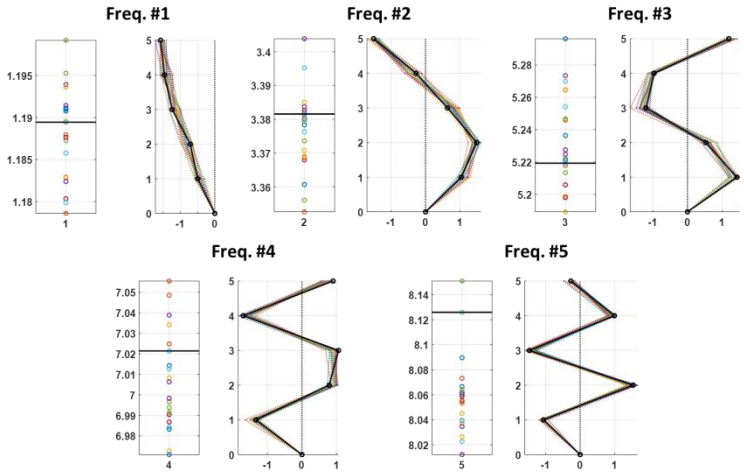

Fig. 4 Synthetic data for first five modes (20 sets)

3.2 Numerical study #1: FEMU with DGM

We performed both conventional and proposed FEMU for the situations that the DGM is included to the candidates of FE models. As calibration data for FEMU, the first five modes were used to find the solutions of FEMU. Genetic algorithm (GA) can be applied to both NLP problem (with only real variables for the updating parameters) and MINLP (with integer variable for model choice and real variables the updating parameters) (Sadatiyan Abkenar et al., 2015). Therefore, GA was implemented as the global optimizer to minimize the objective functions in Eq. (1) and (2).

The estimated best FE models from the proposed method (MINLP) are shown in Fig. 5, while Fig. 6 shows the identified values of the updating parameters from the conventional FEMUs (five NLP problems for each FE model) and proposed FEMU (one MINLP problems with all FE models). The results shows that (1) the proposed FEMU with MINLP can automatically and properly find the DGM (model #3) for all synthetic data; (2) the values of the updating parameters are identified around the target values (Fig. 6); and (3) the boxplots from the conventional FEMU using the DGM and the proposed FEMU are almost similar as shown in Fig. 6.

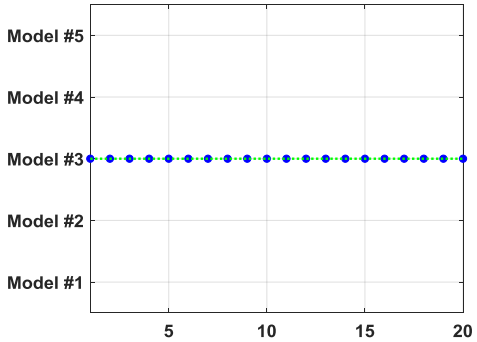

Fig. 5 Estimated best models from proposed method

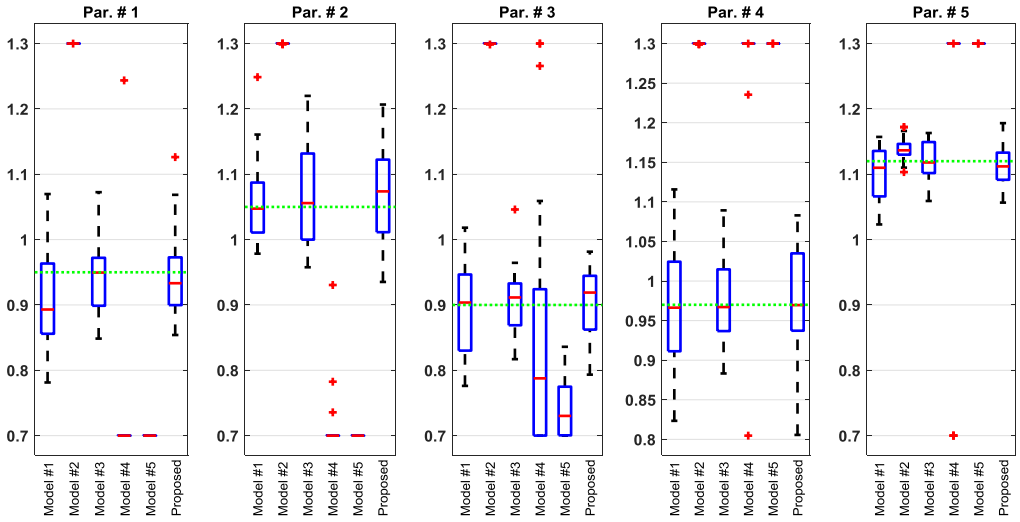

Fig. 6 Results of updating parameters from each FEMU

Fig. 7 shows the computational efforts using the number of the function evaluations (FE analysis). The results indicate that that the proposed method can achieve the optimally updated FE model among competing model candidates with much less computational effort against the conventional method.

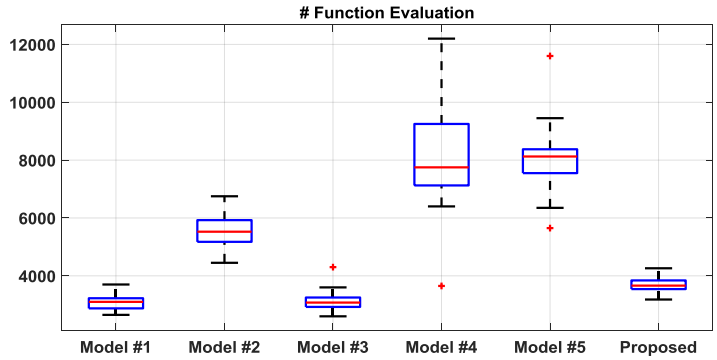

Fig. 7 Computational efforts based on number of FE analysis

3.3 Numerical study #2: FEMU without DGM

We also performed a comparative study under the model space without the DGM. Due to the limitation of the manuscript, we briefly mentioned that results. The experimental results show that the (1) the admissible FE model (herein, model #1) was chosen by the proposed method, and the predictions of this model are reasonable to represent the true dynamic behavior of the target structure; and (2) the identified values of the updating parameters are closed to upper or lower bounds, if there is no admissible FE models in the model spaces. More details on the results will be given in the presentation of the conference.

4. CONCLUSIONS

Since there are various modeling approaches for the existing infrastructures, the model-form uncertainty in FEMU always exists even for simple structures. Although the each modeling approaches simulate different predictions and this has a significant influence on the results of FEMU, this attention for this issue has not been gained. Most previous studies perform FEMU via the iterative process of trying out different FE models using own modeling approaches. Based the each results of FEMU, the best result was chosen. This iterative process for FEMU is the time-consuming and resource-intensive work, so that it is not effective to deal with the modeling uncertainty in FEMU.

To deal with the model-form uncertainty in FEMU, this study proposed FEM solving MINLP problems that assigns an integer code for model choice with the continuous real variables for the model parameters of being updated. The numerical experiments were performed to evaluate and compare the proposed method with the conventional method. The numerical experiments were performed and the results reveal that the proposed method can achieve the optimally updated FE model among competing model candidates with much less computational effort against the conventional method.

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