Editorial: Recent Advances in Stochastic Model Updating

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As a classical technology, *Model Updating* has been developed for nearly 50 years to calibrate the parameters or the numerical model itself, such as to tune its prediction as close as possible to experimental measurements. Industries have benefitted from a more precise model, which further promotes the application of numerical simulation technologies, such as the finite element method and computational fluid dynamics. However, it is widely recognized that the unavoidable uncertainties in both operational experiments and numerical analyses must be understood by the process of model updating. Uncertainty analysis has enabled the progression of model updating from the deterministic domain to the stochastic domain. Non-deterministic modelling approaches enable characterization, propagation, and quantification of the inevitable uncertainties, providing predictions over a possible range of outcomes (distributional, interval, fuzzy, etc.) rather than a unique solution with maximum fidelity to a single experiment. Such approaches provide confidence in structural dynamics, and computer-aided engineering generally, backed up by detailed uncertainty quantification.

However, challenges emerge from modern developments of aerospace, mechanical, and civil industries, where large-scale and multi-physics systems are designed and employed with huge parameter dimensions, discrepant parameter sensitivity, multifarious sources of uncertainties, huge calculation burden, etc. Thus, it requires further development of the current techniques for uncertainty treatment to enhance the trustworthiness of computational simulations in complex structural dynamics and coupled multi-physical mechanics.

This special issue is dedicated to summarizing the latest development of stochastic model updating, including novel uncertainty treatment approaches, efficient parameter calibration algorithms, advanced test techniques, etc. The collections of the special issue are not limited to the activity of model/parameter calibration, but outreach to load identification, structural health monitoring, reliability analysis, and model class selection, demonstrating the vitality of the traditional topic in modern engineering applications.

This special issue consists of 15 articles, which are divided into five groups according to their research topics and application domains: one tutorial article [1] on advanced sampling methods; four papers [2–5] on Bayesian updating and its applications, four papers [6–9] on uncertainty quantification and propagation, three papers [10–12] on system/damage identification, and three papers [13–15] on thermal and nonlinear model updating. The papers are introduced according to different groups as follows.

**Group I: Advanced sampling approach**

The Monte Carlo sampling is one of the most important tools for uncertainty analysis, and naturally for stochastic model updating, to estimate the calibrating parameters (or their probabilistic features) from a large number of random samples. However, as the probabilistic distribution of the target parameter becomes more complicated, and the model for each single sampling becomes evermore time-consuming, the standard (direct) Monte Carlo method tends to be prohibitive. Paper [1] provides a tutorial of the implementation and setting of three advanced Monte Carlo sampling techniques, i.e. the Markov Chain Monte Carlo, Transitional Markov Chain Monte Carlo (TMCMC), and Sequential Monte Carlo methods. Merits and demerits are compared in three case studies with both simulated and experimental data.

**Group II: Bayesian updating and its applications**

The Bayesian approach possesses a significant interest in stochastic model updating because of the ability to calibrate parameters in the context of probabilistic description, and the applicability for limited measurement data. There are four papers in this group focusing on either the theoretic development of the Bayesian approach or on the specific applications.

Paper [2] is dedicated to the challenge when the experimental data is too sparse to provide an appropriate hypothesis of the probabilistic distribution. A distribution-free approach employing the staircase random variables and the Bhattacharyya distance is proposed to characterize the hybrid uncertainties of the model parameters based on very few experimental observations. Paper [3] proposes two improvements of the basic Bayesian approach, i.e. the vectorization to construct a simplified likelihood function when comparing the model predictions and measurements, and the parallel computing scheme of TMCMC in a network to reduce the calculation time. This work makes it possible to employ the raw FRF as model output without any smoothing and windowing treatment. Paper [4] utilizes the Bayesian model updating in a specific application, the contaminant source identification of water distribution networks. This is achieved through a Bayesian model class selection framework using the TMCMC algorithm, where the model class with the highest posterior probability is identified as the possible contaminant source. Paper [5] focuses on Bayesian Updating with Structural reliability (BUS), to assess the slope stability when the spatial variability of soil parameters must be considered.

**Group III: Uncertainty quantification and propagation**

Four papers investigating the forward uncertainty quantification and propagation are included in this group to deal with challenges such as limited observation, huge calculation burden, and multi-sources of uncertainty involved in complicated systems.

The quantification of spatial variation from limited observation in the form of random fields has been a general difficulty in practical model updating. Paper [6] proposes an integrated Bayesian Compressive Sensing and Stochastic Harmonic Function (BCS-SHF) scheme to cope with the above difficulty by reproducing the target mean and covariance of the stochastic response of civil structures under cyclic leading. An efficient uncertainty propagation approach is proposed by Paper [7] to “break the double-loop” which is generally encountered in the reliability analysis when both aleatory and epistemic uncertainties are presented. Paper [8] is dedicated to a uniform framework of reliability analysis for both static and dynamic structures based on the Direct Probability Integral Method (DPIM). The DPIM is improved by the adaptive formula of smoothing parameters in the probability space of the performance function, which is employed as a substitution of the consuming Monte Carlo sampling approach. Paper [9] proposes another uncertainty treatment approach instead of the Monte Carlo simulation, i.e. the Interval Field approach, to capture the spatially varying mechanical compliance of the finite element model, which is used in the crash analysis of adjacent automobile structures.

**Group IV: System/load/damage identification**

Model updating has a natural connection with the topic of system identification. This group includes three papers focusing on the processes either prior to model updating, i.e. sensor placement, or posterior to model updating, i.e. force and damage identification.

Paper [10] aims at appropriate sensor configuration to provide as sufficient as possible experimental observations for model updating with a limited number of sensors placed optimally. This is achieved through the optimal load-dependent sensor placement, where multi-source uncertainties are quantified using intervals and the time-dependent reliability-based index is optimized by the NAGA-II algorithm. A force reconstruction process is developed by Paper [11] to identify the time history of uncertain forces for the linear time-invariant systems, employing the Kalman filter and interval uncertainty quantification. Paper [12] develops the fatigue-induced damage prediction model based on the lumped damage mechanics of civil steel structures. This model is updated by a damage index measured using local wireless sensors in substructure tests, subsequently employed for the remaining-life assessment of structures.

**Group V: Thermal/nonlinear model updating**

Nonlinear and multi-physics updating is an important aspect of model updating since the modern structures are always designed to be light-weight and large-deformable, and serve in multi-scenarios under severe conditions of temperature and pressure. This group includes three papers on topics of nonlinear modelling/testing and thermal-mechanical coupling.

Paper [13] develops a nonlinear model updating approach based on the Bayesian framework which is divided into two phases: Phases (1) for the updating of Young’s modulus of a linear model, and Phases (2) for the updating of nonlinearity coefficients of a reduced-order model. The nonlinear normal modes of the structure are predicted in good agreement with the experimentally measured ones. Paper [14] proposes a full-field measuring technique for nonlinear structures based on the 3-Dimensional Laser Vibrometer (3DLV). A Multi-step Interpolated-FFT procedure is designed to assure the full-field measuring on large-scale industry structures by introducing a super-short sampling interval. A hierarchical thermal updating process is developed in Paper [15], where the thermal field is updated in the first level and the mechanical characters are regarded as temperature-dependent variables to be updated in the second level. Both the mean and covariance are calibrated in a Monte Carlo simulation, ensuring the thermal updating is performed in the stochastic sense.

**Summary**

This special issue integrates various-but-interconnected topics of stochastic model updating (e.g. imprecise-probabilistic/non-probabilistic uncertainty quantification, efficient uncertainty propagation, load and damage identification, nonlinear testing and updating, etc.) with a wide range of applications in aerospace, civil, and automobile industries. The aspiration of this special issue is to stimulate further development of model updating with the new challenges of multi-sources of uncertainties, strong nonlinearity of complex systems, and scarcity of on-site experiments.

We appreciate all the authors who contribute their valuable works and all the reviewers whose time and effort are critical for the success of this special issue.

**List of contributions**

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