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Stochastic frequency domain surrogate models for linear structural dynamics

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When conducting measurement on existing structures, e.g. collecting the time-response of a building, and trying to compute the same response by a suitable computational method, one often notices discrepancies between the measurement and model data. These discrepancies are due to a wide range of errors, done in both the measurement and the modelling. The model errors can stem from uncertainty in the model parameters and, often more importantly, the model error itself.

One can then use stochastic methods to obtain a more robust response prediction of the structure at hand (forward Uncertainty Quantification (UQ)) and use the data gathered to learn about the model parameters and the errors involved in the modelling (Inverse UQ). Often, Bayesian methods are applied to solve the inverse problem at hand. In any case, applying sampling-based approaches to UQ requires the repeated evaluation of the model and can become infeasible for computationally demanding models.

To address this issue we introduced a novel surrogate model that is especially suitable for approximating linear structural dynamic models in the frequency domain (Schneider et al. 2020). The surrogate approximates the original model by a rational of two polynomial chaos expansions (PCE) over the stochastic input space. The complex coefficients in the expansions are obtained by solving a regression problem in a non-intrusive manner.

One drawback in the PCE based surrogate model is the factorial growth of the number of basis terms in the expansions with the number of input dimensions and polynomial order, known as the curse of dimensionality. To circumvent this restriction, often approaches that find sparse bases representations are applied. One of these approaches is Sparse Bayesian Learning (Tipping, 2001). Implementing such an approach for the rational surrogate model could help in obtaining a sparse and thus efficient surrogate model for UQ in the frequency domain.

Further improvements to the method include extending the approach to work with vector-valued output in an efficient manner, as now, the surrogate is only able to approximate scalar model output. Promising approaches include Proper Generalized Decomposition (PGD) (Chevreuil et al. 2012), among others.

References:

[1] Schneider, F., Papaioannou, I., Ehre, M., & Straub, D. (2020). Polynomial chaos based rational approximation in linear structural dynamics with parameter uncertainties. Computers & Structures, 233, 106223.

[2] Chevreuil, M., & Nouy, A. (2012). Model order reduction based on proper generalized decomposition for the propagation of uncertainties in structural dynamics. International Journal for Numerical Methods in Engineering, 89(2), 241-268.

[3] Tipping, M. E. (2001). Sparse Bayesian learning and the relevance vector machine. Journal of machine learning research, 1(Jun), 211-244.

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