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Uncertainty propagation through an aeroelastic wind turbine model using polynomial surrogates

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ABSTRACT

Polynomial surrogates are used to characterize the energy production and lifetime equivalent fatigue loads for different components of the DTU 10 MW reference wind turbine under realistic atmospheric conditions. The variability caused by different turbulent inflow fields are captured by creating independent surrogates for the mean and standard deviation of each output with respect to the inflow realizations. A global sensitivity analysis shows that the turbulent inflow realization has a bigger impact on the total distribution of equivalent fatigue loads than the shear coefficient or yaw miss-alignment. The methodology presented extends the deterministic power and thrust coefficient curves to uncertainty models and adds new variables like damage equivalent fatigue loads in different components of the turbine. These surrogate models can then be implemented inside other work-flows such as: estimation of the uncertainty in annual energy production due to wind resource variability and/or robust wind power plant layout optimization. It can be concluded that it is possible to capture the global behavior of a modern wind turbine and its uncertainty under realistic inflow conditions using polynomial response surfaces. The surrogates are a way to obtain power and load estimation under site specific characteristics without sharing the proprietary aeroelastic design.

1. Introduction

The wind turbine design standard IEC 61400-1 [1] provides wind climate specifications which are used as a reference for the structural design of the wind turbines. For achieving type certification of a new turbine model, the designer has to demonstrate that the structural capacity of the turbine is sufficient for withstanding the reference wind conditions over the entire lifetime of the turbine. Such a demonstration is normally given by dynamic load simulations which characterize the behavior of the turbine under the reference wind conditions. Once certification is achieved, the given turbine model can safely be installed on sites where the wind conditions are identical or more benign than the reference standard conditions. However, in many occasions one or more of the parameters describing the site environmental conditions will be outside the ranges which are sufficiently covered by the IEC reference conditions. In such cases, it is necessary to estimate the actual loads which the turbine will experience over its entire lifetime, by considering the full joint distribution of the variables that describe the turbulent inflow. This is similar to a propagation of uncertainty problem in which the distribution of the atmospheric conditions on the site needs to be propagated through the aeroelastic model of the turbine.

If a full design load case setup similar to the IEC 61400-1 design cases is used for that purpose, the problem quickly becomes time-consuming as new dynamic simulations would be required for each site. As an example, the number of simulations required to predict within 1% error the lifetime equivalent fatigue loads on a floating wind turbine where the inflow conditions (sea/wind) are characterized by five stochastic variables can reach up to $3,200,000 = 20^5$ using regular grid-based estimates or in the order of 50,000 using Monte-Carlo (MC) simulation [2]. An approach that alleviates these issues is mapping the turbine response to different environmental inputs by means of a fast and accurate surrogate model. Several techniques can be used to predict the behavior of

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the turbine from a limited set of model evaluations such as: interpolation techniques, response surface techniques [3], Gaussian process (Kriging) [4] and machine learning techniques [5,6].

Polynomial chaos expansion is a methodology used to efficiently propagate input uncertainties through a non-linear model. This methodology consists in building a polynomial response surface to capture the global dependency of the output as a function of the uncertain inputs. PCE is widely used in the uncertainty quantification field because of its simplicity and fast convergence in comparison to a full MC simulation based on the original model [7–11]. Furthermore, adaptive PCE training algorithms can be used to obtain a sparse surrogate that minimizes the number of terms that have multiple variable dependency, making the surrogates extremely efficient response surfaces in multiple dimensions [12–14]. In the case of smooth continuous models with multiple input variables, sparse polynomial chaos expansion methodology is the most efficient technique to build the surrogates in terms of the number of model evaluations required, the number of input dimensions they can handle and the rate of convergence [12].

One of the main difficulties in building a surrogate of an aeroelastic wind turbine model is the fact that the turbulent inflow realization (TIR, i.e. turbulent structures in the flow field) causes variations in the different wind turbine model outputs: such as power, thrust, fatigue and extreme loads in the different components of the turbine. This can be restated as: an aeroelastic wind turbine model has stochastic/non-deterministic outputs. Many studies have analyzed the difficulties of studying fatigue and extreme loads under different turbulent inflow realizations [3,4,15–17]. Different TIR activate different dynamics of the structure and have different control system responses; therefore are an important source of uncertainty in the prediction of the outputs of the model [15]. The high variability in the model response to certain turbulent inflow structures has also been shown to be problematic when MC simulation was used to predict lifetime averages of fatigue loads on a floating wind turbine [2].

1.1. *Response to the problem*

The aim of the present study is to demonstrate a method for building a quick and accurate surrogate of a wind turbine model that predicts the turbine response as a function of multiple stochastic input variables that describe the turbulent inflow on a site ($\mathbf{x}$). The surrogate for the turbine model is a set of two independent sparse polynomial response surfaces that allow to predict the variability caused by different input variable distributions and by different turbulent inflow field realizations (TIR). One response surface characterizes the expected output with respect to TIR: $\widehat{y}_{\mathbb{E}}(\mathbf{x}) \approx \mathbb{E}_{\mathrm{TIR}}(y|\mathbf{x})$. The other one describes the standard deviation of the output with respect TIR: $\widehat{y}_{\mathbb{S}}(\mathbf{x}) \approx \sqrt{\mathbb{V}_{\mathrm{TIR}}(y|\mathbf{x})}$; which is a model that predicts the uncertainty in the turbine response due to different turbulent structures hitting the turbine. Finally, a sample can be obtained from the normal distribution constructed using the mean and the standard deviation surrogates in order to make a prediction of the variability in the output at a given input point:

$$\widehat{y}(\mathbf{x}) \sim \mathrm{Normal}(\widehat{y}_{\mathbb{E}}(\mathbf{x}),\ \widehat{y}_{\mathbb{S}}(\mathbf{x})) \tag{1}$$

The final surrogate $\widehat{y}(\mathbf{x})$ can then be used to obtain distributions of the wind turbine power and fatigue loads in a given year whose input parameters (wind, wind/sea, or wind/geological conditions) follow the distribution used to train the surrogate PDF($\mathbf{x}$). Since the surrogate is a response surface it can also be used to predict the distribution of the outputs when the input distributions is close but not exactly the distribution used for training the surrogate. This setup is considered a multi-leveled uncertainty propagation and it is the scenario that occurs when there is uncertainty in the parameters that characterize the WS distribution for example. This approach is necessary to estimate the uncertainty in annual energy production and lifetime averaged equivalent fatigue load.

1.2. *Article overview*

A general overview of the PCE methodology in multiple dimensions is presented in Section 2. This section describes the Rosenblatt transformation, the design of experiments used to define the training simulation points, the approach used to train sparse polynomial response surfaces and the logistic transformation used to limit the output. In Section 3, the methodology is then applied to the response of the DTU 10 MW reference wind turbine HAWC2 model [18] to turbulent inflow fields characterized by four input parameters. The four input parameters are the 10-min averaged hub height wind speed (WS), the turbulent standard deviation of the instantaneous wind speed in the streamwise component (σ_1), the shear exponent (α) and the yaw misalignment angle (γ). A study of how many independent realizations of the turbulent inflow field are required to achieve a certain error tolerance in the surrogate is presented in the Section 3.7. Finally in Section 3.8, the surrogates are used in an example of prediction of the uncertainty in the annual energy production and the uncertainty in lifetime averaged equivalent fatigue loads.

2. Methods

This article proposes the use of two different variable transformations to simplify the polynomial response surface fitting problem, see Fig. 1. The first transformation is the Rosenblatt transformation [19], which is used to de-correlate the set of D input variables $\mathbf{x} = (x_0, x_1, \dots x_{D-1})$ into a set of independent uniform variables, $\mathbf{w} = (w_0, w_1, \dots w_{D-1})$. The second transformation is a logistic transformation, and it is used to enforce constraints on the polynomial surrogates [20]. This transformation enables the use of polynomial surrogates in problems where the output has a minimum and/or maximum value. Without the logistic transformation the polynomial surrogates will present oscillations in the regions where the model has a constant output. The power production of a turbine is an example of a variable with a strict upper constraint corresponding to the rated power.

2.1. *1D PCE theory*

Consider a model with a single uncertain input (x) and a single output (y). PCE consists of defining a polynomial family that is orthogonal with respect to the input distribution, PDF(x). Orthogonal polynomial families with respect to the most important distributions are well known, see Table 1. For details on how to define new polynomial basis to an arbitrary input distributions refer to Gautschi et al. [21].

The orthogonal polynomials are used to build a polynomial approximation of the output, i.e. a polynomial response surface, see Equation (2). Where, $\phi_l(x)$ is the l order orthogonal polynomial, c_l is its correspondent coefficient and M represents the truncation order of the PCE.

$$y(x) \approx \widehat{y}(x) = \sum_{l=0}^{M} c_l\, \phi_l(x) \tag{2}$$

There are two different approaches to determine the c_l coefficients:

Semi-Spectral projection consists in using quadrature rules to