Computational Challenges in Bayesian Uncertainty Quantification of Large-Order Models

Costas Papadimitriou[1*]

[1]University of Thessaly
Department of Mechanical Engineering
Pedion Areos, Volos 38334, Greece
costasp@uth.gr

ABSTRACT

Bayesian inference is used for quantifying and calibrating uncertainty models in structural dynamics based on vibration measurements, as well as propagating these uncertainties in simulations for updating robust predictions of system performance, reliability and safety. The Bayesian tools for identifying system and uncertainty models as well as performing robust prediction analyses are Laplace methods of asymptotic approximation and sampling algorithms. These tools involve solving optimization problems, generating samples for tracing and then populating the important uncertainty region in the parameter space, as well as evaluating integrals over high-dimensional spaces of the uncertain model parameters. They require a moderate to very large number of system re-analyses to be performed over the space of uncertain parameters. Consequently, the computational demands depend highly on the number of system analyses and the time required for performing a system analysis.

The computational challenges for Bayesian uncertainty quantification and propagation of large-order models in structural dynamics are addressed. High performance computing techniques are integrated with Bayesian techniques to efficiently handle large-order models of hundreds of thousands or millions degrees of freedom, localized nonlinear actions activated during system operation, and stochastic loads. Fast and accurate component mode synthesis (CMS) techniques are proposed, consistent with the finite element model parameterization, to achieve drastic reductions in computational effort. Surrogate models are also used within multi-chain MCMC algorithms with annealing properties to substantially speed-up computations, avoiding full system re-analyses. Significant computational savings are achieved for stochastic simulation algorithms by adopting parallel computing algorithms to efficiently distribute the computations in available GPUs and multi-core CPUs. Important issues related to the computational efficiency of the asymptotic approximations versus the stochastic simulation algorithms for serial or parallel computing environments are discussed. The proposed Bayesian computational framework for reconciling high-fidelity models and experimental data in system simulations is applicable to diverse fields of engineering sciences. It is demonstrated in this work using applications in civil infrastructure and vehicle dynamics.

Acknowledgement: This research has been implemented under the “ARISTEIA” Action of the ”Operational Programme Education and Lifelong Learning” and was co-funded by the European Social Fund (ESF) and Greek National Resources.