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Wind turbine power curve modelling using artificial neural network

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ABSTRACT

Technical improvements over the past decade have increased the size and power output capacity of wind power plants. Small increases in power performance are now financially attractive to owners. For this reason, the need for more accurate evaluations of wind turbine power curves is increasing. New investigations are underway with the main objective of improving the precision of power curve modeling. Due to the non-linear relationship between the power output of a turbine and its primary and derived parameters, Artificial Neural Network (ANN) has proven to be well suited for power curve modelling. It has been shown that a multi-stage modelling techniques using multilayer perceptron with two layers of neurons was able to reduce the level of both the absolute and random error in comparison with IEC methods and other newly developed modelling techniques. This newly developed ANN modeling technique also demonstrated its ability to simultaneously handle more than two parameters. Wind turbine power curves with six parameters have been modelled successfully. The choice of the six parameters is crucial and has been selected amongst more than fifty parameters tested in term of variability in differences between observed and predicted power output. Further input parameters could be added as needed.

1. Introduction

Wind power plant operators generally focus their efforts on two main objectives: minimizing operational expenditure (OPEX) and maximizing the revenues (through energy output) of their assets. While the first objective is primarily a question of administrative optimization, the second involves more technical fields of expertise such as preventive, predictive (condition-based monitoring), and corrective maintenance. In each of these processes, maximization of energy outputs involves the use of power performance evaluation tools followed by diagnostics and corrective actions. Therefore, wind power plant operators require daily access to efficient power performance evaluation methodologies. Methods with lower level of errors will enable faster detection of wind turbines exhibiting underperformance issues.

Recent efforts were mainly oriented toward the improvement of actual power performance evaluations in a warranty context where the focus was placed primarily on ensuring a high level of repeatability between turbines not necessarily located in similar environments. The IEC 61400-12-1 [1] is the mostly prescribed method for power performance evaluation of wind turbines. Attempts using discrete [1–5], parametric [6,7], non-parametric [7–9], or stochastic [10–12] models have also been developed in this context. These methods have shown some difficulties in incorporating multiple inputs (parameters) simultaneously. Experiences have also shown that these methods are also inapplicable in the day-to-day context of operators. This is due to the fact that the stringent criteria's involve in a warranty context (i.e. meteorology mast's location, topographical effects, obstacles, wakes, etc.) are inapplicable to the vast majority of wind turbines that operators need to manage.

In order to more appropriately address wind turbine operators' needs, this work focused on the reduction of scatter for site-specific wind turbine power curve evaluations (also known as Type A uncertainty). Because this method is mainly based on nacelle anemometry, it need less stringent criteria that the one specified in the IEC 61400-12-1 standard. The following sections describe the various steps that have been followed in the elaboration of Artificial Neural Network (ANN) modeling technique using multiple parameters simultaneously. A comparison of these results with other types of models is also provided herein.

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2. Wind turbine power curve modelling

Several attempts using, discrete, parametric, non-parametric, or stochastic methods have been made to improve wind turbine power curve modelling. However, nearly all of these attempts were conducted in a warranty context with the consequence that the main focus was on improving the power curve repeatability independently of site-specific conditions. The present study concerns site-specific power curve modelling where the emphasis is placed on the reduction of both the absolute and random errors. In this context, the conditions for elaborating the power curve are therefore considerably less stringent. The next sections synthesize the review of literature that has been completed on wind turbine power curve modelling.

2.1. Discrete methods

Discrete methods consist of modelling a continuous process with discrete approximations. The IEC 61400-12-1 and IEC 61400-12-2 standards [1,2] use this type of method. In these standards, all wind speeds are discretized in 0.5 m/s bins. Power output is then modelled according to these discrete inputs. In these power performance evaluation techniques, wind speed at hub height and air density are implicitly considered the only relevant input (independent) variables; power is the output (dependant) variable. Frandsen [4] and Albers [5], amongst others, mention that other parameters could significantly affect the power curve evaluation if not taken into account. With the objective of producing power curves that are repeatable and independent of the turbulence intensity characteristic, Kaiser [13] and Albers [14] propose alternative adjustment methodologies. Kaiser used the Taylor series expansion in order to linearize the relationship between the power output of a turbine and the incident turbulence intensity at hub height. More recently, Albers proposed a turbulence intensity normalisation algorithm. Experimental results [3,5,15–18] have also demonstrated the impact of wind shear on the power performance of wind turbines. Wagner [19], using higher-than-hub-height towers, have demonstrated that using an increased number of wind speed measurement points significantly improves the correlation between wind input and power output.

2.2. Parametric methods

Parametric models are built from a set of mathematical equations that include parameters that must be adapted through a set of continuous data. Parametric methods generally use linear, non linear, polynomial or differential equations to name a few. The parameters present in these equations are generally determined through standard regression methods like error minimisation and maximum-likelihood. Numerical methods can also be used to establish the parameter's value. The shape of the wind turbine power curve has inspired some author in their choice of parametric models. Sainz [6] compares the use of polynomial and exponential parametric models to evaluate wind turbine power curves. Kusiak [7], through genetic algorithm, also compares power curves with a 4-parameter logistic function.

2.3. Non-parametric methods

With the recent arrival of powerful database tools that allow the archiving of tremendous amounts of data, new modelling methods have emerged. Instead of assuming a physical or analytical relationship between the input and output data, the non-parametric methods establish a correlation based only on the data provided. This is why these methods are called “learning methods”. In 2009, Kusiak [7] studied learning method using data mining techniques such as MLP, M5P tree, Random forest, Boosting tree and k-NN to model power curves. He concluded that the k-NN method represented the method ensuring the highest precision. Li [20], Kusiak [7], and Carolin [9] developed an ANN with the objective of forecasting the power output of wind power plant. Very few authors have used ANN to model wind turbine power curve in the context of power performance validation. To the author's knowledge, none of them ever modelled a power curve with more than three inputs simultaneously.

2.4. Stochastic methods

Anahua [21], Boettcher [22] and Gottschall [12] present several papers related to the stochastic analysis of wind turbine power output and wind speed. They use the Markov chain theory to elaborate the power curve of wind turbines. The Markov chain analyzes the dynamical behaviour of a system (wind turbine) with respect to a stochastic signal or input (turbulent wind speed). This method resulted in power curves that are independent of the turbulence intensity level. While this method has the advantage to enable a wind turbine power curve within a few days, it has the disadvantage that no other parameter than wind speed and TI are taken into account. This disadvantage makes these types of models inapplicable in the long term operation context.

3. Database description

Data from two operational wind power plants located in Nordic and complex environments were used for this research. An advanced data acquisition system directly connected to the turbine controllers was used to gather data over a period of approximately one year from more than 140 wind turbines. Data from 80 m IEC 61400-12-1 meteorological masts (met masts) installed in proximity to the tested turbines on each site have also been acquired. Fig. 1 and Fig. 2 represent the general set-up of the two experimental wind turbines used in this study.

For each turbine, over 100 parameters were archived, including power, meteorological data, operational data, vibration, temperature of components, turbine status. For the met masts, meteorological parameters at different measurement levels (40 m, 50 m, 60 m, 70 m and 80 m) were acquired. Though the data were recorded and logged at a high sampling frequency (1 Hz), the standard 10-min averages were calculated and used in this work.

3.1. Data pre-processing

As the volume of collected data is substantial, errors caused by sensors or the data acquisition system are possible. For example, out-of-range values, missing data due to turbine availability and/or electrical shut-down or corrupted data due to icing events are possible incidents that would require the removal of recordings from the data set. Multiple quality control algorithms were used [23]. Additionally, a filtering technique similar to the one used by Kusiak [7] was used to remove remaining outliers. Site-specific adaptation of the statistic Tukey criteria [24] were implemented.

Furthermore, data corresponding to directional sectors prone to wake effects on the tested turbines were not retained for analysis. Figs. 1 and 2 illustrate the valid wind direction sectors in order to avoid wake effect. These sectors were widened compared to the IEC 61400-12-1 standard.

The low recovery rates (5.6% and 35.2%, see Table 1) are mainly due to the removal of data that were not in the valid wind direction sectors as defined in the norm IEC 61400-12-1. This is done in order to remove all operating data corresponding to wake operation.