Recursive Bayesian Filtering approaches for parameter estimation of a wind turbine numerical model

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Abstract:

In the context of energy transition, wind power generation is developing rapidly. Meanwhile, in the framework of digitization of industry, the exploitation of collected data can be optimized by combination with wind turbine numerical models. Such numerical models can be complex and costly as they involve non-linear dynamic equations with different physics such as stochastic loading from the wind. Moreover, some input parameters of the models can be poorly or badly known as the structure ages over time and defaults can appear. Consequently, model predictions are affected by uncertainties. Characterization and reduction of these uncertainties is important for decision making. In this context, uncertainty quantification and reduction methods have been developed.

However, the conventional methods used in uncertainty quantification are not suitable in the present industrial context because of the stochastic nature of the external solicitation and the time consuming behavior of the simulator. Formally, the function $\mathcal{M}$ represents the time-consuming numerical model which generates a vector of discretized functional outputs $\mathbf{y} = (y_1, \ldots, y_m) \in R^m$ such that:

$$\mathbf{y} = \mathcal{M}(\mathbf{x}, V)\,, \tag{1}$$

where, $\mathbf{x} = (x_1, \ldots, x_p) \in \mathcal{P} \subseteq R^p$ are the model input parameters, V is a stochastic simulator.

In this context, we aim at quantifying and reducing the input parameter uncertainties involved in a finite element wind turbine model. Our main contributions are twofold.

Firstly, we wish to quantify the sources of uncertainties affecting the fatigue behavior of a wind turbine. Let g be the function mapping the functional loads of the structure in $\mathbf{y}$ to the damage quantity of interest (QoI), defined as:

$$g(\mathbf{y}) := g \circ \mathcal{M}(\mathbf{x}, V)\,\cdot \tag{2}$$

We propose a variance-based global sensitivity analysis (GSA) methodology, based on the so-called Sobol' indices [6], for stochastic computer simulations. Such techniques, which often refer to the probabilistic framework and Monte Carlo (MC) methods, require a lot of calls to the numerical model. The uncertain input parameters are modeled by independent random variables gathered into a random vector and characterized by their probability density function. Variance-based SA for time consuming deterministic computer models has been mainly performed by approximating the model by a mathematical function, a.k.a a surrogate model. Among the different surrogate models, we focus on Gaussian process (GP), a.k.a. Kriging, which is characterized by its mean and covariance functions. One advantage of the GP model is to provide both a prediction of the numerical model and the associated uncertainty. However, classical GP model-based GSA cannot tackle the inherent randomness from stochastic simulation. We propose to model the mean of the

QoI $E_{\mathbf{V}}[g \circ \mathcal{M}(\mathbf{X}, V)]$ with a GP model with heteroscedastic nugget effect. Then, this surrogate model is used to perform a sensitivity analysis based on classical MC estimation procedure [5].

After identification of the less influential input parameters on the fatigue behavior of the wind turbine, we propose a Bayesian inference framework to carry out a model calibration procedure based on in situ-measurements. It uses some measurements $\mathbf{y}^{mes}$ to update some prior probability density functions about the unknown input parameters $\mathbf{X} \sim p(\mathbf{x})$ and yields some posterior probability density functions, through the Bayes' theorem $p(\mathbf{x}|\mathbf{y}^{mes}) \propto p(\mathbf{y}^{mes}|\mathbf{x})p(\mathbf{x})$. Numerous batch techniques have been developed to solve such Bayesian problems. Nevertheless, recent decades have been marked by a simultaneous development of sensor technologies and Internet of Things capabilities. Thus, our research efforts have been directed toward inference techniques where the data are sequentially processed when new observations become available. In this context, the model parameter inference can be carried out using sequential Bayesian techniques. In geosciences, these techniques are called data-assimilation methods. We carry out the calibration using a recursive Bayesian inference approach based on an Ensemble Kalman Filter [2]. However, such problems can be solved assuming that several conditions of well-posedness and identifiability are achieved. These conditions have been summarized by Hadamard [3]. As highlighted in [1], a relationship between the non-identifiability of input parameters and the GSA can be established. Indeed, insensitive input parameters to the measured outputs imply their non-identifiability. Therefore, for the purpose of identifiability a second GSA is performed on the calibration parameters. Due to the functional behavior of the measurements, we propose to first reduce their dimensionality through Principal Component Analysis. Then, a GP is fitted to the different principal components and used to compute an aggregated Sobol' index for each model parameter [4].

Lastly, the proposed framework has been applied to a wind turbine numerical model. The developed recursive inference procedure has shown promising results in the industrial inversion problem.

References

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Short biography – Adrien Hirvoas is a second year PhD. student in applied mathematics at IFP Energies Nouvelles, in collaboration with the university of Grenoble Alpes. He received a master's degree in structural and mechanical engineering from the French Institute of Mechanics in Clermont-Ferrand (France). This thesis, started in April 2018, is funded by IFP Energies Nouvelles.