and mode shape components of these three modes. These considered levels of uncertainty in modal parameters are selected based on previous experience with this test structure [10-11]. In this study, the modal parameter estimators are assumed to be unbiased (i.e., mean value of parameter estimates coincides with the “exact” parameter value). For each natural frequency and mode shape component of a vibration mode at a considered level of uncertainty, 20 noise realizations are generated from zero-mean Gaussian distributions with standard deviations scaled to result in the considered COV. The random estimation errors added to the natural frequencies and mode shape components are statistically independent (across the realizations and across natural frequencies and mode shape components). Statistics in terms of mean and standard deviation (over the 20 identification runs for each combination of input factors) of the identified damage extent at each location (i.e., substructure) are studied as a function of the variability/uncertainty of the input factors.

Spatial Density of the Sensors

During the dynamic testing of the shear wall building, the web wall of the test structure was instrumented with 14 longitudinal accelerometers. The measured data were used later for modal identification of the test structure. To study the performance of FE model updating for damage identification as a function of the spatial density of the sensor array (i.e., number of sensors), two different subsets of the 14 sensor array are considered, namely (1) 10 accelerometers on the web wall at all floor levels (i.e., top of floor slabs) and at mid-height of each of the three stories, and (2) 14 accelerometers on the web wall at all floor levels and at mid-height of each story.

Mesh Size of FE Model Used for Damage Identification

The last input factor considered in this study is the modeling error due to the mesh size of the FE model (i.e., spatial discretization of the test structure) used for damage identification. This input factor is considered at two levels, i.e., two FE models of the building are used in the FE model updating process. The first model is defined by 340 nodes and 322 shell and truss elements. The web wall at each story is modeled using 4 shell elements and the floor slabs are discretized into 12 shell elements each. The second model, which has a more refined mesh, is defined by 423 nodes and 398 elements. In this model, the web wall at each of the first three stories is modeled using 16 shell elements, while the higher stories (5 to 7) are modeled using 4 shell elements each. The 4th story of the web wall is modeled using 8 shell elements. The floor slabs are modeled using 24 shell elements for each of the first three floors and 12 shell elements each for the higher floors (4 to 7). The back wall, post-tensioned column, gravity columns and steel braces are modeled in the same way in both FE models. It should be noted that these two FE models with different mesh size have different modal parameters (especially for the 3 modes considered in this study), even though the same material properties are used in the two models. The modal frequencies computed using the first model (coarse mesh) are

\[
\begin{bmatrix}
2.35 \\
11.19 \\
25.34
\end{bmatrix}\text{Hz}
\]

which are slightly higher than their counterparts obtained using the second model (fine mesh) (see Figure 3). The “true” modal parameters of the damaged structure are computed using the second model (fine mesh) with damage represented as change of material stiffness (i.e., effective modulus of elasticity) distributed spatially and intensity-wise over the FE model according to the observed damage in the actual test structure [13].

Table 2 summarizes the input factors and their levels considered in this study. A design of experiments (DOE) provides an organized approach for setting up experiments (physical or numerical). A common DOE with all possible combinations of the input factors set at all levels is called a full factorial design. A full factorial design is used in this study and therefore a total of \(2 \times 2 \times 2 \times 2 \times 2 \times 20 = 640\) identification runs are performed for the damaged case considered. These 640 damage identification runs were performed using two fast server computers with dual-core Intel Xeon processors (3.0GHz) and also parallel computation on the “On Demand
Cluster® of the San Diego Supercomputer Center (SDSC). Each of these identifications takes approximately an hour of CPU time on the fast server computers (for the fine mesh FE model).

<table>
<thead>
<tr>
<th>Factor</th>
<th>Description</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>Uncertainty in modal parameters of mode 1</td>
<td>2 levels (0.5, 1% COV)</td>
</tr>
<tr>
<td>M2</td>
<td>Uncertainty in modal parameters of mode 2</td>
<td>2 levels (0.5, 1% COV)</td>
</tr>
<tr>
<td>M3</td>
<td>Uncertainty in modal parameters of mode 3</td>
<td>2 levels (0.5, 1% COV)</td>
</tr>
<tr>
<td>S</td>
<td>Spatial density of sensors</td>
<td>2 levels (10, 14 sensors)</td>
</tr>
<tr>
<td>E</td>
<td>FE mesh size</td>
<td>2 levels (322, 398 finite elements)</td>
</tr>
</tbody>
</table>

Sensitivity Based Finite Element Model Updating for Damage Identification

In this study, a sensitivity-based FE model updating strategy [8, 9] is used to identify (detect, localize and quantify) the numerically simulated damage in the structure. The residuals in the objective function used for the FE model updating process are based on the natural frequency and mode shape estimates of each of the first three longitudinal modes of the test structure. It should be recalled that the modal parameter estimates are based on the exact modal parameters computed from the FE model of the damaged structure and then polluted with random noise added at the level of estimation uncertainty considered. As already mentioned, damage in the structure is introduced as changes (reduction) in material stiffness (effective modulus of elasticity) distributed over the finite element mesh of the web wall in the (fine mesh) FE model. For the purpose of damage identification, the web wall is subdivided into ten sub-structures (each assumed to have a uniform value of the effective modulus of elasticity), 6 along the first three stories (every half story each) and 4 along the 4th to 7th stories (every story each). The level of damage simulated in these sub-structures is selected based on the profile of the observed damage in the real test structure [13] as

$$a_{\text{exact}} = [45\% \ 25\% \ 66\% \ 20\% \ 10\% \ 7\% \ 4\% \ 4\% \ 2\% \ 1\%]^T$$

from bottom to top of the web wall, where the damage factors $a_{\text{exact}}$ in percent represent the reduction in effective material modulus relative to the undamaged state. The bottom of the second story was observed to be the most damaged location in the building due to a lap-splice failure of the longitudinal steel reinforcement at this location. In order to identify damage in the structure, the effective moduli of elasticity of the sub-structures in the FE models are updated through minimization of an objective function. It should be noted that the sub-structures used in the updating process are the same as those used in simulating the damaged structure, which makes it possible to identify the exact damage in the absence of estimation uncertainty in the modal parameters. The natural frequencies of the first three longitudinal modes computed using the fine mesh FE model of the structure with simulated damage given in Equation 2 are

$$f_{\text{Damaged Structure}} = [1.97 \ 9.97 \ 22.96] \text{Hz}$$

Objective Function

The objective function used for damage identification is defined as

$$\min_\theta f(\theta) = r(\theta)^T W r(\theta) = \sum_j [w_j r_j(\theta)]^2$$

where $r(\theta) = \text{residual vector containing the differences between FE computed and experimentally estimated modal parameters}; \ \theta \in \mathbb{R}^m = \text{a set of physical parameters (effective moduli of elasticity), which must be adjusted in order to minimize the objective function}; W = \text{a diagonal weighting matrix with each diagonal component inversely proportional to the square of the COV of the natural frequency of the corresponding vibration mode}[17]. A combination of residuals in natural frequencies and mode shape components is used to define the objective function as

$$r(\theta) = [r_f(\theta) \ r_s(\theta)]^T$$

$$f(\theta) = \sum_j [w_j r_j(\theta)]^2$$
in which \( \mathbf{r}_j(\mathbf{0}) \), \( \mathbf{r}_r(\mathbf{0}) \) = natural frequency and mode shape residual vectors, respectively. The two types of residuals are expressed, respectively, as

\[
\mathbf{r}_j(\mathbf{0}) = \left[ \begin{array}{c} \frac{\hat{\lambda}_j(\mathbf{0}) - \hat{\lambda}_j}{\hat{\lambda}_j} \\ \end{array} \right], \quad j \in \{1, 2 \ldots N_m\} 
\]

\[
\mathbf{r}_r(\mathbf{0}) = \left[ \begin{array}{c} \frac{\hat{\phi}_r(\mathbf{0}) - \hat{\phi}_r}{\hat{\phi}_r} \\ \end{array} \right], \quad (l \neq r), \quad j \in \{1, 2 \ldots N_m\} 
\]

where \( \hat{\lambda}_j(\mathbf{0}), \hat{\lambda}_j \) = FE computed and experimentally identified eigenvalues (i.e., \( \hat{\lambda}_j = \left(2\pi f_j\right)^2 \)), respectively; \( \hat{\phi}_r(\mathbf{0}), \hat{\phi}_r \) = FE computed and experimentally identified mode shape vectors. In Equation 6b, the superscript \( r \) indicates a reference component of a mode shape vector (with respect to which the other components of the mode shape are normalized), the superscript \( l \) refers to the components that are used in the updating process (i.e., at the sensor locations), and \( N_m \) denotes the number of vibration modes considered in the residual vector. In this study, the natural frequencies and mode shapes of the first three longitudinal modes (see Figure 3) of the structure are used to form the residual vector that has a total of 42 (when using 14 sensors) or 30 (when using 10 sensors) residual components consisting of 3 eigen-frequencies and \( 3 \times (14 - 1) = 39 \text{ or } 3 \times (10 - 1) = 27 \) mode shape residuals, respectively.

**Damage Factors and Residual Sensitivities**

In the process of FE model updating, the effective moduli of elasticity of the ten sub-structures are used as updating parameters. These ten sub-structures are distributed along the height of the web wall, with 6 of them along the first three stories (one per half story) and 4 from the 4th to the 7th story (one per story). Instead of the absolute value of each updating parameter, a dimensionless damage factor \( a^j \) is defined as

\[
a^j = \frac{E_{undamaged}^j - E_{damaged}^j}{E_{undamaged}^j} 
\]

where \( E^j \) is the effective modulus of elasticity of the elements in sub-structure \( j \) (\( j = 1, 2, \ldots, 10 \)). The damage factor \( a^j \) indicates directly the level of damage in substructure \( j \) (relative reduction in effective modulus of elasticity). The sensitivity of the residuals with respect to the damage factors \( a^j \) can be obtained through the modal parameter sensitivities as

\[
\frac{\partial \mathbf{r}_j}{\partial a^j} = \left[ \begin{array}{c} \frac{1}{\hat{\lambda}_j} \frac{\partial \hat{\lambda}_j}{\partial a^j} \\ \end{array} \right] \quad \text{and} \quad \frac{\partial \mathbf{r}_r}{\partial a^j} = \left[ \begin{array}{c} \frac{1}{\hat{\phi}_r} \frac{\partial \hat{\phi}_r}{\partial a^j} - \frac{\partial \hat{\phi}_r}{\partial \phi} \frac{\partial \phi}{\partial a^j} \\ \end{array} \right] 
\]

where the modal sensitivities \( \frac{\partial \hat{\lambda}_j}{\partial a^j} \) and \( \frac{\partial \hat{\phi}_r}{\partial a^j} \) are available in [18].

**Optimization Algorithm**

The optimization algorithm used to minimize the objective function defined in Equation 3 is a standard Trust Region Newton method [19], which is a sensitivity-based iterative method available in the MATLAB optimization Toolbox [20]. The damage factors were constrained to be in the range \([0 \quad 0.90]\) for updating the undamaged FE model. The upper-bound of 90% was selected because no sub-structure of the building is expected to be damaged even close to 90% (largest simulated damage factor is 66%), while the lower bound of zero was selected considering that the identified effective moduli of elasticity cannot increase due to damage. The optimization process was performed using the “fmincon” function in Matlab, with Jacobian and first-order estimate of the Hessian matrices calculated analytically based on the sensitivities of the modal parameters to the updating variables, as given in Equation 8. It is important to mention that the proposed method was verified to be able to identify the exact simulated damage (given in Equation 2) in the absence of estimation uncertainty in the modal parameters used.
Uncertainty Quantification

In this section, analysis-of-variance (ANOVA) [21] is employed to quantify the uncertainty of the identified damage factor at each sub-structure due to variation of the five input factors considered. Figure 4 shows the spread of the identified damage factors at the different sub-structures along the wall height for all 640 damage identification runs. The horizontal solid line in each subplot indicates the value of the exact simulated damage for the corresponding substructure. The ensemble of identified damage factors is obtained by varying the five input factors M1, M2, M3, S and E, resulting in $2 \times 2 \times 2 \times 2 \times 2 = 32$ combinations. For each combination of these five factors, 20 damage identification runs are performed based on modal parameters polluted with statistically independent realizations of the estimation errors, resulting in a total of $32 \times 20 = 640$ identification runs. Table 3 reports the mean and standard deviation of the 640 sets of identified damage factors at the different sub-structures. The large bias and standard deviation in the identified damage factors in some sub-structures are due to the fact that the residuals used in the objective function are less sensitive to the updating parameters representing in these sub-structures. The uncertainty quantification is performed on the mean and standard deviation of the identified damage factors (over the sets of 20 damage identification runs each). This analysis can be viewed as a crude variance reduction technique that reduces the variability of the output features (identified damage factors) arising from the 20 seed numbers corresponding to the 20 realizations of the random modal estimation errors. From Figure 4, it is not possible to quantify the contribution of each input factor or combination of input factors to the total uncertainty of the mean or standard deviation of the identified damage factors. Therefore ANOVA is used for the uncertainty quantification of the mean and standard deviation.

Effect Screening

To investigate the source of the observed uncertainty of the mean and standard deviation of identified damage factors, ANOVA is performed and the results are presented and discussed in this section. The theoretical foundation of ANOVA is that the total variance of the output features can be decomposed into a sum of partial variances, each representing the effect of varying an individual factor independently from the others. These partial variances are estimated by the so-called R-square values. The input factor with the largest R-square value for an output feature has the most contribution to the uncertainty of that output feature. In this study, ANOVA is applied to 32 data sets of output features (i.e., mean and standard deviation of the identified damage factors over the set of 20 identification runs with independent realizations of the modal estimation errors). A full-factorial design of
experiments is used, where the five factors M1, M2, M3, S, and E (see Table 2) are varied in the design space. The full-factorial design requires a total of 640 damage identification runs (a set of 20 identification runs for each combination of factors), but it offers the advantage of minimizing aliasing during the ANOVA [21]. Figure 5 shows the R-square values of the mean and standard deviation of the identified damage factors for the 10 sub-structures considered. These R-square values are scaled such that their sum over all factors equates 100%. From Figure 5, the following observations can be made. (1) Mesh size (E) is the most significant input factor in introducing uncertainty in the mean value (i.e., estimation bias) of the identified damage. (2) Variability in the spatial density of the sensors (S) produces the least amount of uncertainty in the mean value of the identified damage factors at the different locations. However, this input factor has more relative contribution on the standard deviation of the identified damage. (3) In general, the level of uncertainty in the modal parameters (as measured by COV of estimated modal parameters) of the second and third longitudinal modes (M2 and M3) introduces more uncertainty on both mean and standard deviation of the identified damage than the uncertainty in the modal parameters of the first longitudinal mode (M1). This can be due to the fact that mode shape curvatures are well known to be one of the most sensitive features to local damage and higher modes have higher curvatures. (4) Mesh size (E) also introduces considerable amount of uncertainty to the standard deviation of the identified damage. However, this factor contributes less to the total uncertainty of the standard deviations than to that of the mean values of the identified damage.

Table 3. Mean and standard deviation (STD) of identified damage factors at different sub-structures

<table>
<thead>
<tr>
<th>Sub-Structure Location</th>
<th>Exact [%]</th>
<th>Mean [%]</th>
<th>STD</th>
</tr>
</thead>
<tbody>
<tr>
<td>7th story</td>
<td>1</td>
<td>1.6</td>
<td>2.8</td>
</tr>
<tr>
<td>6th story</td>
<td>2</td>
<td>1.6</td>
<td>2.6</td>
</tr>
<tr>
<td>5th story</td>
<td>4</td>
<td>5.0</td>
<td>4.4</td>
</tr>
<tr>
<td>4th story</td>
<td>4</td>
<td>3.7</td>
<td>4.9</td>
</tr>
<tr>
<td>3rd story (top)</td>
<td>7</td>
<td>5.4</td>
<td>8.3</td>
</tr>
<tr>
<td>3rd story (bottom)</td>
<td>10</td>
<td>18.3</td>
<td>14.5</td>
</tr>
<tr>
<td>2nd story (top)</td>
<td>20</td>
<td>19.7</td>
<td>10.9</td>
</tr>
<tr>
<td>2nd story (bottom)</td>
<td>66</td>
<td>64.9</td>
<td>3.1</td>
</tr>
<tr>
<td>1st story (top)</td>
<td>25</td>
<td>22.1</td>
<td>7.9</td>
</tr>
<tr>
<td>1st story (bottom)</td>
<td>45</td>
<td>48.2</td>
<td>3.9</td>
</tr>
</tbody>
</table>

Figure 5. R-square of the mean and standard deviation (STD) of identified damage factors at different sub-structures due to variability of factors M1, M2, M3, S, and E.
Conclusions

A full-scale seven-story reinforced concrete (R/C) shear wall building slice was tested on the UCSD-NEES shake table in the period October 2005 - January 2006. The shake table tests were designed so as to damage the building progressively through several historical seismic motions reproduced on the shake table. A sensitivity-based finite element (FE) model updating approach was used to identify damage at each of several damage states of the building based on its identified modal parameters. The estimation uncertainty in both the system identification and damage identification results was observed to be significant. This motivated the authors to perform (through numerical simulation) an uncertainty analysis on these system and damage identification results. In this study, the performance of the FE model updating for damage identification is systematically investigated. The damaged structure is simulated numerically through a change in stiffness in selected regions of a FE model of the shear wall test structure. The uncertainty of the identified damage (location and extent) is quantified through analysis-of-variance (ANOVA) due to variability/uncertainty of the following input factors: (1-3) level of uncertainty in the (identified) modal parameters of the first three longitudinal modes (M1, M2, M3), (4) spatial density of measurements (number of sensors) (S), and (5) mesh size in the FE model used for damage identification (modeling error). A full factorial design of experiments is used in this study, resulting in 2 x 2 x 2 x 2 x 2 = 32 combination of the input factors. For each combination of these five factors, 20 damage identification runs are performed based on modal parameters polluted with statistically independent realizations of the estimation errors, resulting in a total of 32 x 20 = 640 identification runs.

From the results of ANOVA, the following observations can be made. (1) Mesh size (E) is the most significant input factor affecting the uncertainty in the mean value (i.e., estimation bias) of the identified damage. (2) Variability in the spatial density of the sensors (S) produces the least amount of uncertainty in the mean value of the identified damage factors. However, the relative contribution of this input factor (S) is stronger for the standard deviation of the identified damage. (3) In general, uncertainty in the modal parameters of the second and third longitudinal modes (M2 and M3) affects more significantly both the mean and standard deviation of the identified damage than the uncertainty in the modal parameters of the first longitudinal mode (M1). This is most likely due to the fact that mode shape curvature is well known to be one of the most sensitive features to local damage and higher modes have higher curvatures.

This systematic investigation demonstrates that the level of confidence in the damage identification results obtained through FE model updating, is a function of not only the level of uncertainty in the identified modal parameters, but also choices made in the design of experiments (e.g., spatial density of measurements) and modeling errors (e.g., mesh size).

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