Development of an inverse method for the calibration and continuous update of Wind Turbines Digital Twins

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Recent decades have been marked by a concurrent development of sensor technologies and high-fidelity numerical modelling capabilities in particular in the field of the wind-turbine modelling, see e.g. [3]. At the intersection of these two advancements lies an interesting evolution of real-time monitoring of a system. During monitoring, measurements obtained from a structure are used to learn parameters involved in mathematical equations characterizing a physics-based model of the system. By using statistical calibration we will be able to reduce the uncertainty affecting these parameters in order to improve the prediction and the performance assessment.

In this work, *online* identification approaches for mainly non-linear systems are described. These approaches are based on the Bayesian inference framework. By *on-line*, we mean that the data are sequentially processed when new observations become available.

As a consequence, the presented work focuses especially on sequential Bayesian methods such as the Ensemble Kalman Filter [2] or the sequential Monte-Carlo methods, also called particle filters [1], which can handle non-linear and non-Gaussian systems. In most of the cases, the main objective of these methods is to estimate the posterior density of the latent dynamic state variables defined in Hidden Markov Model given the observation variables.

The main goal of our study consists in the development of an *on-line* method to learn static parameters, denoted $\boldsymbol{\theta} \in \Theta \subseteq \mathbb{R}^p$ involved in a Wind-Turbine numerical model. One of the aims of the proposed method is to deal with uncertainties in the inputs, the measurements and/or the model. In this context, the Bayesian inference framework is well-suited. Bayesian methods treat $\boldsymbol{\theta}$ as a random vector and are able to tackle ill-posed problems where some (or all) targeted parameters cannot be identified based on available data. In order to use sequential Bayesian methods for static parameter inference, we can introduce an *artificial dynamism* for the static parameter vector $\boldsymbol{\theta}$. Under this consideration, each time period subset t of the system can be seen as a state-space model (or Hidden Markov Model):

$$\left\{ \begin{array}{lcl} \boldsymbol{\theta}_t & = & \boldsymbol{\theta}_{t-1} + e_{t-1} \\ \boldsymbol{y}_t & = & g(\boldsymbol{x}_0, \boldsymbol{\theta}_t, \boldsymbol{F}_t) + \nu_t \end{array} \right. \tag{1}$$

Where, the variables e_{t-1} and ν_t are independent noise sequences with known probability density functions (p.d.f.). The quantity $\boldsymbol{x}_0$ is the known initial condition given to the simulator at each iteration and $\boldsymbol{F}_t$ is the external force during the iteration term which is also known. g is a (non-linear) function with the same constraints than the industrial Wind-Turbine model, such as an initialisation phase. By using filtering methods, the measurements lead to update some prior knowledge on $\boldsymbol{\theta}_t$ (prior p.d.f.) and thus yield to a posterior knowledge (posterior p.d.f.) according to available data $\boldsymbol{y}_t \in \boldsymbol{\mathcal{Y}} \subseteq \mathbb{R}^m$.

Some filtering algorithms developed have been tested on toy-model and have shown promising results in the field of static parameters inference. Thus, a deployment on a real industrial numerical Wind-Turbine will be led. The aspect of identifiability is currently being considered. Other filtering approaches are also under study in order to deal with highly non-linear and non-Gaussian models.

Références

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