MODEL CALIBRATION OF A BASE-ISOLATED REINFORCED CONCRETE BUILDING

T. Yu¹, E. A Johnson², P. T Brewick³, and R. E Christenson⁴

ABSTRACT

Modelling the behavior of base-isolated buildings is crucial to evaluating their performance, identifying damage mechanisms, and developing retrofit strategies. For the modelling to be of practical value, it is essential that the dynamic behavior of the numerical model resembles that of the real building. However, this can be hard to achieve, especially for large-scale structures. In this study, system identification is performed to identify the dynamic properties of a four-story base-isolated RC building which was tested at E-defense Laboratory (part of Japan’s National Research Institute for Earth Science and Disaster Resilience), and numerical models are developed and calibrated to match the dynamic properties of the real building.

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ABSTRACT

Modelling the behavior of base-isolated buildings is crucial to evaluating their performance, identifying damage mechanisms, and developing retrofit strategies. For the modelling to be of practical value, it is essential that the dynamic behavior of the numerical model resembles that of the real building. However, this can be hard to achieve, especially for large-scale structures. In this study, system identification is performed to identify the dynamic properties of a four-story base-isolated RC building which was tested at E-defense Laboratory (part of Japan’s National Research Institute for Earth Science and Disaster Resilience), and numerical models are developed and calibrated to match more closely the dynamic properties of the real building.

Introduction

Large-scale dynamic seismic structural tests are essential for validating structural design methodologies. Given the high cost of such experiments, it is essential to leverage data from completed tests by utilizing numerical models of the test structures, calibrated from experimental data, to pursue additional studies that could not be tested physically. However, calibrating complex numerical models from experimental data is always challenging.

This paper investigates the calibration of numerical models of a 686-ton full-scale four-story base-isolated reinforced-concrete frame building that was tested in 2013 on the NIED E-Defense Laboratory’s 6-DOF shake table in Japan [1]. The structure’s geometric asymmetry and the corner

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stairway-core walls induce significant lateral-torsional coupling in the superstructure response. For the experiments concerned in this study, the isolation layer used sliding bearings, rubber bearings, and U-shaped steel damper pairs. Tri-directional accelerometers were placed at three corners on each floor at levels 0–3, and two corners on the roof (the top story is different), for a total of 14 locations and 42 superstructure accelerations. A series of experiments were conducted in August 2013 with excitations including low-intensity filtered white noise as well as scaled versions of both historical and synthetic earthquake records.

**Figure 1** Test specimen

**Figure 2** Evolution of GA population

### System Identification

The primarily linear responses to the low-level random excitations were used [2] to estimate modal parameters (natural frequencies, damping ratios and mode shapes) using the N4SID subspace system identification method. The linear dynamic characteristics of the building were identified using the 12 table acceleration responses as inputs and the 42 superstructure acceleration responses as outputs [2]; the identified natural frequencies are listed in Figure 3.

### Numerical Model and Calibration

A finite element model (FEM) was developed based on the structure design drawings. The beams, columns, and shear walls were modeled by solid concrete elements and embedded reinforcing steel bars were modeled by truss elements. The floor slabs and the nonstructural walls (autoclaved lightweight concrete [ALC] plates) were modeled with shell elements. The isolation-layer devices were modeled with spring elements.

In this study, the to-be-updated 30×1 parameter vector $\mathbf{\theta}$ includes the Young’s moduli of the x- and y-direction beams at levels 1–4 (8 parameters); the columns in stories 1–4 (4 parameters); the nonstructural walls; the shear walls; the floor slabs; and the stairs. For these Young’s moduli, the initial values are either taken from design codes or chosen as typical. Parameters also included are the x- and y-direction stiffnesses of the rubber bearings, slider bearings, and U-shaped steel damper pairs; the initial values were chosen according to a force-displacement linear regression analysis of the isolation devices [3].

A metric $J(\mathbf{\theta})$ is defined to quantify the modal characteristic discrepancies between the identified values and those computed from FEM.
\[ J(\theta) = \sum_{i=1}^{8} w_i \left[ (f_i^{\text{FEM}}(\theta) - f_i^{\text{ID}})^2 / f_i^{\text{ID}} \right] + \lambda \sum_{i=1}^{8} w_i [1 - \text{MAC}(\phi_i^{\text{FEM}}(\theta), \phi_i^{\text{ID}})]^2 \]  

where \( f_i^{\text{ID}} \) is the \( i \)th identified frequency and \( f_i^{\text{FEM}} \) is the corresponding FEM frequency; \( \phi_i^{\text{ID}} \) and \( \phi_i^{\text{FEM}}(\theta) \) are the corresponding identified and FEM mode shapes, respectively;

\[
\text{MAC}(\phi, \phi) = \phi^T \phi / \sqrt{\phi^T \phi \phi^T \phi}
\]

is the modal assurance criteria; \( \lambda \) is a weighting factor to trade-off the contribution of error from frequencies versus error from mode shapes. The \( w_i \) are modal weighing factors defined as the \( i \)th mode’s effective relative mass.

\[
w_i = \frac{m x,i + m y,i + m z,i}{3m} / I x,i / I y,i / I z,i
\]

where \( m \) is the total mass, \( I x,i \), \( I y,i \), and \( I z,i \) are the total rotational mass moments of inertia about the \( x \)-, \( y \)-, and \( z \)-axes, respectively; \( m x,i \), \( m y,i \), and \( m z,i \) are the effective \( i \)th modal mass in the \( x \), \( y \), and \( z \) directions, respectively, and \( I x,i \), \( I y,i \), and \( I z,i \) are the effective rotational mass moments of inertia. With this definition for \( w_i \), more weight will be given to modes with higher effective mass or effective moment of inertia.

To minimize the error metric \( J(\theta) \), a genetic algorithm (GA), using the MATLAB® Global Optimization Toolbox, is chosen since, relative to conventional hill-climbing optimizers, a GA can more thoroughly explore the parameter space and is less likely to get stuck at local minima. In this case, the GA uses a population of 200 for 30 generations, with defaults for other GA parameters (5% elite rate, 80% crossover fraction, 1% mutation rate). The evolution of the population for one sample run of GA is shown in Figure 2. To ensure that parameter values remain realistic and physical, they are constrained to be within 30% of the initial values.

**Results**

The natural frequencies of the identified modes and those of the initial updated FEMs are shown in Figure 3 (on the horizontal and vertical axes); the relative errors of the FEM natural frequencies are shown in Table 1, as well as the relative effective masses and mass moment of inertias of the modes (and their sums). For most of the modes, the error in frequency has been reduced, especially those with relatively large error.

<table>
<thead>
<tr>
<th>Identified mode number</th>
<th>Frequency error (%)</th>
<th>( m_{x,i} / m )</th>
<th>( m_{y,i} / m )</th>
<th>( m_{z,i} / m )</th>
<th>( I_{x,i} / I )</th>
<th>( I_{y,i} / I )</th>
<th>( I_{z,i} / I )</th>
<th>( w_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original FEM</td>
<td>Updated FEM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.44</td>
<td>1.02</td>
<td>0.097</td>
<td>0.744</td>
<td>0.000</td>
<td>0.067</td>
<td>0.039</td>
<td>0.123</td>
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<tr>
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<td>0.902</td>
<td>0.082</td>
<td>0.000</td>
<td>0.007</td>
<td>0.315</td>
<td>0.725</td>
</tr>
<tr>
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<td>0.000</td>
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<td>0.000</td>
<td>0.013</td>
<td>0.000</td>
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<td>0.004</td>
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</table>
The comparisons between the mode shapes of identified modes and those of the initial and updated FEMs are shown in Figure 3. Before updating, the first two mode shapes do not match well, this mismatch is successfully eliminated by model updating. Since these two modes are the most dominant for this building, the dynamic behavior of the updated FEM will provide a significantly better match to the real structure.

For motion in the $x$ and $y$ directions and rotation about the $z$ axis, the sums in Table 1 are nearly 100%, so the dynamic properties in these “direction” are well represented by these modes; for rotation about the $x$ axis, however, some additional higher-frequency modes may need to be considered.

![Comparison of mode shapes](image)

(a) MAC values before updating  (b) MAC values after updating

Figure 3  Comparison of mode shapes

**Conclusions**

A FEM has been constructed for the 2013 E-Defense base-isolated building. The FEM was updated so that its natural frequencies and mode shapes more closely match those identified from experimental response measurements. The genetic algorithm is less likely to get stuck at local minima like conventional hill-climbing optimizers. Including reinforcing bars and non-structural walls resulted in reasonable parameter changes (preliminary updates to a simpler model without these features resulted in large non-physical changes in many parameters) with a significantly better match in identified modal characteristics. The dynamic properties for transverse motions in $x$ and $y$ direction, and rotation about $z$ axis of the real building can be well captured by the updated numerical model.

**References**


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