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System identification of a bridge structure and its effects on reliability estimation

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ABSTRACT: Adaptation of system identification strategies into structural engineering dates back to the late 70s, and numerous works have been accomplished except the ones which extensively investigate the effect of system identification results on reliability estimation. Therefore, the purpose of this study is to perform system identification of a bridge structure and integrate results into reliability estimation process. A two-span bridge structure is excited by separate shaking tables, and structural damage is monitored throughout the experiment by measurements and visual inspection. During white noise and earthquake excitations, accelerometers are used to obtain time history signals of structural response. A base finite element model, which is based on design drawings, is developed to simulate different models changing in structural parameters such as bent stiffness and damping ratio. Finite element model updating is performed properly with the best approximation of simulation results to system identification results. As an alternative approach, finite element model is modified according to the ductility values obtained from nonlinear time history analyses. Such procedure is applied for different damage states to obtain finite element models corresponding to each damage state. Finally, fragility curves based on updated and non-updated models are compared to investigate the effect of system identification on structural reliability. It is concluded that integration of system identification into reliability estimation significantly changes results, which may be crucial for accurate performance evaluation by introducing experimental information into residual life assessment process.

1 INTRODUCTION

Doebling et al. (1996) refers to residual life estimation as the ultimate goal of the structural health monitoring. In contrast, number of studies on this topic is limited. Park et al. (1985) introduced damage index for the reinforced concrete columns and connected it with real-world structural damageability. Beck & Katafygiotis (1998) and Katafygiotis & Beck (1998) proposed an approach to update structural model and their uncertainties based on measured data in Bayesian framework. Singhal & Kiremidjian (1998) used Park-Ang damage index and Bayesian updating method for integration of the 1994 Northridge Earthquake structural damage inventory into fragility analysis. Shinozuka et al. (2000a) developed empirical fragility curves for bridges with nonlinear dynamic analyses using 1994 Northridge Earthquake and 1995 Kobe Earthquake. Shinozuka et al. (2000b) compared fragility functions obtained from nonlinear dynamic and static analyses. Moreover, Shinozuka et al. (2003) integrated empirical, experimental and numerical information to calibrate and verify fragility models. Soyoz et al. (2010) discussed the effect of identified structural parameters on structural reliability.

In this study, the effect of system identification on structural reliability is investigated by comparing fragility curves obtained from updated and nonupdated models. Updated models are obtained from system identification results, whereas nonupdated models are obtained from nonlinear time history analysis results. As this procedure is repeated for different damage states, the influence of structural damage on fragility curves is also inspected. The following sections describe experimental setup and procedure, system identification, nonlinear time history analysis, and reliability estimation process in details.

2 EXPERIMENTAL SETUP AND PROCEDURE

The shaking table experiment was conducted at the University of Nevada, Reno on the behalf of NEES projects (http://nees.unr.edu). The model is a quarter-scale reinforced concrete bridge structure which consist of two spans and three bents with different column lengths. As a result of the difference between bent lengths, stiffness values of each bent is expected to be different. Therefore, torsional modes dominate the dynamic behavior of the structure, also due to additional masses at deck ends. Figure 1 illustrates the schematic view and the locations of acceleration sensors.

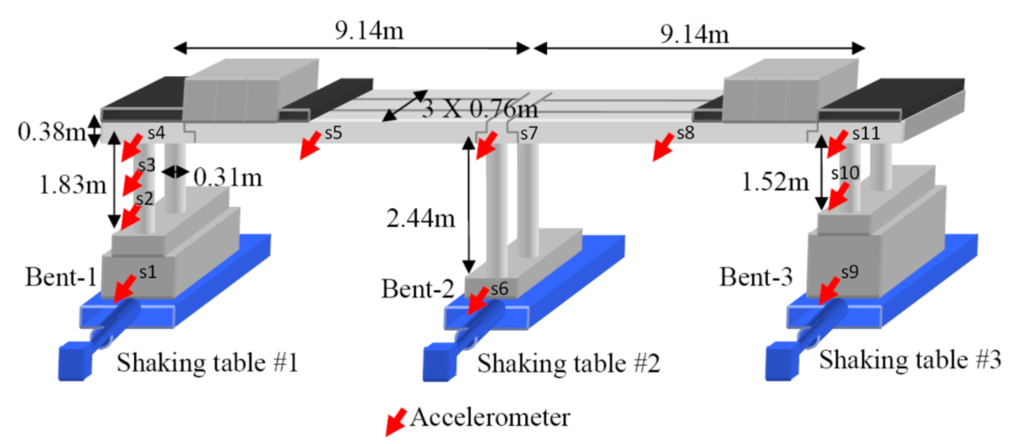

Figure 1. Schematic view of the model and sensor layout.

As the details are shown in Table 1, the bridge model is exposed to earthquake excitations whose amplitudes differ in ascending order, and exposed to white noise excitations between each earthquake excitation. Three separate shaking tables are used to impose ground motions simultaneously to each bent. Accelerometers, mostly located on the deck of the structure, are used to measure acceleration time history outputs of structural response, which are to be processed for system identification purposes. The time history of the complete ground motion is illustrated in Figure 2.

Table 1. Test procedure

Test	Ground Motion	PGA(g)	Damage Description
WN-1	White Noise	0.07	
T-13	Low EQ	0.17	Bent-1 yields
T-14	Moderate EQ	0.32	Bent-3 yields
WN-2	White Noise	0.07	
T-15	High EQ	0.63	Bent-2 yields
WN-3	White Noise	0.07	
T-19	High EQ	1.70	Bent-3 steel buckles
WN-4	White Noise	0.07	

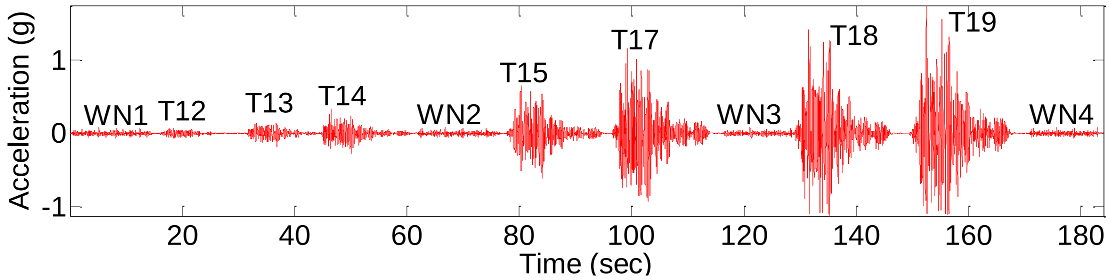

Figure 2. Input motions.

As the earthquake tests with increasing intensities proceed, progressive damage is measured and observed. Observations, which are based on visual inspection and strain gauge measurement, are made throughout the tests. Structural damage with the progression of tests can be documented by the crack mark photos at the plastic hinge locations of column ends, such as in Figure 3.

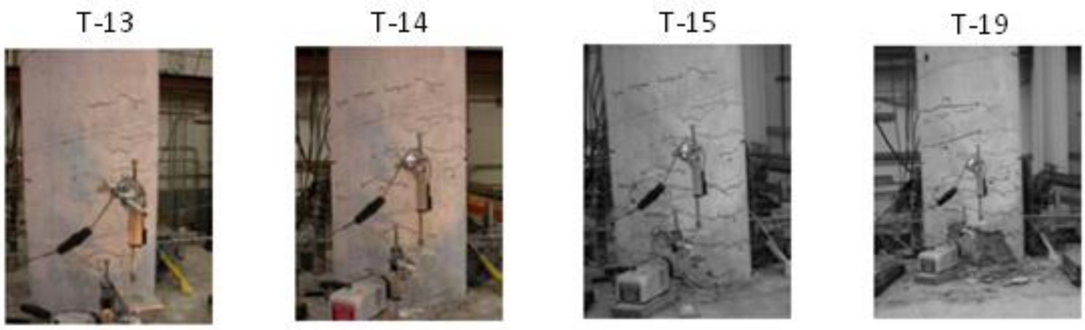

Figure 3. Damage observed on Bent-1 after earthquake excitations.

3 SYSTEM IDENTIFICATION

White noise in between each damaging event contains information about the current structural state, as they have low intensity and broad banded frequency content. In other words, structural behavior under such circumstances is considered as linear time-invariant. Therefore, time history responses of the structure could be utilized to locate and quantify structural damage by structural system identification at each damage state. In this study, identification is carried out both in frequency and time domain. In frequency domain, frequency domain decomposition (FDD) method was used to obtain modal parameters of the structure. Then, finite element model updating is performed in order to minimize the error between modal parameters obtained from simulated models and the identified model. This error includes the difference in modal frequencies, and modal assurance criteria (MAC) representing the correlation of mode shapes. In time domain, acceleration time histories on top of each bent is simulated and finite element model updating is performed to obtain the least square estimation of the measured response. OpenSees platform is used for modeling, analysis, and simulation of modal parameters and time history response. Matlab is integrated into the model updating process, in order to automatically change structural paramaters and reproduce several finite element models accordingly within a certain domain range.

The modal frequencies of the structure tend to decrease as a result of increasing structural damage, as it is seen from the peaks of Fourier Spectra shown in Figure 4. Figure 5 shows the correlation between measured and simulated mode shapes after finite element model updating.

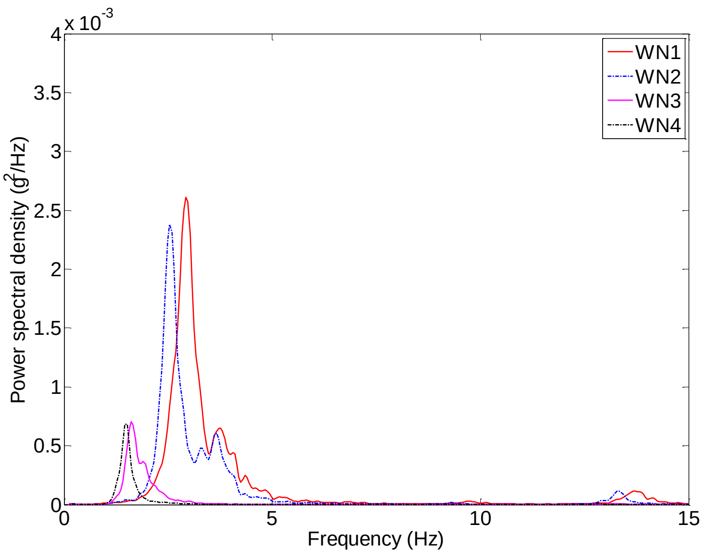

Figure 4. Identified modal frequencies.

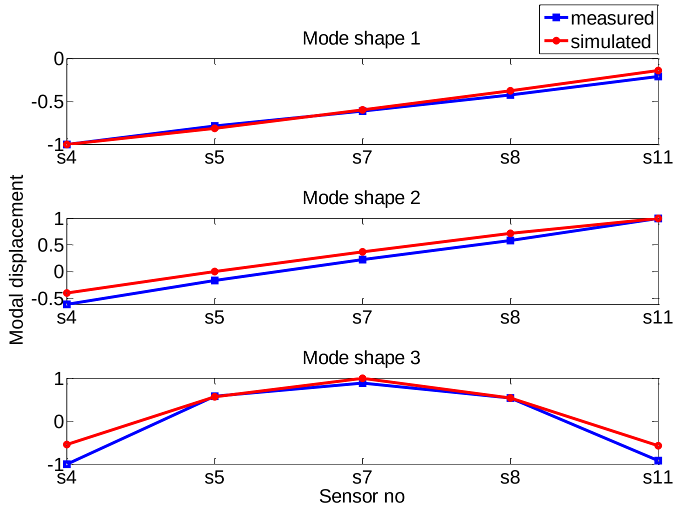

Figure 5. Measured and simulated mode shapes at WN2.

Figure 6 shows the measured and simulated time history response at sensor-7 location under WN-2 excitation. It is observed that updated model represents the actual response more accurately than nonupdated model. Therefore, it could be concluded that finite element model updating procedure increases the performance of the simulation.

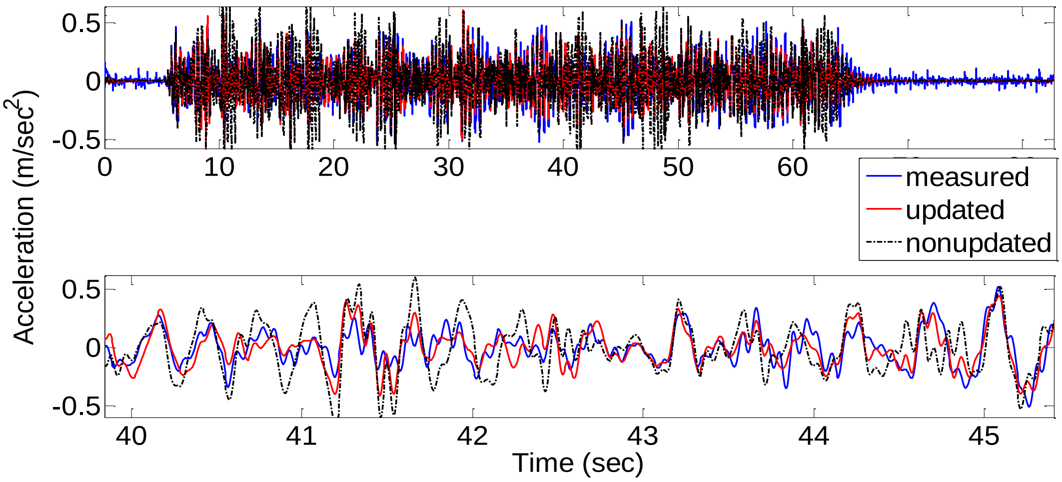

Figure 6. Time history response to WN2 at sensor-7 location.

4 NONLINEAR TIME HISTORY ANALYSIS

As an alternative to system identification, structural damage is simulated using nonlinear time history analysis. Column end rotation is considered as damage indicator, and hinge behavior is idealized by elastic-perfectly plastic moment-curvature relationship, as shown in Figure 7. As a result of a nonlinear time history analysis, damage state is obtained by maximum hinge rotations of bent columns. The maximum hinge rotation could also be interpreted in terms of ductility demand, which in turn represent the extent of the structural damage of the element. Therefore, instead of updating the structural parameters using system identification results, ductility demands obtained from nonlinear time history analysis could be used to quantify effective stiffness of an element.

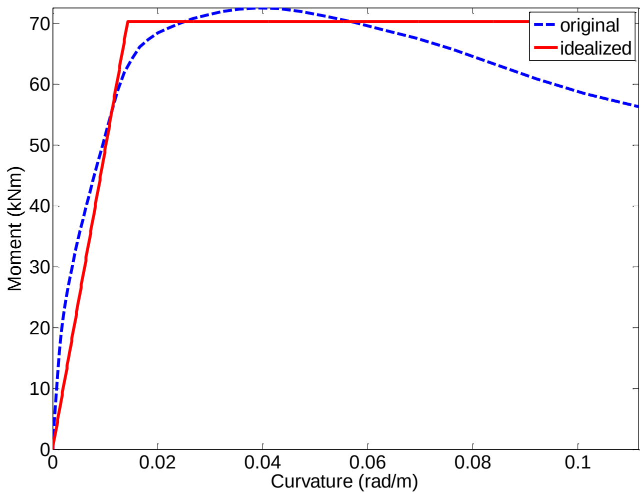

Figure 7. Moment-curvature relationship of column cross-sections.

5 RELIABILITY ESTIMATION

To summarize the generation of base models, two sets of models such as updated and nonupdated models are produced at the end of previously mentioned procedures. Updated models are obtained from system identification, whereas nonupdated models are determined based on nonlinear time history analysis. Furthermore, each set is composed of 4 different models which represent different damage states of the structure. For instance, stiffness of Bent-1 is a structural parameter and its value in each set and state is given in Table 2. Likewise, Bent-2 and Bent-3 also changes according to the different models.

Table 2. Stiffness Modification Factor of Bent-1

	WN-1	WN-2	WN-3	WN-4
Updated (Time)	0,60	0,37	0,12	0,11
Updated (Frequency)	0,50	0,35	0,11	0,08
Nonupdated	0,70	0,54	0,13	0,09

Using the modified finite element models based on system identification results and nonlinear time history analysis results, reliability estimations are made using analytical fragility curves.

These fragility curves refer to the cumulative probability density functions where peak ground acceleration (PGA) is considered as the random variable for demand parameter.

Approximately 150 input ground motions are used to perform nonlinear time history analyses. Each analysis refers to a certain ductility demand which corresponds to the PGA of the input ground motion. A ductility threshold is specified to determine whether structure would fail or not fail when it is exposed to such input ground motion. If the threshold is exceeded, the failure probability would be set equal to 1, otherwise it would be set equal to 0. Using these analysis results, maximum likelihood estimation is performed to determine fragility curve parameters such as mean and standard deviation.

Eventually, fragility curves for different damage levels are generated. Figure 8 shows fragility curves obtained from updated and nonupdated models and different damage states. State 1, State 2, State 3 refers to the conditions at WN-1, WN-2, and WN-3, respectively.

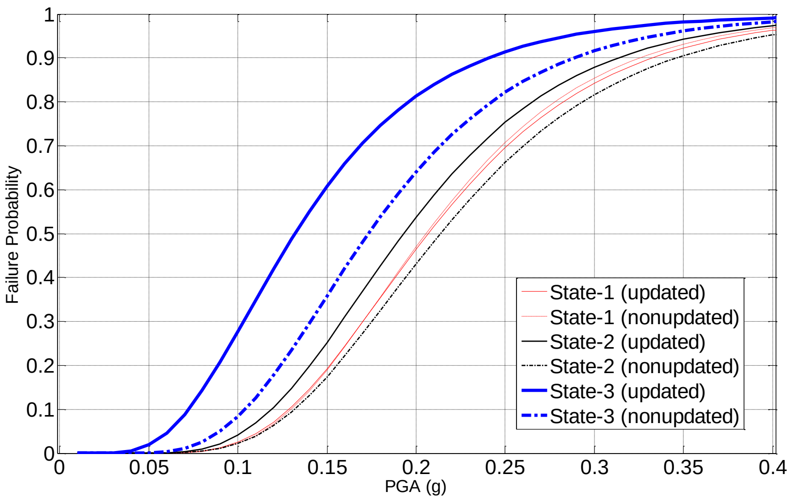

Figure 8. Fragility curves of updated and nonupdated models for different damage states.

According to Figure 8, the effect of structural damage on residual reliability is observed as failure probability increases in the later damage states. Furthermore, it should be mentioned that fragility curves are sensitive to finite element model updating, as updated and nonupdated models at the same state leads to different failure probabilities.

6 CONCLUSIONS

In this paper, the effect of use of system identification on reliability estimation is discussed. In addition, the effect of structural damage on reliability estimation is investigated using fragility curves. A quarter-scale bridge structure is exposed to a series of earthquake and white noise excitations by shaking tables. Different damage levels are measured and observed as a result of damaging excitations with increasing ground motion intensities. Modal parameters and time history responses are used to identify bent stiffness values and update finite element models. Based on ductility values obtained from different time history analysis results with different inputs, fragility curves are developed.

Comparing fragility curves of different damage states, it is possible to quantify structural damage in a probabilistic manner. For instance, failure probability at 0.2g refers to 0.47, 0.55, and 0.81 for damage State-1, State-2, and State-3, respectively.

Furthermore, the effect of system identification on reliability estimation could be inspected by comparing updated and nonupdated fragility curves of the same damage state. Such difference is prominent in State-3 where failure probability at 0.2 g refers to 0.64 and 0.81 for nonupdated and updated models, respectively.

In conclusion, integration of system identification into reliability estimation has significant effects on residual life assessment. Therefore, the procedure discussed in the paper may contribute to the residual life estimation or performance assessment of structures by offering a probabilistic approach supported with experimental information.

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