Evaluation of Parametric and Non-Parametric Methods for Power Curve Modelling of Wind Turbines

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Abstract

The growing applications of wind power systems and their essential roles in renewable energy production require development of accurate methods for their parameter identification such as the wind turbine power curves. This paper evaluates and compares the parametric and non-parametric approaches for power curve modelling of wind turbine which is a very complicated and nonlinear function of different mechanical, electrical and metrological input parameters. In fact achieving a complete model that can accurately describe the turbine output characteristic is very difficult. However, there are different modelling techniques that could lead to have a better estimation of turbine generation model. In this paper, four different algorithms for modelling the output power of wind turbines in form of two strategies using two case studies will be developed and the results of different models will be compared.

1. Introduction

Global interest in replacing fossil fuel energy sources with clean and renewable energy sources have introduced new areas of research and development for more efficient implementation of renewable energy in the traditional energy market and make them competitive in comparison to the fossil energy resources.

Wind energy is one of the most economic sources of renewable energies with very complicated and nonlinear characteristics. One of the most important issues with the wide usage of wind energy is difficulties in predicting the power generation of wind farms. Power curve models can be used for different proposes such as forecasting the output power of wind turbines, studying the effects of aging on turbine output, planning maintenance schedules and performing feasibility studies for wind farms, as well as simulating the planned extension of existing wind farms. Metrological parameters like wind speed could be predicted by forecasting techniques for future periods and consequently, an accurate power curve estimates the output of turbine based on forecasted inputs. Several researches has been conducted for modelling the wind turbine power curve, generally these researches could be divided into three main categories; i) parametric modelling, ii) non-parametric modelling and iii) probabilistic modeling.

Parametric models try to find a mathematical relationship between the input and output parameters of wind turbine. Different curve fitting and regressions techniques has been employed for parametric models including liner regression models, polynomial regression, logistic regressions and weighted polynomials regression [1-5]. Unlike parametric methods, non-parametric models do not look for a mathematical relationship between the outputs and inputs by establishing a model and train it in a way to minimize the deviation between observed data and outputs. Neural networks, fuzzy-clustering centers, random forest and data mining methods are samples of non-parametric methods [1-5]. These techniques are usually less sensitive to outliers in the observation data, more flexible, and do not have the global error penetration problems that most parametric models suffer from [3]. The idea of probabilistic model is based on the fact that for each wind speed value, the output of wind turbine is a random variable which is symmetrically distributed over the mean power value at that speed with a standard deviation of σ_ϵ. In fact the actual output power can be considered to be a random variable [1].

This paper will simulate, analyze and compare the results of three parametric (conventional liner regression, conventional polynomial regression and robust polynomial regression) and one non-parametric (neural networks) methods for modeling the wind turbine power curve. Two case studies will be implemented using the datasets of two different turbines, moreover the effect of power curve segmentation and outlier filtering will be studied.

2. Problem Formulation and models

Wind turbine power curve is considered to be a nonlinear function of wind speed. Fig. 1 shows a typical power curve which is usually provided by the turbine manufacturer [6]. This power curve could be characterized by three different wind speed levels, $V_{cut\text{-}in}$ is the speed which the wind turbine starts to operate; the speeds lower than this value cannot spine the wind turbine blades. $V_{cut\text{-}out}$ is the highest designed speed for the safe operation of wind turbine; at speeds higher than this value the turbine shall be locked. V_{rated} (V_r)is the speed that the turbine is expected to have nominal output power; in fact the turbine is designed to be mostly operating at this speed. Theoretically, the power that could be captured by a wind turbine is calculated by Bitz formula as follow:

$$\begin{cases} P = \frac{1}{2}\eta C_p \rho A V_w^3 & (V_{cut-in} \leq V_w \leq V_r) \\ P = P_r = \frac{1}{2}\eta C_p \rho A V_r^3 & (V_{rated} \leq V_w \leq V_{cut-off}) \\ P = 0 & (V_w > V_{cut-out} \ or \ V_w < V_{cut-in}) \end{cases} \quad (1)$$

where V_w is the measured wind speed at turbine hub, ρ is the air density *(kg/m^3)*, C_p is power coefficient, η is machine efficiency (mechanical and electrical) and A is the area swept by rotor. In spite of the above formulation and initial power curve which is usually provided by turbine manufacturer, the real (actual) output power of wind turbines vary by different parameters such as geographical and metrological situation of the site, efficiency of electro-mechanical parts of turbine which significantly changes by the time and aging, etc. Fig. 2 shows the scatter diagram of real data measured for a typical wind turbine working in real site condition versus theoretical power curve submitted by manufacturer [7].

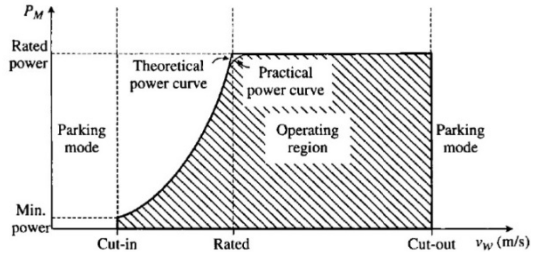

Fig. 1. A sample power curve provided by manufacturer [6]

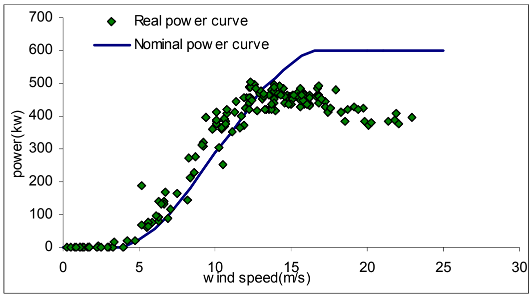

Fig. 2. Real power measured versus the manufacturer curve [7]

As discussed in the previous section, different parametric and non-parametric methods for power curve modelling will be implemented to existing data sets as mentioned below:

2.1 Linear Regression Models

Regression analysis is the part of statistics that deals with investigation of the relationships between two or more variables related in a non-deterministic fashion [8]. For example, the power curve of a wind turbine can be modelled as a straight line:

$$\hat{P}_i = \beta_0 + \beta_1 V_i + \varepsilon_i \qquad (2)$$

where, $\hat{P}$ is the output power of turbine, V_i is the measured wind speed, ε_i is the deviation between the real and estimated values which is a random variable with $E(\varepsilon) = 0$ while $Var(\varepsilon) = \sigma_\varepsilon^2$, β_0 and β_1 are intercept and slop of the regressions model, respectively [9].

The least square method will be used for minimizing random deviations (ε_i) using the following objective function:

$$f(\beta_0, \beta_1) = \sum_{i=1}^{n} (P_i - \hat{P}_i)^2 \qquad (3)$$

where, P_i is measured value of power, $\hat{P}_i$ is power estimated by model and n is the number of observation points. β_0 and β_1 will be calculated based on minimizing Eq. 3.

2.2 Polynomial Regression

According to Bitz formulation (Eq. 1), the following 3rd degree polynomial can be used as a basic model close to the ideal situation of wind power:

$$\hat{P}_i = \beta_0 + \beta_1 V_s + \beta_2 V_s^2 + \beta_i V_i^3 + \varepsilon_i \qquad (4)$$

Again the set of parameters $[\beta_0\ \beta_1\ \beta_2 \beta_3]$ will be calculated based on the least square method.

2.3 Robust Regression

Linear regression models are based on the normal distribution of residuals in the observed points. In real situation, the dispersion of observed data over the mean is not symmetrical and there are different anomalies and outliers within the data; therefore, using robust techniques could lead to better performance in the model. Robust regression works by assigning a weight to each data point. Weighting is done automatically and iteratively using a process called iteratively reweighted least squares. In the first iteration, all points are assigned equal weights and model coefficients are estimated using ordinary least squares. At subsequent iterations, weights are recomputed so that points farther from model predictions in the previous iteration are given lower weight. Model coefficients are then recomputed using weighted least squares. The process continues until values of the coefficient estimates converge within a specified tolerance [10].

2.4 Neural Network

The neural network (NN) is a powerful tool in parameter estimation and curve fitting using the historical data of the system under review. Each neural network is established by layers of different neurons which interconnects each layer to the next layer, a feed-forward neural network is a nonlinear function of it's inputs which is the composition of the function of it's neurons, neuron is a nonlinear, parameterized, function that could be modelled by below function [11]:

$$Net_j = \sum_{i=1}^{n} x_i \times w_{ij} + bi \qquad (5)$$

where x_i , w_{ij} and b_i are the input of neuron i, weight matrix between neurons i and j and the bias vector for that layer respectively. The base model for a layer of neurons has been introduced in Fig. 3.

The NN used in this research is a feed forward perceptron neural network. Perceptron networks generated great interest due to their ability to generalize from the training vectors and learn from initially randomly distributed connections.

The Perceptron structure that used in this paper, consist of three layers, one input layer including three neurons with liner filtering function, a hidden layer with six neurons including a sigmoid filter function (*tansig(x)*) and finally one layer in the output with liner filter function. The structure of perceptron neural network is shown in Fig. 4. The method which will be used for learning of FNN is called the resilient back propagation (RBP) [11].

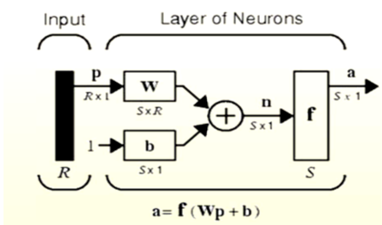

Fig. 3. Base model for a layer of neurons [11]

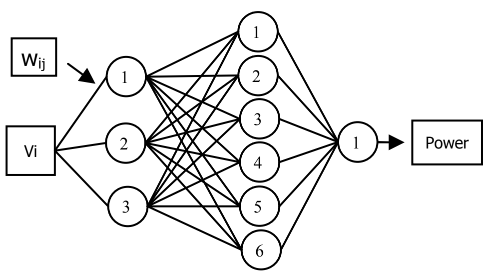

Fig. 4. Structure of perceptron neural network

Considering the nonlinear nature of turbine power curve, this paper will divide it into two sections and try to allocate a separate model to each section. For each model, the power curve section between $V_{cut\text{-}in}$ and V_r will be modelled with one function while the remaining parts between V_r and $V_{cut\text{-}out}$ will be modelled with another function. This strategy will be discussed in the following sections in more detail.

3. Data Sets and Data Preprocessing

The farm selected as a case study is the Norrekaer Enge II wind farm with 42 turbines and two metrological station (Mast#1,2) within the farm for measurement of wind speed and direction in different heights [7]. A set of data for a period of one year is used for development of power curve models. The database consists of wind speed/ direction of two masts and wind speed and output power of each turbines in the farm. Time interval for data logging is 10 minutes. For all simulated methods, 2/3 of data sets for one year has been used for developing the model and training proposes, while the remaining data has been used for verification proposes and testing the performance of developed models.

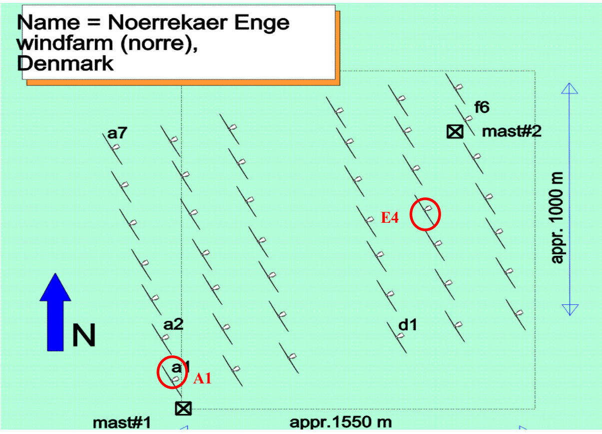

Fig. 5. Layout of turbines in the Farm [7]

3.1 Filtering Measured Data

Considering the fact that the quality of data is an important factor in converging the model residuals and also to achieve better training of the model, this paper applies some filtration and pre-processing methods to reduce the effect of anomalies and outliers in the measured data. As a first step the values lower than $V_{cut\text{-}in}$ and higher than $V_{cut\text{-}out}$ were removed from data sets, in the next stage for segmented methods (second Strategy), standard deviation of measured power values were calculated and according to below criteria the outliers were reduced:

- For segment one, σ_1 was equal to 73, then for each wind speed the measured power values which were farther than $0.5 \times \sigma_1$ from the mean values of power at that wind speed were removed from data sets.
- For segment two, σ_2 was equal to 15, then for each wind speed the measured power values which were farther than $3 \times \sigma_2$ from the mean of power at that wind speed valves were removed from data sets.

4. Simulation Results and Discussions

This section presents the simulation results of power curve modelling methods presented in section II. The methods were implemented using data sets of two wind turbines A_1 and E_4 as two different case studies, moreover two different strategies (segmented and non-segmented) were used.

In the first strategy, the models were built based on the whole range of each datasets while in the second strategy the data sets were segmented into two subsets, data points lower than rated wind speed and higher than the rated wind speed (V_r=*16 m/s*), two sets of different models were developed for each segment.

Turbine A_1 as the first case study is located in the south-west corner of wind farm, exactly exposed to wind flown from south west [7]. As seen from Figs. 6-7, the non-segmented models were fitted properly to the linear part of the power curve; however for the speeds higher than the rated speed, models did not follow the measured data properly as they had mostly been affected by the linear part of datasets.

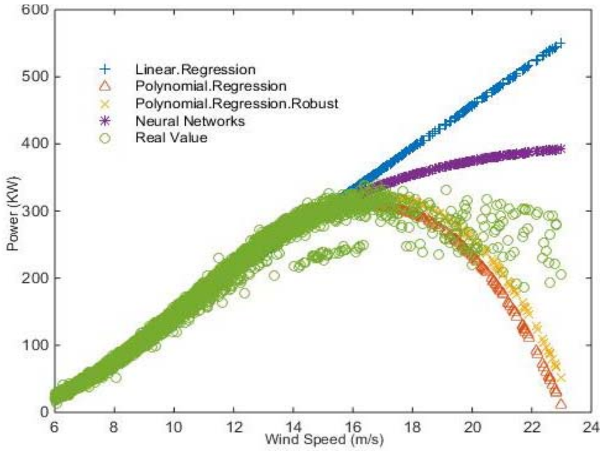

Fig. 6. "A1", non-segmented modelling versus measured data

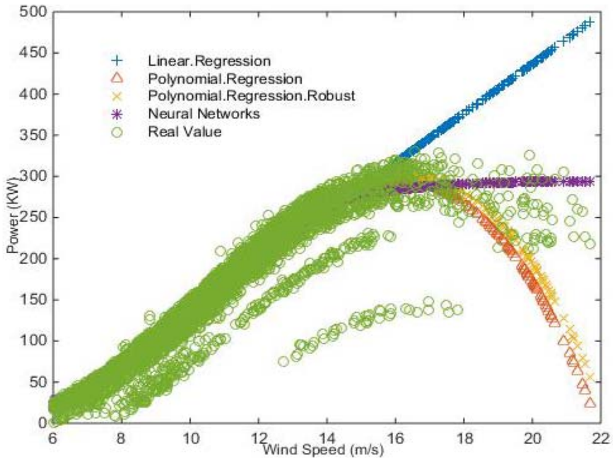

Fig. 7. "E4", non-segmented modelling versus measured data

To demonstrate the effect of outliers, they were not filtered in non-segmented models. The randomly dispersed green points in Figs. 6-7 are samples of outliers. Comparing these figures will explore another important issue; E4 which is located in the middle of the farm and surrounded by different turbines has more outlier data in comparison to A1 which is located in the corner. This shows the effect of location and could be explained as the disturbance and turbulence made by other turbines surrounded the turbines like E4.

In the second strategy, the power curves were divided into two segments, section one included the data below the rated speed (16 m/s) and section two included the measured power data higher than the rated speed. For each section, different sets four parametric models and one nonparametric model were developed. Figs. 8-13 show the results of different models for turbines A1 and E4. As it can be seen, fitted models tried to follow the data sets in each section individually. This tendency was more sensible in conventional regression models which suffer more from their global nature.

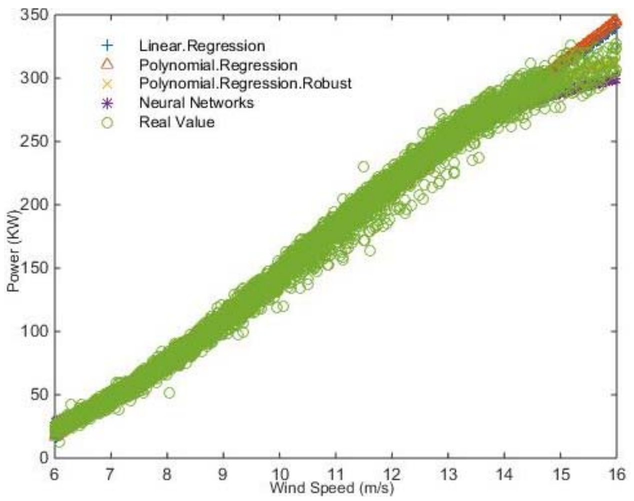

Fig. 8. “A1”, Segment 1 Modelling versus real power

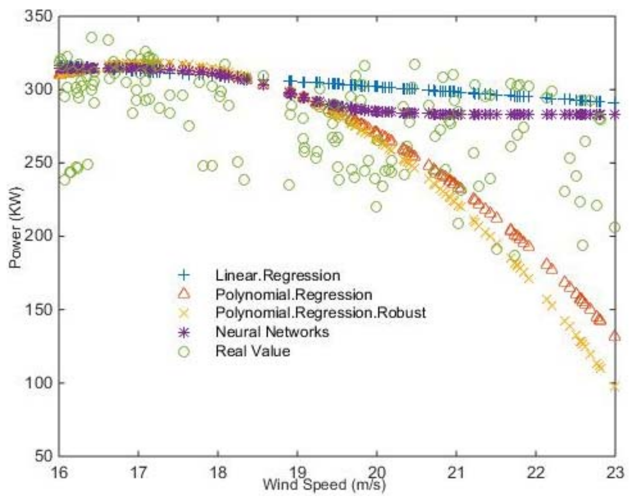

Fig. 9. “A1”, Segment 2 Modelling versus real power

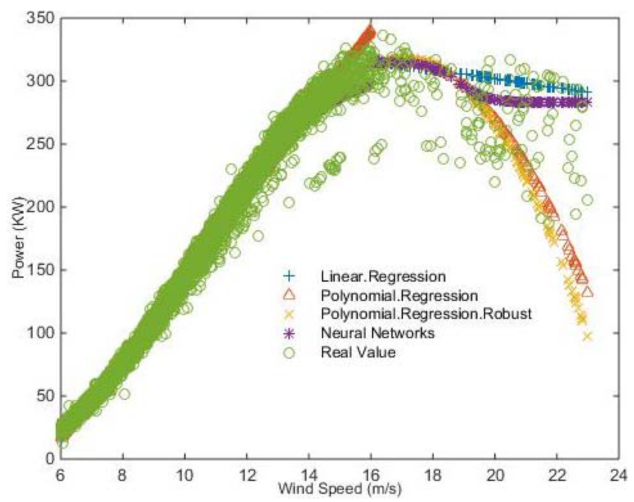

Fig. 10. “A1”, both segment models combined versus real power

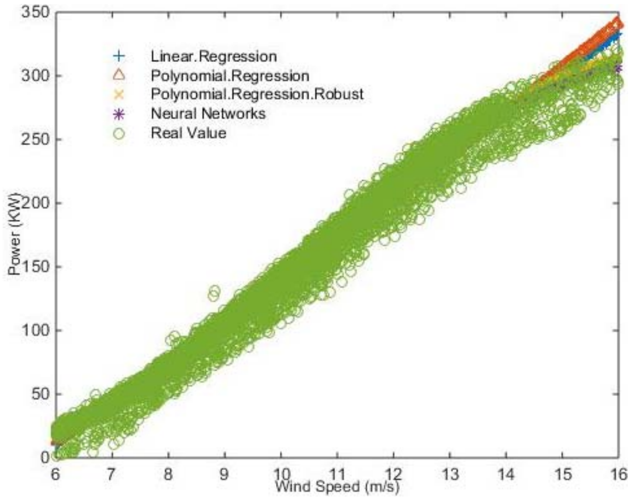

Fig. 11. “E4”, Segment 1 Modelling versus real power

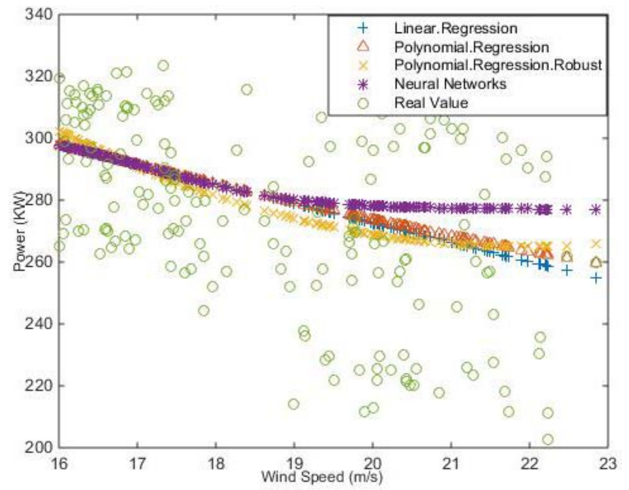

Fig. 12. “E4”, Segment 2 Modelling versus real power

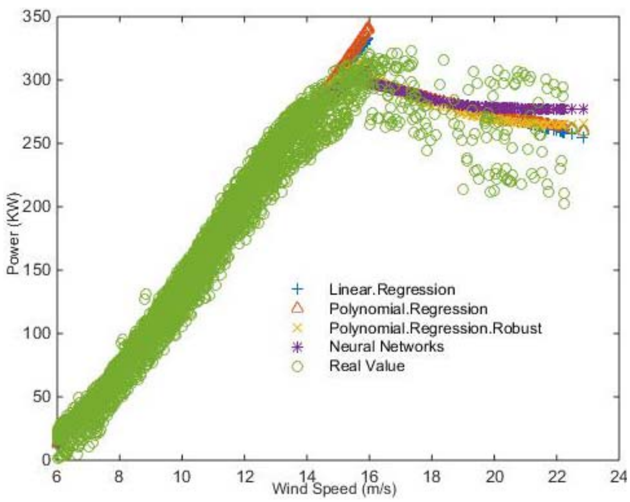

Fig. 13. “E4”, both segment models combined versus real power

Table I. Error results of fitting models

	Segmented Models						Non-Segmented Models					
	Turbine A1			Turbine E4			Turbine A1			Turbine E4		
	MAPE (%)	MAE	RMSE	MAPE (%)	MAE	RMSE	MAPE (%)	MAE	RMSE	MAPE (%)	MAE	RMSE
Conventional Linear Regression	5.86	6.18	9.54	9.49	7.22	10.36	6.87	9.53	25.59	13.39	12.76	26.96
Conventional Polynomial Regression	5.81	6.27	10.47	8.70	7.05	10.52	6.87	7.31	13.36	11.19	9.70	21.30
Robust Polynomial Regression	4.02	4.70	10.49	6.89	5.96	9.59	4.17	4.93	11.58	11.18	9.62	20.94
Neural Networks	4.47	4.78	8.05	7.22	6.03	9.57	5.05	6.40	14.97	12.65	10.14	19.47

Three different error criteria were deployed to evaluate the simulation results for power curve modelling. These include mean absolute error (MAE), root mean squared error (RMSE) and mean absolute percentage error (MAPE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|P_i - \hat{P}_i\right|$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - \hat{P}_i)^2} \qquad (6)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|P_i - \hat{P}_i\right|}{P_i}$$

where, P_i is measured value of power, $\hat{P}_i$ is power estimated by each model and n is the number of observation points. Table I presents the error values in detail for two case studies (Turbine A1, E4), with four different methods as described in section II, considering non-segmented and segmented power curve strategies.

Generally, segmented models showed better response to fitted models in comparison to the non-segmented models. This could be proved by comparing the three different error values for both case studies. The difference between error values in non-segmented and segmented strategies were more sensible in case two (E4) compared to case one (A1) as outlier dispersions were more governing the fitting models rather than valid measured data.

5. Conclusion

This paper has evaluated parametric and non-parametric methods for power curve modelling of wind turbines through detailed simulation and analysis. Three parametric models (including conventional liner regression, conventional polynomial regression and robust polynomial regression) and one non-parametric model based on feed-forward neural network were explained and implemented in two case studies (using data sets of A1 and E4) considering two different segmented and non-segmented strategies. Simulation results were also used to investigate the effect of outliers on the developed models. The main conclusions are:

- By considering non-segmented models as a bench mark of previous researches done with similar techniques, the results of methods developed in this paper were far more improved in comparison to the previous works, this was achieved by power curve segmentation, filtering outliers and using more robust techniques for modeling.
- Robust Polynomial regression between the parametric methods and neural network as a non-parametric model had the lowest error results (less than 5%).
- The segmented models showed better response to fitted models rather than non-segmented models.
- The difference between error values in non-segmented and segmented strategies are more sensible in case two ("E4") compared to case one ("A1") as outliers dispersion were more governing the fitting models rather than valid measured data.

Our future research will aim to identify more parameters engaged with output power of wind turbines and also study their effect on the accuracy of developed models, as well as employ more robust modelling techniques.

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