Data-Driven Bayesian Uncertainty Quantification and Propagation Framework for Dynamical Systems

†*Costas Papadimitriou[1]

[1]Department of Mechanical Engineering, University of Thessaly, Greece.

*Presenting author: costasp@uth.gr
†Corresponding author: costasp@uth.gr

Abstract

Bayesian analysis provides a logical framework for integrating physics-based models and test data for the purpose of selecting parameterized models of dynamical systems at component, component interface and system levels, quantifying uncertainties in model selection and parameter estimation, as well as propagating uncertainties in dynamical system simulations. The framework can also be used for monitoring the state of the system and its components, identifying the location and size damage, as well as making optimal decisions under uncertainty for cost-effective system design and maintenance actions that meet performance/safety requirements. Bayesian tools such as Laplace asymptotic approximations and sampling algorithms require a moderate to very large number of system re-analyses to be performed. Computational demands may become excessive, depending on the model complexity, the time required to perform a simulation, and the number of model runs.

This work covers selected theoretical and computational developments of a hierarchical Bayesian modeling (HBM) framework for uncertainty quantification and propagation (UQ+P) in dynamical system simulations. In contrast to classical Bayesian framework, the proposed HBM framework is used to embed most of the model uncertainty into the model parameters, effectively dealing with the redundant information contained in the large number of measured data arising from large number of sensors, higher than required sampling rates or multiple experiments. In particular, it is demonstrated that the level of uncertainty predicted by the proposed HBM framework is insensitive to the redundant information contained in the data. Theoretical and computational challenges related to model embedded uncertainty and model prediction uncertainty are addressed using asymptotic approximations. The formulation is applicable to data consisting of response time history measurements required for data-driven nonlinear system modeling, as well as experimentally identified modal data usually processed for data-driven linear system modeling. Computational challenges, in particular, are encountered in large-order finite element models of hundreds of thousands or millions degrees of freedom, and/or localized nonlinear actions activated during system operation. Efficient model reduction techniques, consistent with the model parameterization, drastically speed up computations within the Bayesian UQ+P framework. Applications focus on the use of the framework for FE model selection/calibration, as well as structural health monitoring using vibration measurements.

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