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FINITE ELEMENT MODEL CALIBRATION OF UCLA FACTOR BUILDING BY DARWIN PARALLEL OPTIMIZATION

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ABSTRACT

In this paper, a finite element model calibration method is presented and applied to the UCLA Factor building with the dynamic measurements. The calibration procedure is formulated to search for a set of the chosen structural parameters so that the difference between the FE-analyzed and field observed responses (natural frequencies and mode shapes) is minimized. It is an implicit nonlinear optimization problem and solved by using Darwin parallel optimization framework, based on competent genetic algorithm. An initial finite element model constructed with the architectural and structural drawings was calibrated by applying the integrated Darwin FE model calibration tool that iteratively updates the parameters of FE model and minimizes the discrepancy between the monitored and analyzed responses of mode frequencies and mode shapes. Meanwhile the Darwin optimization takes full advantage of the computing power offered by a cluster of many-core computers, which significantly speed up the optimized calibration runs. The calibration results indicate that, the proposed optimization approach is effective at adequately calibrating the finite element model of the building structure so that the calibrated model reflects the dynamic integrity of the real building structure. The calibrated finite element model is a valuable tool for condition assessment and prognostic maintenance evaluation.

KEYWORDS

Finite element model, model calibration, building health monitoring, parallel optimization.

INTRODUCTION

A calibrated finite element model (FEM) for civil structure can adequately represent the conditions of existing structure and yield the reliable responses under the prescribed dynamic loadings. It is an important tool for civil engineers to capture the dynamic characteristics, to assess the conditions and to enable the sound evaluation of a possible maintenance solution. However, the FE model parameters such as material properties and geometric attributes for an existing structure are always subject to the variations due to material imperfection, construction, deterioration and ambient (corrosion, temperature and humidity) effects. Meanwhile, the boundary conditions and the structural connections are seldom understood with certainty. The structural identification by updating or calibrating the nominal FE model with the field data, e.g. natural frequencies and mode shapes extracted from the dynamic measurements, is an essential task to establish an adequate FE model. With the growing concerns on the safety and the security of the deteriorated infrastructure systems around the world, developing an effective and efficient model calibration methodology is of great importance for assessing the structural health performance of the aged civil infrastructures.

Model calibration is an iterative procedure of adjusting a set of the FEM parameters so that the discrepancy between the observed and the simulated structural responses is minimized. The general practice follows these steps (Mottershead and Friswell 1993). First of all, the finite element shape functions are determined along with the types of finite elements. Then, the problem of the FE model calibration is reduced to the model parameter estimation. It usually involves a search process for adjusting the FEM parameters (i.e., elastic modulus, density and etc.) so that the updated model can adequately emulate the dynamic responses of the subject structure. FEM parameter estimation can be formulated as an optimization problem of searching for the near-optimal values of these parameters such that the objective function is minimized. Regardless of any calibration criteria for FEM calibration, the objective function is a function of stiffness and mass matrices, which leads to nonlinearity (Sanayei *et al.* 2006). Soh and Dong (2001) proposed an inverse problem that solves for material uncertainty of Young's modulus. Hao and Xia (2002) applied genetic algorithm (GA) to identify a set of stiffness reduction factor (SRF) as the indicator of structure damages. SRF is defined as the ratio of stiffness reduction to the initial stiffness. One finite element is assigned with SRF to be identified. Stiffness reduction seems to be more

meaningful to indicate structural property variation than Young's modulus variation, but both types of parameters are not directly related to the physical property of structure damage. More recently, Wu and Xu (2011) proposed a FE model identification formulation for damage detection. Structural damage is represented with a set of meaningful geometric parameters while a finite element model identification method is formulated by proposing a unified objective function that is based on the errors in both static and modal responses. A prototype of software framework is designed and implemented for FE model parameter estimation and structure damage detection. The framework takes the advantages of the well-developed structural analysis software. It offers the flexibility of parameter selection and the functionality of parameter grouping. To estimate the parameters efficiently, Darwin optimization tool, based on a competent GA (Goldberg 2002), is applied to search for the near-optimal model parameters.

Generally, model calibration is merely one part of the structural health assessment which also includes field testing, signal processing, initial modeling and condition assessment/prediction. In this study, a FE model calibration method is presented and applied to the Factor building located at the University of California, Los Angeles (UCLA) campus. After the 1994 Northbridge Earthquake, the Factor building was instrumented by the U.S. Geological Survey with a 72-channel accelerometer network. The accelerometers are distributed at various locations and in different directions throughout the building. The level of instrumentation makes the building become the most densely instrumented building in North American. By constantly acquiring and recording the vibration data, the Factor building provides an excellent platform for model calibration practice.

The objective of this study is to demonstrate the effectiveness of the previously developed optimization framework, which has been integrated with the model calibration technology. The rest of this paper is organized as follows. Section 2 gives the brief introduction of the Factor building and compares the field-measured with the initial FEM-analyzed responses. Section 3 presents the FEM calibration method and the implementation procedure with advanced computation techniques. In Section 4, the comparison of the field-measured and the calibrated responses is demonstrated, the validity and efficacy of the presented method are confirmed. Finally, Section 5 gives the overall concluding remarks.

UCLA FACTOR BUILDING AND INITIAL MODELING

Before conducting the model calibration study of the Factor building, we first investigate the dynamic behaviors of the real structure and generate the nominal FEM of the building.

Field Data and Dynamic Behavior

The UCLA Factor building as shown in Figure 1 is a 17-story steel frame structure, which has 15 stories above ground and 2-story basement.

Figure 1. UCLA Factor building facing east direction

The necessary information to create the finite element model comes from architectural and structural drawings and consists of the followings:

- Geometric information that describes the orientation of the seismic framing system and each floor layout;
- Definition of the members that make up the model (steel moment frame, concrete slab, glass curtain wall and brick veneer);

- Definition of moment-resisting connection for girder-to-column flange;
- Foundation of the building at basement;
- Material properties;

The dynamic measurement is implemented by the instrumentation network, which consists of an intensive array of 72-channel uni-axial force-balance accelerometers. These sensors continuously record the vibration data of the building with a sampling rate of 100 Hz. For each floor, there are four sensors. Two are in north-south direction and the other two are in east-west direction. Figure 2 shows the raw vibration data (nees.ucla.edu/factor) of acceleration history in time domain in east-west direction under ambient vibration. This raw data needs to be processed to extract the dynamic characteristics of the building. The auto-regressive moving-averaging method in conjunction with the natural excitation technique (James et al 1993 and 1996) is employed to extract the dynamic information from the vibration data. Table 1 lists the extracted natural frequencies from the ambient vibration data recorded. Meanwhile, Figure 3 plots the corresponding mode shapes in east-west direction. The mode shapes in the other two directions are in similar pattern.

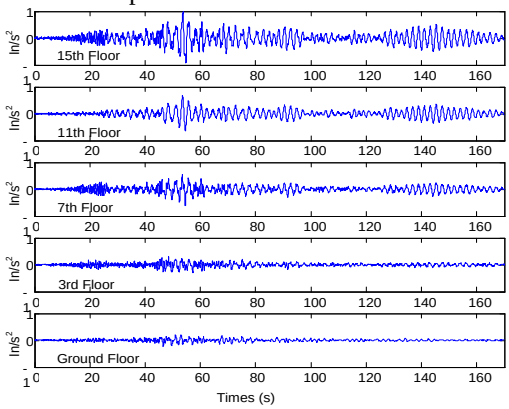

Figure 2. Raw acceleration data in east-west direction

Table 1. Identified natural frequencies (Hz) from ambient vibration

Mode	Direction	Frequency
1	East-West	0.466
2	North-South	0.496
3	Torsion	0.666
4	East-West	1.480
5	North-South	1.635
6	Torsion	2.875
7	East-West	2.625
8	North-South	2.348
9	Torsion	3.915

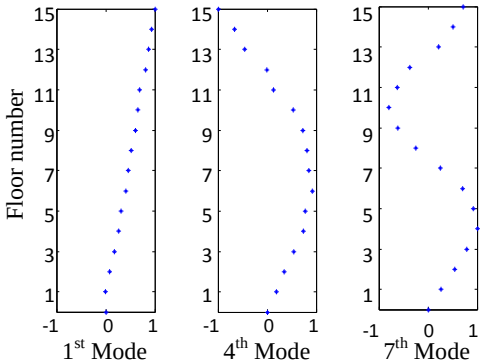

Figure 3. Normalized mode shapes in east-west direction

Initial Finite Element Model

Based on the work by Skolnik *et al.* (2006) and the information from the website (nees.ucla.edu/factor), the FE

model of the building as shown in Figure 4 is constructed by converting the model in format of SAP 2000 to the format of STAAD.Pro (Bentley 2012). The FE model considers the floors above ground. Therefore, there are 15 floors. The detailed FEM shown in Figure 4(a) contains 3227 elements, which includes beam elements and plate elements. Generally speaking, for a structure with thousands of elements, the dynamic analysis computation is very intensive. In order to reduce the computational cost while still capture the major dynamic characteristics, a simplified model in Figure 4(b) with only beam elements provides an alternative to the detailed FE model.

Another important modelling consideration, which plays a significant role in the dynamic behaviour of structures, is the boundary condition. Traditionally, when setting up a finite element model for a building, the fixed boundary condition exercises the root foundation of the infrastructure system. However, it brings uncertainty in the complete rigid boundary assumption while the real situation is truly not. In this study, the uncertainty comes from the potential soil structure interaction. No exact interaction force can be found from the architecture drawing or from previous experiences. Based upon these concerns, we propose that it is more appropriate to apply elastic support assumption to certain degree-of-freedom on the boundary of the structural model, and thus to determine the elastic stiffness parameters in model calibration procedure.

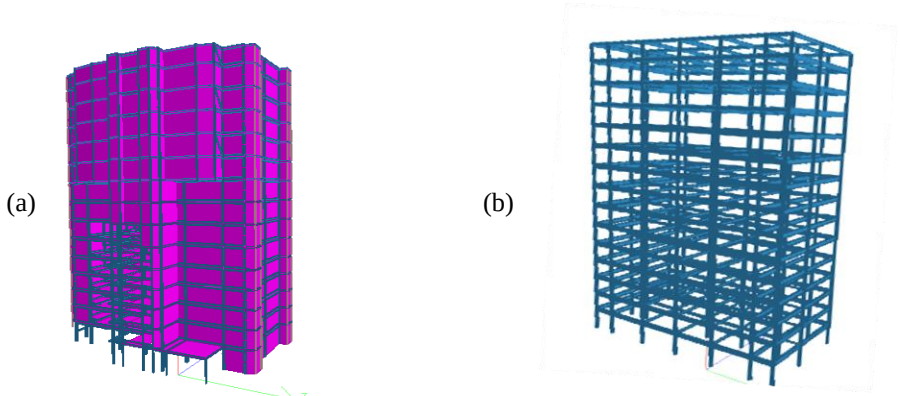

Figure 4. (a) Detailed model; (b) Simplified model

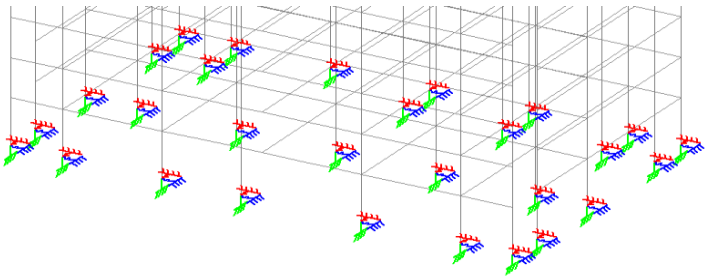

Figure 5. Boundary condition supports in Factor building model

For each node on the boundary in Figure 5, the elastic support treatment applies to the horizontal x, z direction by using k_{ix} and k_{iz} to denote the stiffness variables. Here *i* represents the node ID and *x*/*z* represents the direction. By several manually adjustment trials, we assign the horizontal stiffness variables $k_{ix,iz} = 2000\ Kip/Ft$ in the nominal FE model. These merely are the initial values, which will be further adjusted in model calibration.

Table 2. Numerical natural frequency (Hz) from initial FEM

Mode	Direction	Frequency
1	East-West	0.596
2	North-South	0.600
3	Torsion	0.721
4	East-West	1.665
5	North-South	1.738
6	Torsion	1.980
7	East-West	2.872
8	North-South	3.182
9	Torsion	3.490

After the nominal FEM is generated, we now investigate the dynamic responses of the Factor building using FE model. Table 2 lists the numerical natural frequencies for the first 9 modes. Compared with the values in Table 1, clearly there are significant differences in the values of natural frequency. Undoubtedly, the nominal FEM needs to be adjusted to reduce the difference as the evaluation criteria of model calibration.

MODEL CALIBRATION AND IMPLEMENTATION

The discrepancy between the FEM-analyzed and the field-measured responses demonstrates that the nominal FEM represents the actual structure with a very limited accuracy. Thus the initial model needs to be calibrated and the calibration is formulated as nonlinear implicit optimization problem that is solved by using the Darwin parallel optimization tool.

Objective Function

The quantitative criterion, which measures the correlation between the FEM and the real structure, is calculated from the static response, the dynamic response or both of them. The common expression of the total objective function is defined as (Wu and Xu 2011):

$$E_T = E_{static} + E_{freq} + E_{mode} \tag{1}$$

where E_{static}, E_{freq} and E_{mode} are the static response-based, frequency-based and mode shape-based error function, respectively. In this study, the available information is merely dynamic response. Therefore, E_{static} is not included in the objective function. For most infrastructures, the lower modes consume the primary (up to 90%) energy of the vibration, and thus it is far more important and desirable to have the primary modes match well with the observed ones. However, the calibration search process is relatively blind to the error of each individual mode, but is guided by the single value of the objective function value (the overall errors of all the modes). In order to better direct the optimization to search for the set of parameters such that the frequencies and mode shapes of the desired primary modes match up well with the observed values, the objective function needs to be slightly modified by allowing a user-specified weighting factor to be applied to each mode. The detailed definitions of the weighted frequency-based and mode shape-based error function are, respectively

$$E_{freq} = \sqrt{\sum_{i=1}^{n} \omega_i (f_i^A - f_i^O)^2} \tag{2}$$

$$E_{mode} = \sqrt{\sum_{i=1}^{n} \omega_i (\varphi_i^A - \varphi_i^O)(\varphi_i^A - \varphi_i^O)^T} \tag{3}$$

Here ω_i is the weighting factor applied to the *i*-th mode, f_i is the mode frequency and φ_i is the mode shape, the superscript A denotes the responses from the FE analysis and the superscript O denotes the observed response from the field data. Theoretically, for a structure with *n* degree-of-freedoms, all the mode frequencies and shapes are required to put into the calculation. In practice, however, only several lower primary modes can be measured due to the limitation of sensing techniques and complexity of structure. For FEM calibration, the primary modes hold sufficient information for a good finite element model of the real structure. In this study, only the first 9 modes are available, and thus $n = 9$ in Eq.(2) and Eq.(3).

Implementation of Model Calibration

In FEM calibration, the target of optimization problem is to search for a set of FEM parameters so that the discrepancy between the real structure and the nominal FEM can be minimized. The FEM parameters to be optimized can be element geometry, elastic stiffness on boundary condition and material attribute including element cross section, elastic modulus and mass density. In this study, the optimized parameters are limited to the elastic modulus and the elastic stiffness values on the boundary condition.

As shown in Figure 6, the implementation of the optimization procedure consists of three major components. The first part is to specify the field measured dynamic data, to generate the initial FE model and to define the decision variables and the corresponding updating ranges. All these information are the input for the model calibration framework. After the input data is processed, the second part “FE Model Updater” assigns the calibration definition to present a set of FE model parameters. With the Darwin Optimization Framework (Wu *et al.* 2012) generating trial solutions which are passed to the FE model updater, the FE solver of the structural analysis software performs the dynamic analysis and produces the structural responses for the corresponding solution. The calculated responses are compared with the field-measured dynamic data. The fitness value are computed as Eq.(1) – Eq.(3). Afterwards the fitness values are passed back to the Darwin Framework, where a

new population of the solutions is generated by emulating the principles of natural selection and genetic reproduction. Thus one generation is completed. With generation after generation, the FE model parameters are expected to be optimized.

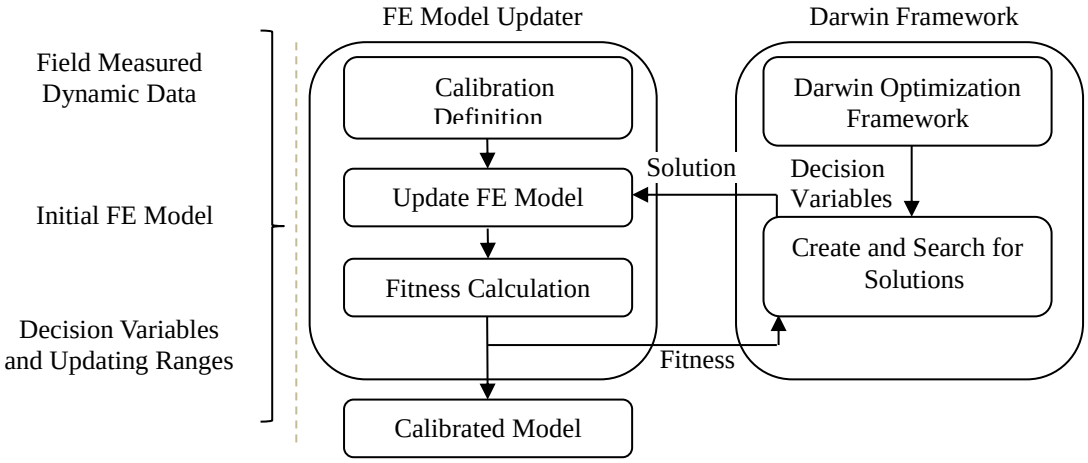

Figure 6. Model calibration method implementation

The optimization can be terminated in different ways. If the fitness value achieves the convergence criteria or the limit of number of generation is reached, the program will stop searching. Otherwise, the model calibration will generate new trials according to the fitness values. The framework will keep evolving the solutions.

The aforementioned diagram is the implementation of the model calibration on one computer core. Since the genetic algorithm usually requires a large number of function evolutions or the FE analysis, the parallel optimization using multi-core computers has been applied to ensure the scalable efficiency for the project. A generic parallel GA tool, which is named the Darwin Optimization Framework, is developed by Bentley Systems for high performance analysis of infrastructure systems (Wu *et al.* 2012). The parallel optimization computer architecture is based upon a so-called manager-worker configuration as shown in Figure 7.

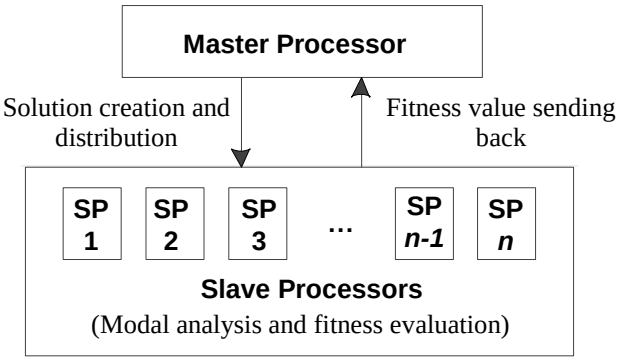

Figure 7. Manager-worker parallel optimization computing (Wu, Wang and Butala 2011)

The commutation and computation scope for manage-worker parallelism is as follows:

1) Manager processor creates and distributes solutions over worker processors;
2) Worker processors simultaneously implement model analysis and solution evaluation;
3) Worker processors send the fitness values back to manager processor;
4) Manager processor searches for an improved solution on the fitness values from worker processors.

CALIBRATION PERFORMANCE

With the method and the principles described above, this section demonstrates the performance of the model calibration within the Darwin optimization framework in a quantitative manner.

Parameter Setup

The dynamic analysis is intensive computation problem, especially when the DOF of the structure is large. For the simplified FEM of the UCLA Factor building, there are more than 1000 beam elements. In order to reduce the dimension of the optimized calibration, multiple beam elements at the same vertical level are aggregated into one calibration group and a total of 30 calibration groups are created to include all the beam elements. For each calibration group, the same calibration parameter is applied to all the elements within the group. For the boundary condition optimization, in order to fully explore the effect of elastic stiffness on the dynamic behavior, the stiffness variables remain individual. Therefore, a total of 88 decision variables are optimized by the Darwin Optimization Framework. It allows user to define a range of the minimum and maximum values for one decision variable to be optimized. Different ranges can be used for different calibration entities. For element property multiplier, a rational optimization range is [0.5, 1.50]. For stiffness multiplier, a wider optimization range is highly recommended, e.g. [0.01 10] in this research. Given the current initial stiffness value $k_i = 2000\ Kip/Ft$, the possible fixed boundary condition scenario can be approximated when the stiffness variable researches 10. And the free boundary condition is covered by the stiffness variable close to 0.01.

Table 3. Calibrated boundary condition stiffness multiplier

Node ID	Multiplier on k_{ix}	Multiplier on k_{iz}
9	2.31	10
22	10	8.51
23	10	7.21
24	9.31	7.51
31	10	7.51
37	10	9.61
38	10	9.71
39	10	8.81
10 to 15, 18 to 21, 25 to 26, 28 to 30, 32, 33, 35, 36, 40, 41	10	10

Calibrated Model

The FE model has been finally calibrated via the Darwin Optimization Framework with the techniques elaborated above. Table 3 lists the updated stiffness variables in the calibrated FEM. Totally, we have 29 nodes on the foundation of the building model, and thus 58 elastic stiffness multiplier variables. As we can see, most stiffness variable k_is are identified with relatively large value 10, which is the upper bound of the optimization range. The result implies the fixed boundary conditions of building foundation. And certain stiffness variable k_is are identified with small values, which means more flexible constraints on those nodes. The identified stiffness parameters have physical significance and reflect the real boundary condition to a fairly acceptable accuracy.

Table 4 lists the simulated frequencies of the calibrated FEM. For comparison purpose, we also include the measured data and the simulated frequencies of the initial FEM. It can be observed, as illustrated in Figure 8, that the calibrated FEM results in the more accurate FEM to represent the real structure. All the relative errors from the calibrated model are less than 18%.

Table 4. Comparison of modal frequency

Mode	Measured Frequency(Hz)	Initial Frequency (Hz)	Relative Error (%)	Calibrated Frequency(Hz)	Relative Error (%)
1	0.467	0.596	27.62	0.508	8.78
2	0.506	0.600	18.58	0.518	2.378
3	0.681	0.721	5.87	0.617	9.40
4	1.488	1.665	11.90	1.657	11.36
5	1.665	1.738	4.38	1.757	5.53
6	2.362	1.980	16.17	1.975	16.38
7	2.677	2.872	7.28	2.843	6.20
8	2.862	3.182	11.18	3.200	11.81
9	3.826	3.490	8.78	3.485	8.91

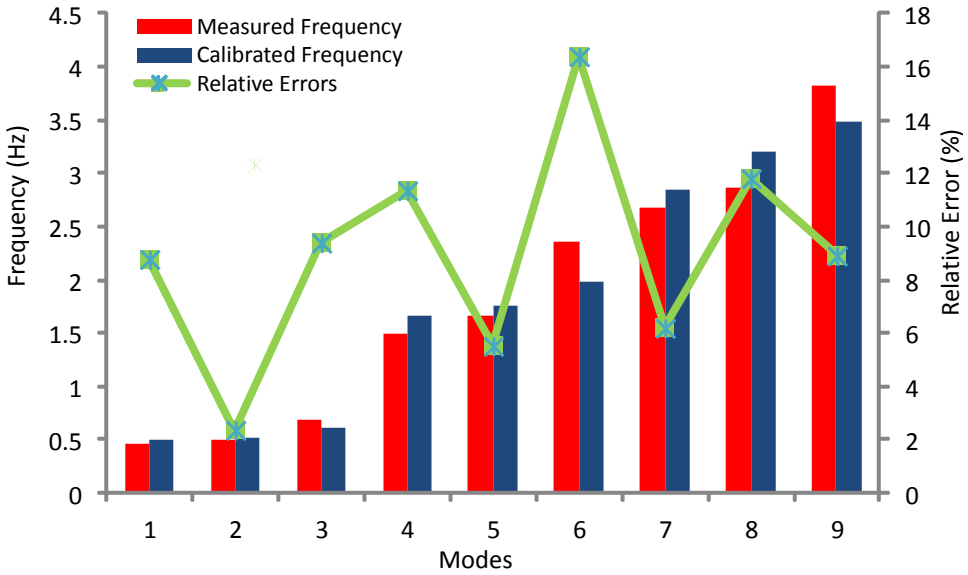

Figure 8. Comparison of mode frequency between the measured and the calibrated FEM

Meanwhile, Figure 9-11 plot the mode shapes for the calibrated FEM with red circle. For comparison purpose, the mode shapes identified from the field data are also included and marked with blue diamond. Figure 9 illustrates the mode shapes in east-west direction. Figure 10 shows the ones in north-south direction. And the ones with torsion are exemplified in Figure 11. Clearly, all the calibrated FEM-analysed mode shapes match well with the field-measured counterparts. The results also verify that the calibrated FEM is a good representation of the real structure. Meanwhile, the mass participation factor in percent is provided in Table 5. For x and z direction motions, the cumulative values of the first 9 modes are already over 80%.

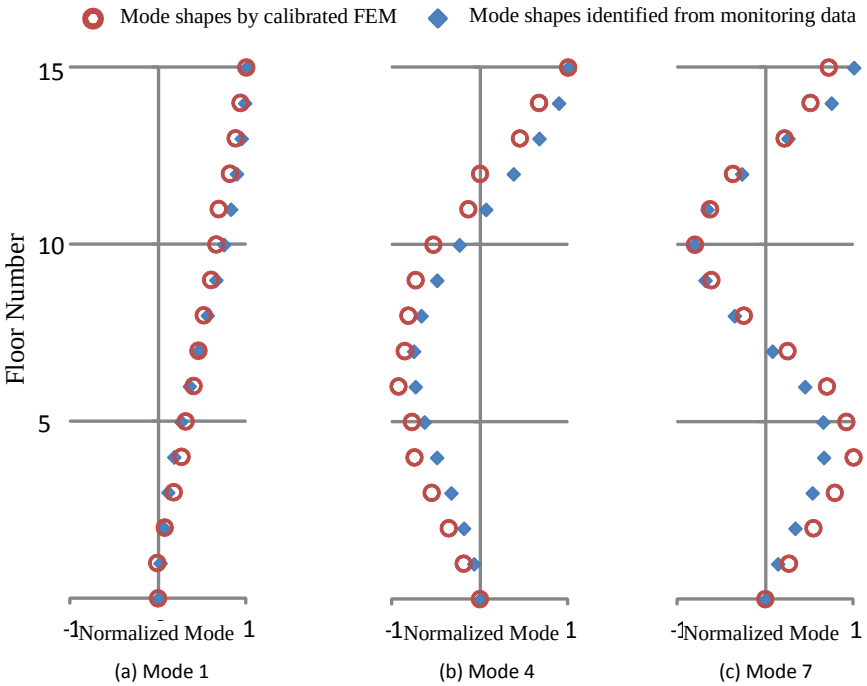

Figure 9. Normalized mode shape in east –west direction

Mode shapes by calibrated FEM
Mode shapes identified from monitoring data

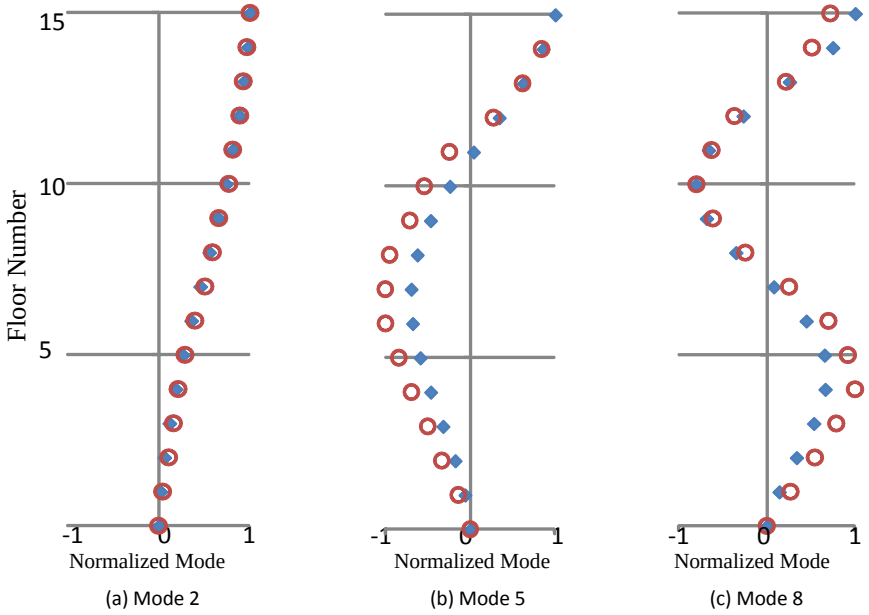

Figure 10. Normalized mode shape in south –north direction

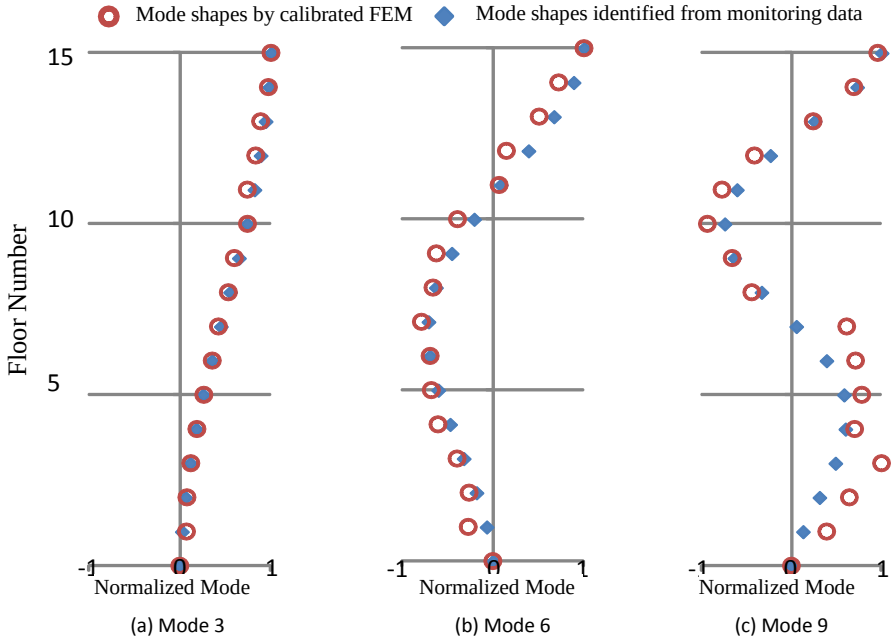

Figure 11. Normalized mode shape in torsion

CONCLUSION

Model calibration, a process of refining the finite element model capable of providing adequate descriptions of the subject structure's behavior, has been and will continue to be an essential component of infrastructure engineering practice. In this paper, a FE model calibration method is presented and applied to the UCLA Factor building with the dynamic measurements. An initial FE model is constructed with the architectural and structural drawings. The calibration procedure is formulated as an implicit nonlinear optimization problem. The optimization procedure searches for a set of the chosen structural parameters and the stiffness variables on the boundary so that the differences between the FE-analyzed and field observed responses (natural frequencies and mode shapes) are minimized. Meanwhile, the optimization framework is integrated with Darwin parallel computing technology, which is based on competent genetic algorithm. By taking full advantage of the computing power offered by a cluster of many-core computers, the Darwin optimization significantly speeds up

the optimized calibration runs. The calibration results indicate that, the proposed optimization approach is effective at adequately calibrating the FE model of the building structure so that the calibrated model reflects the dynamic integrity of the real building structure with sufficient accuracy.

Table 5. Mass participation in percentage for the calibrated modes

Modes	X	Y	Z	SUMM-X	SUMM-Y	SUMM-Z
1	48.32	0	11.61	48.32	0	11.61
2	12.48	0	47.27	60.80	0	58.87
3	0.14	0	2.63	60.94	0	61.50
4	14.74	0	0.05	75.68	0	61.55
5	0.10	0	13.23	75.78	0	74.79
6	0.05	0	1.25	75.83	0	76.04
7	7.32	0	0.00	83.15	0	76.04
8	0.03	0	5.22	83.18	0	81.26
9	0.02	0	1.83	83.21	0	83.09

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