Identification of Simulated Damage on the Dowling Hall Footbridge

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ABSTRACT: This document provides a summary of the damage identification study on the Dowling Hall Footbridge through deterministic and probabilistic finite element (FE) model updating. The footbridge is located at Tufts University and is equipped with a continuous monitoring system that measures its ambient acceleration response. In this study, effects of physical damage are simulated by loading a small segment of the footbridge deck with concrete blocks. The footbridge deck is divided into five segments in a FE model of the test structure and the added mass on each segment is considered as an updating parameter. The damage identification results are found to be in good agreement with the simulated damage on the bridge.

Test Structure and Measured Data

The Dowling Hall Footbridge (Figure 1 left) is located at the Medford, Massachusetts campus of Tufts University. This two-span bridge is 3.9 m wide, 44 m long and is composed of a reinforced concrete deck and a steel frame. A continuous monitoring system was installed on the footbridge in November 2009 and has been providing continuous measurements since January 2010. The monitoring system consists of eight accelerometers (Figure 1 right) and a data acquisition device that is connected to the Tufts wireless network. A five-minute data sample is recorded at the top of every hour or when the root-mean square value of an acceleration measurement exceeds 0.03 g. Details about design and deployment of this continuous monitoring system can be found in [1].

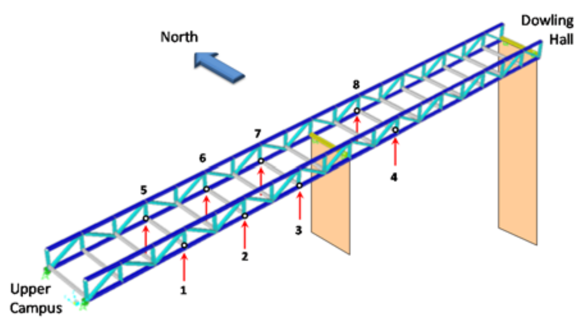

Figure1. South view of the Dowling Hall Footbridge (left), and layout of accelerometers on the bridge (right)

To simulate the effects of damage, a small segment of the footbridge deck was loaded with 2.29 metric tons (2,290 kg) of concrete blocks for 72 hours. The length of the loaded segment is 4.9 meters. The added mass will cause the same reduction in the natural frequency of mode one as a 35% loss of stiffness in the same segment of the bridge. In the FE model updating process, the footbridge deck in the reference FE model is divided to five segments and the added mass of each segment is considered as an updating parameter. Figure 2 shows the blocks on the bridge deck and the considered segments in the updating process. 72 sets of ambient vibration measurements were collected once every hour and their corresponding modal parameters – representing model parameters of the damaged structure – were identified through an automated operational modal analysis framework. Figure 3 shows the effects of added mass on the identified natural frequencies of modes 1 to 6.

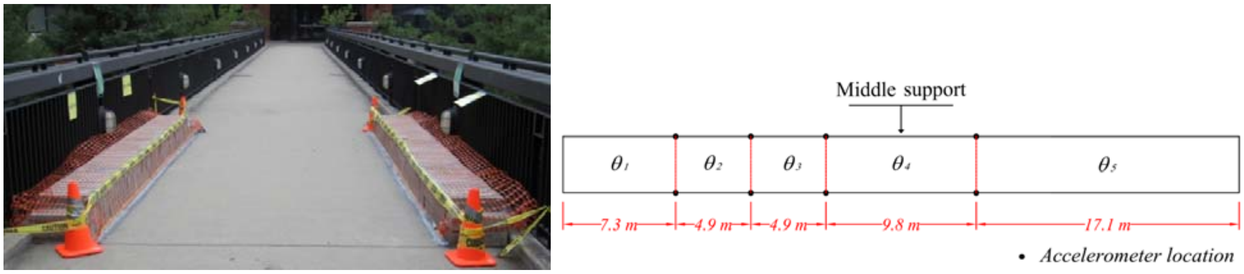

Figure 2. Concrete blocks on footbridge's deck (left) and the five segments along the footbridge deck corresponding to the five updating parameters (right)

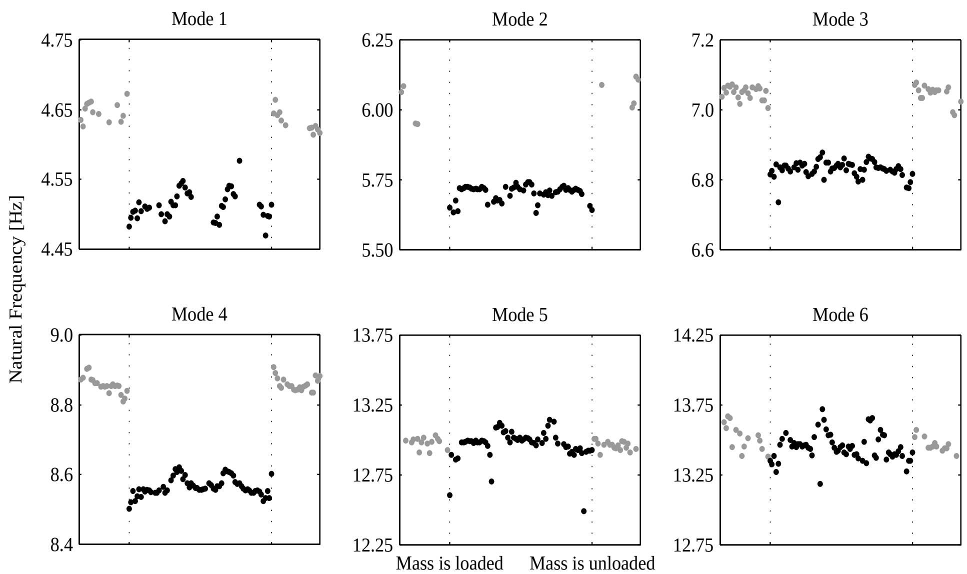

Figure 3. Hourly identified natural frequencies before, during, and after loading

SHM Methodology and Results

A deterministic FE model updating is performed by tuning the updating parameters of the model to minimize the misfit between model-predicted and experimentally-identified modal parameters. Details about the considered objective function and used residuals can be found in [2]. Figure 4 shows the scatter of the updating parameters for all 72 deterministic updating cases. It is observed that, except for a few outliers, the added mass on segments 1, 3, and 4 are accurately estimated as zero with no variability. However, the added mass on segments 2 and 5 are estimated with larger variability. The main sources of estimation errors in updating parameters are incompleteness of identified modal parameters from the corresponding measured data. The modal parameters in the outlier cases are incomplete (at least missing a mode) and are identified with larger estimation errors, which yield to inaccurate model updating results.

A probabilistic/Bayesian FE model updating is also performed to estimate the posterior probability distribution of the updating parameters (i.e., the added mass on considered five segments). Effects of the number of data sets used in the likelihood function on the accuracy of updating results are investigated. Nine cases of model updating are performed using different subsets (1, 2, 6, 12, 24, 36, 48, 60, and 72 sets) of available identified modal parameters. The posterior probability distributions of the added mass at the five considered segments of the footbridge are sampled using the Markov Chain Monte Carlo sampling process.

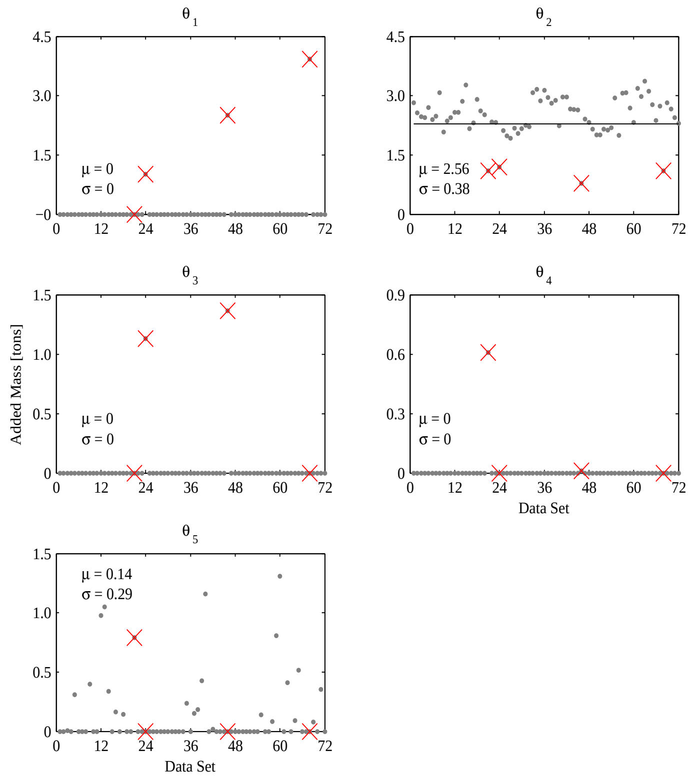

Figure 4. Scatter of updating parameters for the 72 cases of deterministic FE model updating, the outliers are shown by crosses and are not included in the computation of mean and standard deviation values

The MAP, mean, and standard deviation estimates of the posterior probabilities of all five parameters are reported in Table 1 [2].

Table 1. Statistics (maximum a-posteriori [tons], mean [tons], and standard deviation [tons]) for five updating parameters and nine considered cases of model updating

No. of data sets	θ_1			θ_2			θ_3			θ_4			θ_5		
	MAP	mean	STD	MAP	mean	STD	MAP	mean	STD	MAP	mean	STD	MAP	mean	STD
1	0.04	1.97	1.390	2.75	1.66	0.598	0.00	0.65	0.561	0.29	0.65	0.556	0.01	0.16	0.143
2	0.05	0.46	0.418	2.60	2.31	0.251	0.02	0.27	0.249	0.00	0.37	0.335	0.02	0.12	0.097
6	0.00	0.14	0.127	2.56	2.44	0.101	0.00	0.10	0.089	0.00	0.20	0.175	0.01	0.07	0.062
12	0.00	0.07	0.064	2.53	2.46	0.065	0.00	0.04	0.042	0.00	0.14	0.131	0.03	0.06	0.044
24	0.00	0.03	0.028	2.50	2.47	0.044	0.00	0.02	0.023	0.00	0.07	0.065	0.00	0.03	0.026
36	0.00	0.02	0.018	2.44	2.42	0.034	0.00	0.01	0.014	0.00	0.04	0.040	0.00	0.02	0.017
48	0.00	0.01	0.014	2.49	2.47	0.028	0.00	0.01	0.010	0.00	0.04	0.039	0.00	0.02	0.014
60	0.00	0.01	0.011	2.46	2.44	0.026	0.00	0.01	0.008	0.00	0.03	0.028	0.00	0.01	0.011
72	0.00	0.01	0.010	2.48	2.49	0.023	0.00	0.01	0.007	0.00	0.02	0.023	0.00	0.01	0.009

Lessons Learned

The MAP estimates of updating model parameters match the exact values of simulated damage and are in a good agreement with the optimum values from the deterministic FE model updating. Effects of the number of data sets used in the identification process (i.e., “value” of added data) are investigated by using different subsets (1, 2, 6, 12, 24, 36, 48, 60, and 72) of available data. Estimation uncertainty of the updating model parameters are significantly reduced by adding more data sets to the likelihood function, which implies more accurate model updating results. However, this reduction becomes less significant as the number of data sets exceeds 36. Therefore, it is expected that additional data (more than 36 sets) would not drastically improve the estimation accuracy of updating parameters. Such information can be used to quantify the value of additional data for parameter estimation. Adding more data sets also affects the shape of the posterior PDFs of updating parameters resulting in smaller bias between the sample means and the MAP estimates of model parameters. It is also worth noting that in the application of deterministic FE model updating, addition of more data sets will not necessarily improve the model updating results.

Although the implemented FE model updating method has successfully estimated the location and extend of damage in this study, but in general the success of this method depends on the accuracy of the initial FE model, the selected updating parameters, and the considered residuals and their weights in the objective function. Sensitivity of damage identification results to these factors can be viewed as one of the main limitations of this method for implementation by the practicing engineers without experience in model updating and inverse problems. For a robust identification, however, different combination of these factors (i.e., initial models, updating parameters, and objective functions) can be considered as different model classes, and a Bayesian model class selection/averaging technique can be used to select the optimal set of these factors.

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