Uncertainty of Power Production Predictions of Stationary Wind Farm Models

Juan P. Murcia, PhD. Student, Department of Wind Energy, Technical University of Denmark
Pierre E. Réthoré, Senior Researcher, Department of Wind Energy, Technical University of Denmark
Anand Natarajan, Senior Scientist, Department of Wind Energy, Technical University of Denmark
John D. Sørensen, Professor, Department of Civil Engineering, Aalborg University

1 Introduction

There is a need in the wind energy industry for better predictions of wind farm power production. In particular investors and financial institutions are interested in understanding the uncertainty of production predictions in order to help them take better decisions about investing in a particular wind energy project. In this contexts there is a growing interest in performing verification, validation and uncertainty quantification (VV&UQ) of wind farm models. The present article is based on the approaches of Roy and Oberkampf (2011) and Oden et al. (2010) and proposes a framework for validation of stationary wake models. The validation data selected for this study consists on the SCADA data of the Danish wind farm Horns Rev 1 (DONG/Vattenfall). Horns Rev 1 is selected because it is one of the wind farm flow benchmark cases defined by Hansen et al. (2012). The present work has the objective of introducing a methodology to determine the model inadequacy of stationary wind farm flow models under uncertain undisturbed flow conditions. The framework presented in this article is applied to two classical engineering wake models: N. O. Jensen's and G. C. Larsen's models.

2 Approach

The present framework for UQ can be summarized as (1) To perform a detailed input uncertainty elicitation using the spatially averaged undisturbed wind direction and wind speed as input variables. The spatial variation of both wind speed and wind direction are considered using the nacelle position and power production of the free stream operating turbines. The temporal variation inside the Reynolds averaging period (trends) on both wind speed and wind direction are take into account using the measurements from the top anemometers on the met. mast 2. The distribution of ambient turbulence intensity is also considered.

(2) To Propagate uncertainty through the wind power plant model to estimate each individual turbine power production variations and compare them with the experimental power production distribution. Additionally the distribution of power production will be studied as a function of undisturbed wind direction and wind speed for both the models and the experimental data. Monte Carlo simulations are used to predict the power production of each wind turbine in an independent manner (i.e. only using the fitted input distributions).

(3) To perform model validation of the engineering wake model as presented in Kennedy and O ' Hagan (2001). This means that the distribution of the wake model error will be studied as a function of the input variables.

3 Main body of Abstract

3.1 Horns Rev 1 Validation Dataset

The SCADA data of Horns Rev 1 contains 3 years of power measurements for each individual turbine as well as different signals of the individual turbine's operation condition. Additionally, wind resources are measured by the nearby meteorological masts. The Horns Rev 1 validation dataset consists in defining the power distribution of each wind turbine for multiple undisturbed wind speed and wind direction sectors. In the present work the average of the nacelle position sensors of the free flow operating turbines are used to predict the undisturbed spatial averaged wind direction. The SCADA data is processed following the method described by Réthoré et al. (2009). These procedure is done independently in four different wind direction sectors each one with a 90 [deg.] width, see figure 1. Similarly the power production of these turbines are used to predict the spatial averaged undisturbed wind speed using the inverse of the turbine's power curve as proposed by Hansen et al. (2012).

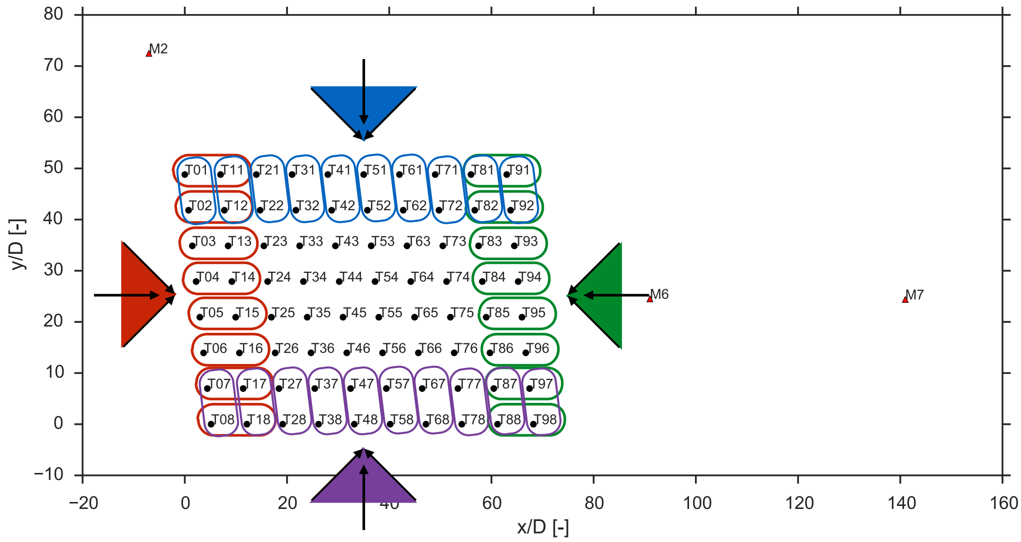

Figure 1: Selected benchmark case in Horns Rev 1. Note that the colored area represents accepted observed wind directions.

3.2 Input uncertainty

The second part of this study focuses on determining the input variable uncertainty. Here uncertainty is considered as the range of variability of local wind directions and local wind speeds inside the wind farm. For each of the quadrants the experimental database is filtered using the spatial averaged wind speed, $\langle u \rangle_A \in [7.5, 8.5]$ [m/s]. The spatial averaged wind direction filter is defined by the following ranges: Western flow cases: $\langle \theta \rangle_A \in [210, 300]$ [deg], Northern flow cases: $\langle \theta \rangle_A \in [-60, 30]$ [deg], Eastern flow cases: $\langle \theta \rangle_A \in [30, 120]$ [deg] and Southern flow cases: $\langle \theta \rangle_A \in [120, 210]$ [deg]. The distribution of the undisturbed flow variables as observed in the database is shown in figure 2. Note that both the undisturbed wind speed and wind direction are uniformly distributed, while the ambient turbulence intensity can be fitted to a log-normal distribution. Furthermore all the input variables are independent. These two properties are caused by the fact that the wind speed range selected is very narrow.

Additionally the spatial variation between the reference wind direction and the wind direction at each individual turbine location is studied by analyzing the distribution of errors in the free-stream operating turbines. Similar analysis is performed for the spatial variation of wind speed. Finally the temporal variation inside the averaging window (10 [min] for HR1 database) is modeled by considering the distribution of the difference in two consecutive mean wind directions and wind speeds in the top anemometers for each nearby met. masts. The Gaussian averaging procedure proposed by Gaumond (2013) is used to take into account the local wind direction uncertainty variation inside the Reynolds averaging time, while maintaining the variation due to the spatial averaged wind direction.

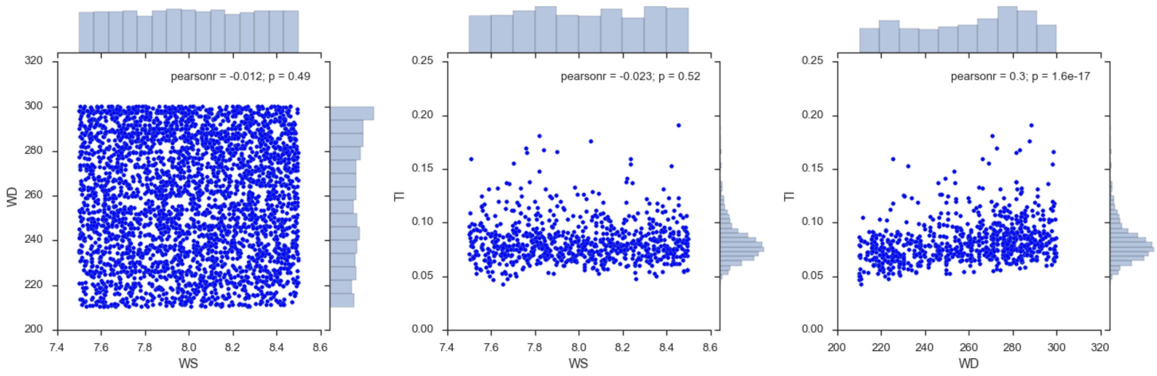

Figure 2: Input variable distribution obtained by filtering the database.

3.3 Output uncertainty

The power distribution for Western flow cases is shown as violin plots (Kernel density estimated PDF) for both models and for the SCADA data in figure 3. It can be observed that the simple engineering models capture most of the variation in the output. Note that the plots are normalized by the expected power of a single turbine for the mean undisturbed wind speed (8 [m/s]).

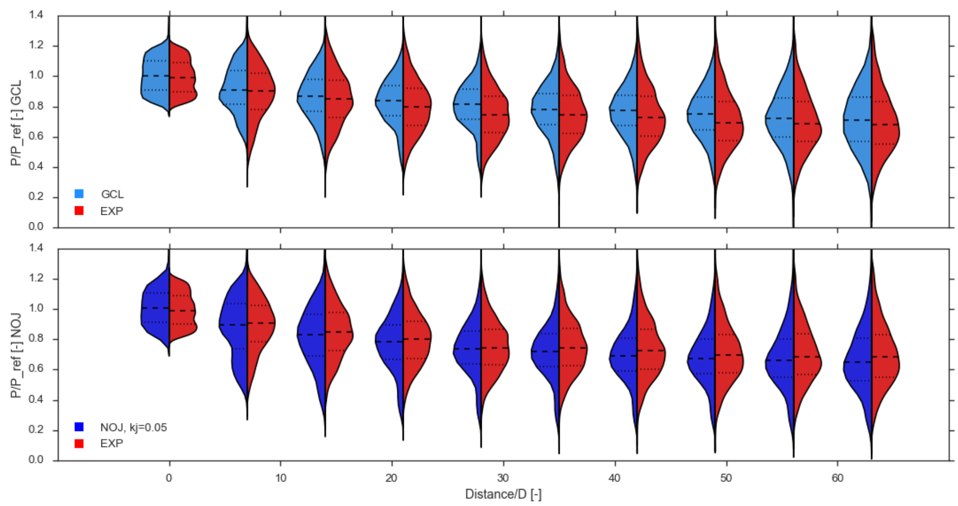

Figure 3: Distribution of power along the row 7 (T07,...,T97) in Horns Rev 1.

Finally the distribution of power along the wind direction sector is presented in figure 4. From this results the model error can be computed as a function of wind direction. The same process needs to be repeated for different wind speed ranges, and for each of the wind direction quadrants in order to have the stationary wake model error as a function of both wind direction and wind speed.

4 Conclusions

It can be concluded that simple stationary wake models can capture the power production variation of individual turbines even in complicated wind power plant layouts. In order to properly model the non-stationary phenomena it is required to consider the spatial and temporal variation of the undisturbed local wind direction and wind speed. The temporal variation can be included in the stationary model by Gaussian averaging the model results as proposed by Gaumond (2013). This correction will reduce the over-prediction of the power deficit when the main flow direction is align to the rows of Horns Rev 1. Note that this correction is

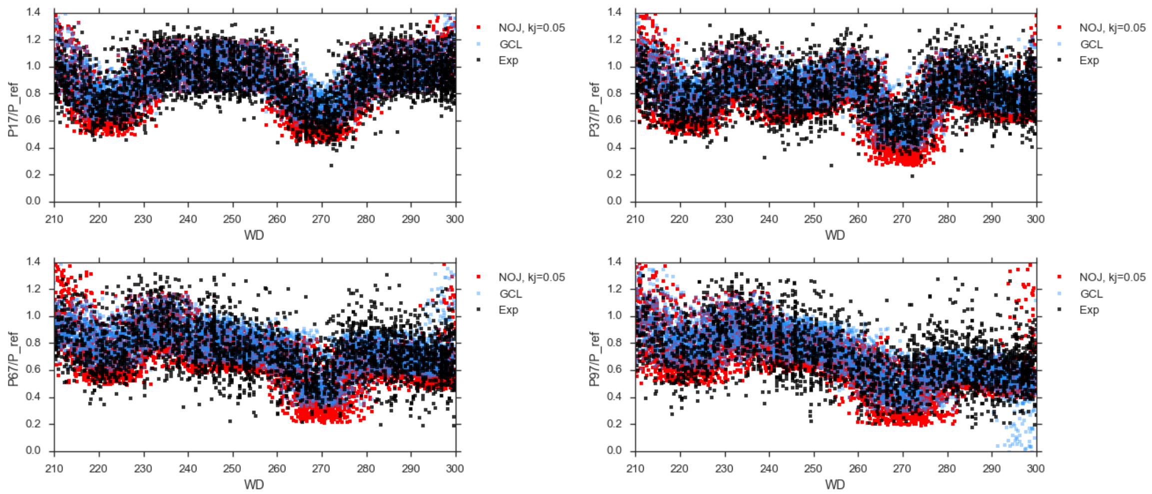

Figure 4: Distribution of power along the row 7 (T07,...,T97) in Horns Rev 1 as a function of spatial averaged wind direction.

necessary because in real flow conditions with wake meandering it is very unlikely that the wind direction will be constant and aligned throughout the entire wind power plant. On the other hand, wind speed variation and spatial variation of wind direction can be used to capture the variation in power production. From these results the distribution of model prediction error (model inadequacy) as a function of both wind speed and wind direction can be studied.

5 Learning Objectives

The present article has the following objectives: (1) To introduce a framework for wind farm flow model validation. This work includes the procedure to treat a wind power plant dataset such that it can be used to quantify the model inadequacy for stationary wind farm flow models. (2) To show the process of input variable elicitation in the case of wind farm flow model validation. (3) To show how simple Monte Carlo propagation can be used to predict individual turbine power production variation inside a wind power plant. (4) To introduce a method to compute the wind farm flow model inadequacy as a function of the undisturbed flow variables.

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