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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.

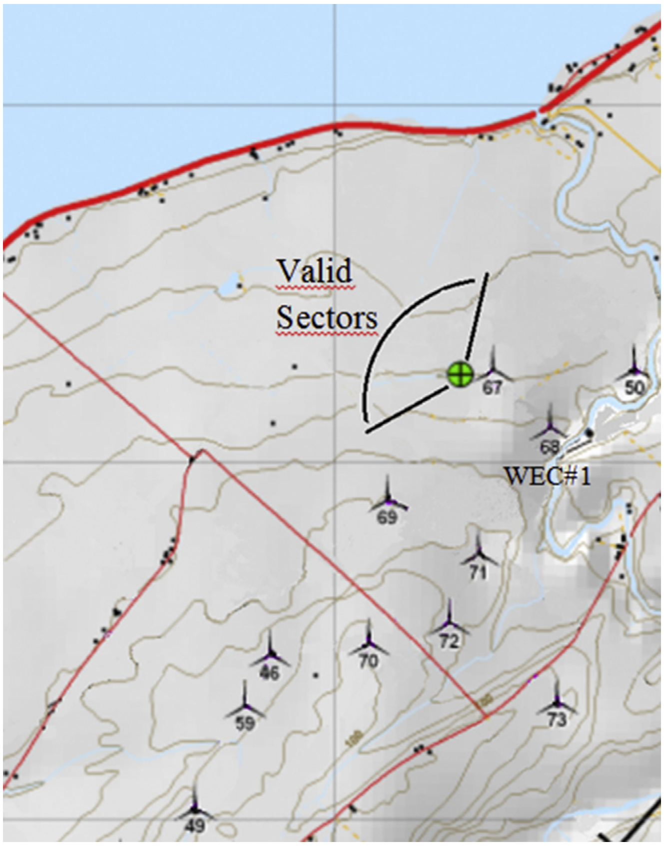

Fig. 1. Layout – Site no. 1.

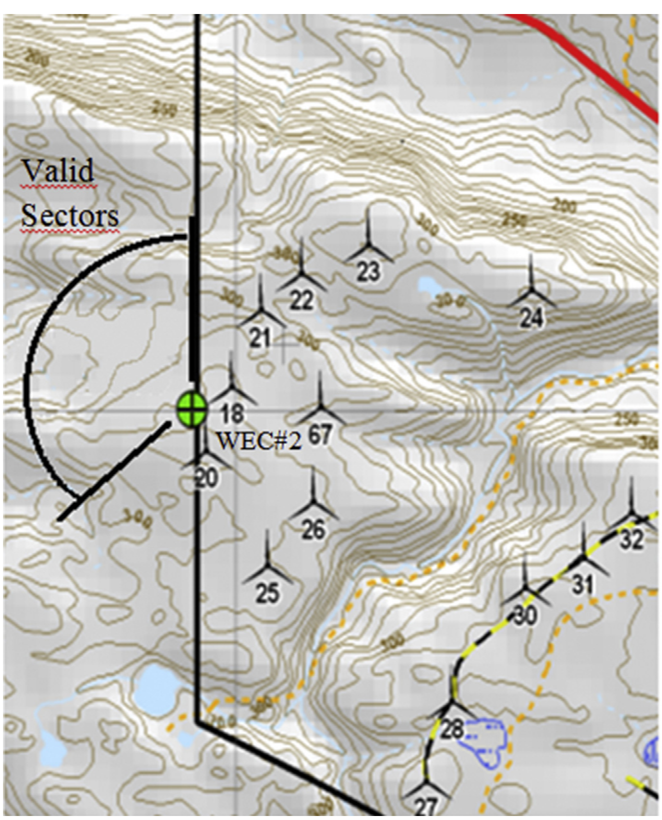

Fig. 2. Layout – Site no. 2.

3.2. Derived parameters

Several parameters used in the model were derived from primary data, including air density ρ, turbulence intensity (TI), and wind shear. Wind shear metrics can be based on analytical wind vertical distributions such as the logarithmic profiles or power law:

$$U(z) = \frac{u^*}{K}\ln\left(\frac{z}{z_0}\right)$$

$$U(z) = U\left(z_{ref}\right)\left(\frac{z}{z_{ref}}\right)^{\propto}$$

where U is the horizontal component of the wind velocity, z is the height with respect to the ground level, u^* is the friction velocity, K is the von Karman constant, z_0 is the roughness length, α is the exponent for the power law, and the subscript *ref* is related to properties at a reference height. Definition of TI can be found in Ref. [1].

Since multiple metrics for the wind shear parameter are possible (e.g. thermal stability metrics, roughness length z_0 based on logarithmic profile, shear exponent α based on the power law, numerous definitions of equivalent wind speeds or vertical gradient, etc. [3]), investigations were conducted to identify the most relevant metric for this parameter in the context of this work. Following these investigations, it appeared that the most appropriate metric to define wind shear is the wind speed gradient evaluated between the 40 m and 80 m heights.

3.3. Database re-sampling

Because 1 Hz data were archived in the database used in this work, it was possible to generate numerous 10-min averaged sets separated by a time delay [25]. A 2-min delay was chosen since time constant of the wind turbines is in the order of 45 s. This 2-min delay thus ensures that all 10-min data are seen as mutually independent by the turbine controller. A static model (as opposed to a dynamic model) can then be assumed. Because ANNs are prone to over-fitting, this 2-min delay, which enables a five-fold increase in the database, is considered an appropriate method to lower this risk.

3.4. Correlation analysis

As it is generally agreed that thermal stability has simultaneous effects on both TI and wind shear values, a correlation between these two parameters is usually assumed [3,5,26–28]. Since a significant correlation between parameters has impact on the modelling quality of a process, a correlation analysis on several parameters was completed. Study was conducted for several 1 m/s wind speed bins. Fig. 3 illustrates an example of the matrix plot for the 3–4 m/s bin at Site no.1. Such illustration of the correlation study is extensively used in statistical analysis and a detailed description can be found in Ref. [29]. As can be seen in this figure, no evident and significant correlation was identified, which indicates a poor relationship between the investigated parameters. The same conclusion was drawn for other wind speed bins and turbine.

This absence of significant correlation between TI and wind shear is potentially attributable to the sites' topographical complexities and surface roughness. The two sites wind regimes are probably more driven by synoptic patterns than by thermal effects. This finding enables the separate modelling of TI and wind shear and all other parameters without the risk of inappropriately

Table 1
Data sets description for WEC1 and WEC2.

	Start time stamp:	End time stamp:	Complete data set: [# 10-min data]	QC data set: [# 10-min data]	% of complete
WEC#1	2009/03/24 13:30:00	2010/01/31 23:48:00	225 796	12 832	5.6
WEC#2	2009/05/01 14:20:00	2010/02/19 01:28:00	218 880	77 131	35.2

considering their mutual dependence. Such an approach greatly facilitates the modelling process and enhances its repeatability.

4. ANN modelling elaboration

Because (i) a sufficient quantity of data has been acquired, (ii) the interaction between the inputs and the output of a wind turbine model (power curve) is non-linear, and (iii) analytical solutions to the impact of many parameters could not be found, ANN seemed to be a logical technique for modelling the power curve of a wind turbine. A feed forward neural network (also known as a multilayer perceptron (MLP)) [30] with back propagation algorithm was therefore implemented using a multi-stage technique (see Fig. 4). Two-layer MLPs with tansig and linear activation functions have been used. This type of topology is known to be a universal approximator [31]. Therefore, the topology elaboration only requires the number of nodes in the first layer to be established. The quantity of nodes in the first layer up to 100 nodes was tested and showed that 4 nodes in the first layer gives the best compromise between the model's precision and the over-fitting risk [31].

The multilayer perceptrons can generally incorporate the number of inputs desired. However, the greater the number of inputs, the greater the number of data necessary to avoid over-learning; moreover, the validation methods used to ensure that

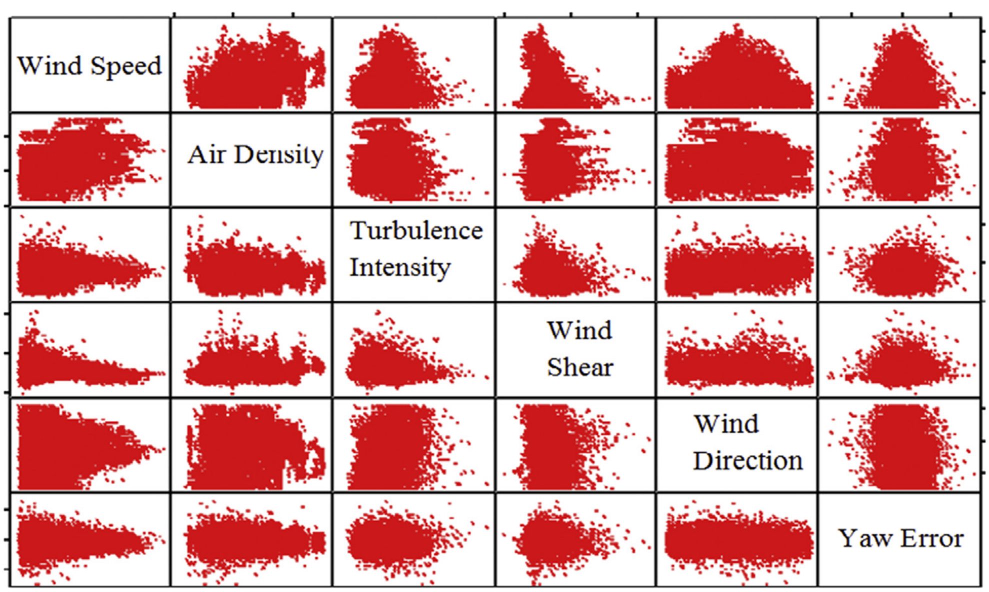

Fig. 3. Typical example of matrix plot for 3–4 m/s bin (Site no.1).

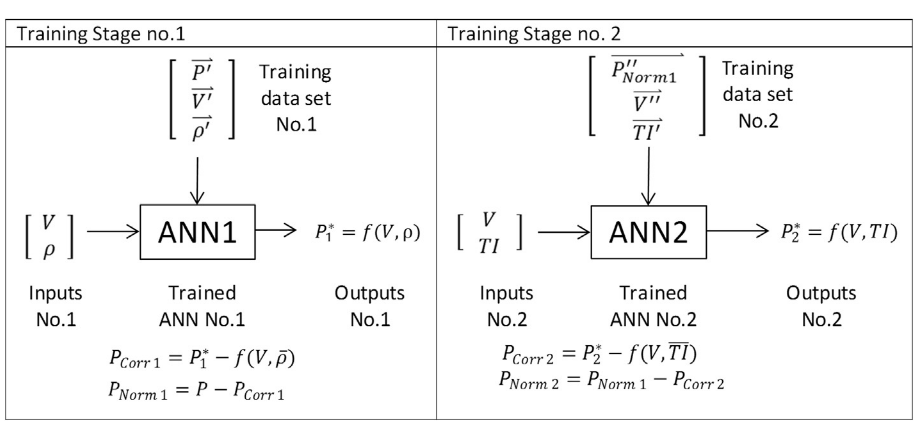

Fig. 4. Multi-stage modelling technique.

there is no overlearning become more complex. For this reason, and because of the fact that no interaction between independent variables has been found, modelling by means of successive steps – multi-stage modelling – was developed. For example, for the first step, the power output is modelled with the wind speed and air density. Once the converged solution of the first ANN has been obtained, the power is normalised for the average density of the experimental data. A second neural network is then trained with the power data (normalised in air density), wind speed data, as well as the subsequent input (i.e. turbulence intensity in our case). Subsequently, the power is re-normalised and this is continued for all variables deemed to have a significant impact on the wind turbine power modelling. These steps can be repeated as long as relevant variables are available. For example, if in the future the wind field above hub height is characterized (with a LIDAR for example), this parameter could be modelled without having to repeat the entire process. Fig. 4 illustrates the first two stages of the multi-stage ANN training process.

In order to properly model the powers output of a wind turbine, over 50 independent variables (directly observed or derived) from the met mast, neighbouring wind turbines or directly from the reference wind turbine were considered and tested. A stepwise forward selection method [31] was used for the proper selection of the input parameters. For the available data set, it has been found that the 6 input parameters ensuring the lower level of errors of the wind turbine power curves were: nacelle wind speed, air density, turbulence intensity, wind shear, wind direction, and yaw error. These inputs are known to have an impact on the power curve [1].

4.1. Training of the ANN

Because non-parametrical models are data-driven, they are more prone to “learn” from the data, thereby representing a risk of over-fitting. In order to control over-fitting, a 70%-15%-15% random distribution was performed to attribute the data to training, validation and test databases respectively. MLP utilizes a supervised learning technique called back-propagation for training the network. Table 2 shows the training algorithm and stopping criteria used.

Table 2
Stopping criteria.

Training algorithm	Levenberg-Marquardt
# of max iterations	1000
Gradient min	1E-10
Mu min	1E-10
Cross-validation	20 successive iterations

5. ANN model validation

The model validation consisted of a qualitative comparison of the ANN power outputs and Power Coefficient (C_p) against the expected results from the literature. Definitions and equation of the power coefficient can be found in Ref. [1].

Fig. 5 illustrates the overall behaviour of the ANN's normalized power curve (the power output divided by the turbine's nominal power) and C_p as a function of air density, turbulence intensity, and wind shear. The red thin and thick lines represent the behaviour of the normalized power curve and the C_p, respectively, for the averaged value of the investigated parameter (air density, TI or wind shear). The green thin and thick lines represent the behaviour of normalized power curve and C_p, respectively, for a lower value than the averaged of the investigated parameter, while the lines represent the behaviour for a higher value than the average. Black arrows indicate the direction of the evolution of the normalized power curves with increasing values of the investigated parameter (with all other parameters being kept equal). Blue dots represent the 10-min data.

As can be seen from Fig. 5, all normalized power curves obtained using the ANN have a standard (sigmoid) shape and are properly located inside the scatter of 10-min data. No normalized power curves have been found to follow outlier data, giving qualitative indication that the quantities of data and the training method were able to properly control the over-fitting. Cp curves also show typical behaviours. Furthermore, the normalized power curve behaviour as a function of a change in air density as shown in Fig. 5a exhibits a similar evolution as that specified in the IEC 61400-12-1 standard. As air density increases, the normalized power curve shifts to the left, meaning that the Annual Energy Production (AEP) as defined in Ref. [1] will increase with increasing average air density. Fig. 5b also illustrates the impact of turbulence intensity (TI) on the normalized power curve. Again, as demonstrated by several authors [32] [14], the same impact on the power curve is observed in the model results. The 10-min average power output tends to increase with increasing turbulence intensity near the cut-in wind speed and decreases with increasing TI in the transition region to rated power. Lastly, some authors present theoretical [26] [27] and experimental [33] results of the impact of the wind shear on the power curve. Again, ANN results, as shown in Fig. 5c, show similar results to what has been found in the literature, i.e. that higher AEP values are obtained when wind shear is low. These qualitative results provide further indication that over-fitting was properly controlled during the modelling process.

6. Results

Results obtained using the ANN model with six inputs (ANN-6P) and 4 nodes in the hidden layer (ANN-6P)were compared with those generated by parametric (5th and 9th order polynomial functions (Poly-5, Poly-9), double exponential (Dbl exp), logistic (Logistic)), non-parametric (i.e.: k-nearest neighbor regression method (KNN)) and discrete (IEC-12-1, IEC-12-2, Albers' turbulence normalization (Turb Norm)) models. All models used the same two data sets each comprising approximately one year of data. The modelling comparison was largely performed using three different methods: power curve visualisation, error calculations for each wind speed bin and global weighted errors according to a representative Weibull wind speed distribution of the sites.

6.1. Power curve comparison

Fig. 6 shows the power curves obtained with all models for WEC#1. Similar results were obtained for WEC#2. The blue dots represent the 10-min data used to model the power curves. Power curves obtained from each model are illustrated as green dots. In order to compare a unique power curve from each model, air density normalization (for the site average air density) was performed prior to running the models.

In our case and as can been seen in Fig. 6, parametric models (Poly-5, Poly-9, Dbl exp, logistic) have difficulty modelling the power curve over the entire wind speed range (this will be further demonstrated in the next section). The k-NN model and the IEC 61400-12-2 present very similar results. The IEC 61400-12-1 generally exhibits lower repeatability since the dependant variable (wind speed) is taken from the measurements at the met mast which is at a greater distance of the wind turbine compared to all other methods (which are using nacelle anemometer wind speeds which is significantly closer to the turbine). Lastly, Alber's turbulence normalization [5] and the proposed ANN models predict a

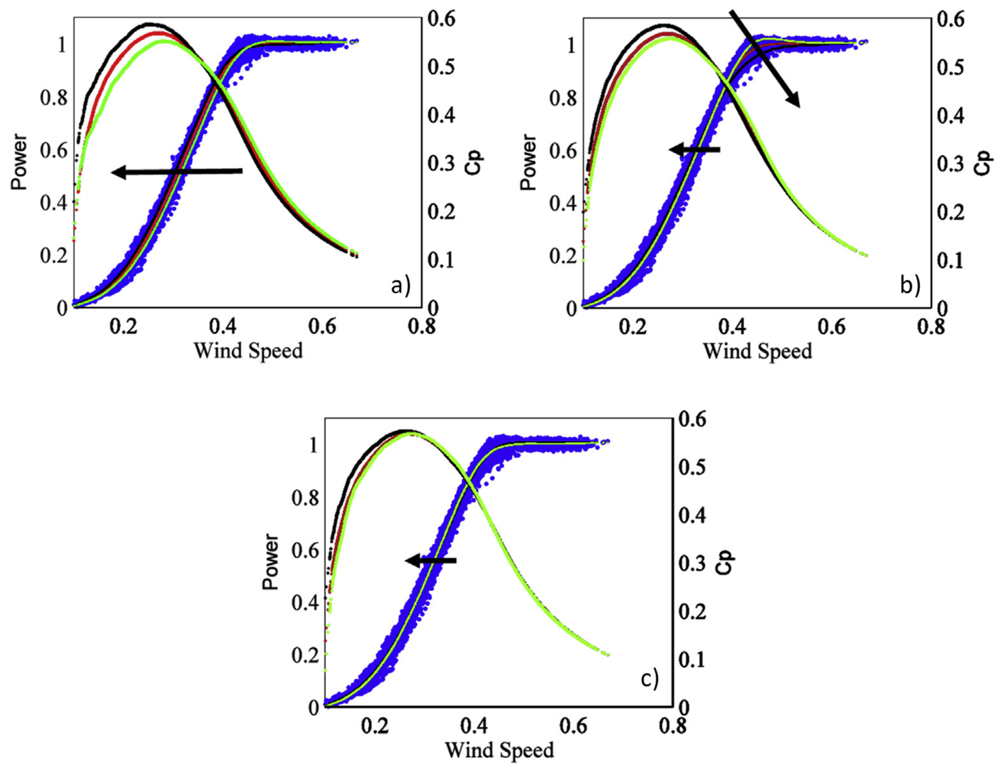

Fig. 5. Impact on power curve and power coefficient (C_p): a) Effect of air density; b) Effect of TI; c) Effect of wind shear.

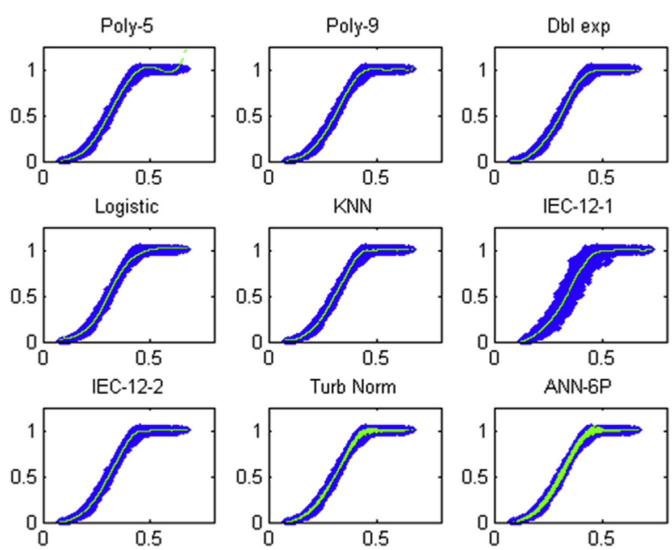

Fig. 6. Wind turbine power curve modelling.

range of power values (rather than a unique power value) for a given wind speed since these two models consider not only wind speed and air density as independent variables but also include supplementary inputs, namely turbulence level for turbulence normalization's model and four non-wind speed parameters (turbulence level, wind shear, wind direction, yaw error) for the proposed ANN model.

6.2. Error calculations for each wind speed bin

In order to compare the performance of the ANN model with the other modelling techniques, error calculations were performed. Two error metrics were used: the mean error (*ME*) and the mean absolute error (*MAE*) have been evaluated according to the following formulae:

$$\varepsilon_i = P_i^* - P_i$$

$$ME = \frac{1}{N}\sum_{i=1}^{N} \varepsilon_i$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |\varepsilon_i|$$

where:

P_i^* is the predicted wind turbine power output in [kW];
P_i is the observed (measured) wind turbine power output in [kW];
ε_i is the residual between the predicted and observed values in [kW]; and
N is the number of 10-min data used for these statistical calculations.

The mean error *ME* is not an absolute measurement of precision as it does not provide information on the prediction errors. For example, a perfect score, $ME \approx 0$, does not exclude that the model is imprecise; rather, it could mean that errors of opposite signs are merely compensating each other. With a significant amount of data, *ME* will provide indications of biases in the model (systematic error). For example, *ME* can indicate if the model is over- or underestimating the phenomena.

The mean absolute error (*MAE*) is a quantity used to measure how close predictions are to the expected value. The *MAE* measures

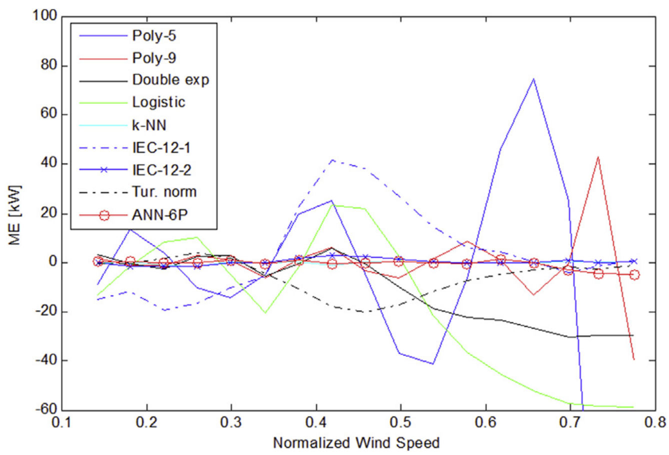

Fig. 7. Mean Error (*ME*) for each normalized wind speed bin (site no. 1).

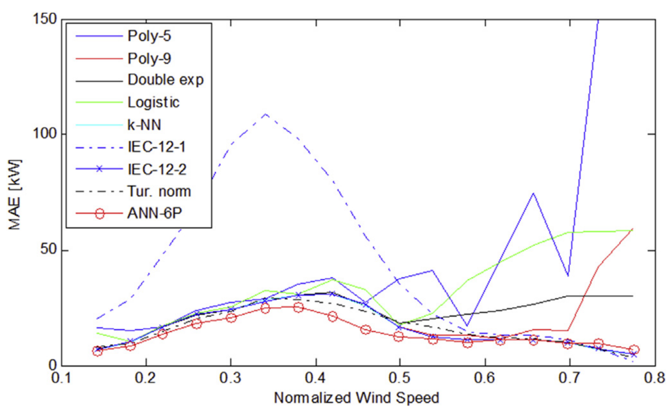

Fig. 8. Mean Absolute Error (*MAE*) for each normalized wind speed bin (site no. 1).

the average magnitude of the errors in a set of predictions, without considering their direction. Therefore, *MAE* provides an indication of modelling level of accuracy.

Because different anomalies may manifest themselves at different portions of the power curve, and because it is critical that power curve modelling be not only sound on the whole but also throughout the entire power curve, calculations were first completed for all wind speed bins of the power curve. Fig. 7 and Fig. 8 illustrate the results obtained for site no. 1 in term of normalized wind speed which is the ratio of the wind speed and the site's annual wind speed.

As demonstrated in Fig. 7, the proposed ANN model (ANN-6P) has a minimum *ME* for almost all wind speed bins. It is also clearly shown that parametric models have important biases for some wind speed bins, especially at higher velocities (at nominal power output). Fig. 8 shows that, for almost all wind speed bins, the proposed ANN model (ANN-6P) gives results with the lower level of errors. Parametric models generally exhibit higher level of errors. The model with the highest level of errors is the IEC 61400-12-1 model. This can be explained by the fact this is the only model were the wind speed is measured at a different location (met mast) as opposed to the other methods which are using wind speed close to the nacelle.

6.3. *Weighted error calculations*

Once calculated for all wind speed bins, the *ME* and the *MAE* were weighed averaged according to site specific Weibull wind speed distribution [34]. Site-specific results are presented in Table 3 and Table 4.

As can be seen in Tables 3 and 4, the proposed ANN model (ANN-6P) shows the lower level of errors for both sites. Furthermore, the proposed ANN is the only model that could incorporate additional inputs (e.g. wind speeds above hub height), which could potentially further improve the model's performance as demonstrated recently by Wagner [27].

7. Conclusion

Artificial neural networks with six inputs have been developed in order to identify an accurate model site-specific wind turbine performance. Results of this modelling technique were compared with parametric, non-parametric, and discrete methods. For the two turbines studied, it has been demonstrated that the strategic incorporation of 6 inputs in a multi-stage ANN modeling technique, the possibility to incorporate further variables as needed and the decrease in the level of errors is able to outperform previously developed models. With further data available (e.g. wind speeds above hub height, wind veer, etc.) more inputs could have been easily added into the model and potential further lower the errors levels obtained. This is rendered possible due to the facts that low interactions between inputs have been found in the two sites considered and that power normalization between each modelling steps is performed. These results demonstrate the potential of the two-layer MLP neural network to properly model the power performance of wind turbines which could be easily used by maintenance application focus on underperformance detection [35]. Furthermore, it has been shown that the choice of the six parameters is crucial and has been selected amongst more than fifty potential parameters tested in term of variability in differences between observed and predicted power output.

Table 3
Modelling error calculations for WEC#1 (Site no.1).

	Poly-5	Poly-9	Double exp	Logistic	k-NN	IEC-12-1	IEC-12-2	Turb. Norm.	ANN-6P
WME	−1.1	0.2	3.3	0.7	0.1	−0.1	−0.3	−2.2	0
WMAE	23.2	19.5	21.1	25.8	18.8	46.9	18.9	17.9	15.3

Table 4
Modelling error calculations for WEC#2 (Site no.2).

	Poly-5	Poly-9	Double exp	Logistic	k-NN	IEC-12-1	IEC-12-2	Turb. Norm.	ANN-6P
WME	−1.9	0	−1.7	−0.3	−1.4	−0.2	−3.9	−3.9	0
WMAE	26.8	20	20.6	19.5	60.4	19.6	18.8	18.8	15.9

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