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A new method of wind farm active power curve estimation based on statistical approach

Abstract. *The purpose of this paper is to solve the wind farm active power estimation problem, introducing the method which is based on a statistical approach and robust fitting. The proposed algorithm uses a statistical approach and compared to existing ones - includes a wind direction as well as the influence of turbine start-up procedure on the estimation. The results show that additional estimation inputs i.e. the wind direction and the turbine state, improve the accuracy of estimated power. Estimation root mean square error captured over three days never exceeded 2%.*

Streszczenie. *W niniejszym artykule opisany został sposób na rozwiązywanie problemów związanych z estymacją mocy czynnej generowanej przez farmy wiatrowe. W opracowanej metodzie posłużono się podejściem statystycznym. W odróżnieniu od przedstwionych w literaturze metod, do wyznaczania krzywej mocy czynnej wykorzystano prędkość i kierunek wiatru a także analizowano stany przejściowe turbin wiatrowych. Opracowany alogorytm pozwala na wyznaczanie mocy czynnej badanej, rzeczywistej farmy wiatrowej z błędem nie przekraczającym 2%.* ***(Nowa metoda estymacji krzywej mocy opara na podejściu statystycznym)***

Keywords: Power estimation, wind energy, wind farms, wind power generation, robust fitting
Słowa kluczowe: Estymacja mocy czynnej, energia wiatrowa, farmy wiatrowe, moc czynna farmy wiatrowej, dopasowanie odporne

Introduction

The share of renewable energy resources in the global energy sector is constantly growing as well as greenhouse gases limits [4]. Wind energy holds a promising answer to the problems of world economies which are looking for non-polluting and cost effective resources without using fossil fuels. Analyses show that in 2019 over 11% of the electricity produced in the world came from renewable resources, including 62% from hydro-power. In 2018, the total installed capacity power available from wind turbines increased by 10% compared to 2017 and finally reached 591 GW [9] e.g. in Denmark, 41% of the energy comes from wind turbines, in Ireland 28%, in Portugal 24%, and in Germany 21%.

Due to the variable and unpredictable nature of wind energy, increasing the share of this source in the energy system poses many difficulties [7],[8]. One of them is the difficulty of accurately estimating the amount of energy produced by wind farms, as well as the difficulty of maintaining a constant frequency in the system, balancing power, power quality and voltage support [3]. These problems greatly complicate the integration of wind farms into existing energy systems [2],[16].

Therefore, methods allowing for forecasting the power generated by wind farms based on the strength and speed of the wind (the power curve) are crucial for mitigating the undesirable effects of connecting the wind energy conversion system with the existing power system [21],[30]. These methods allow to maintain the reliability and stability of the system due to the uncertainty and variability of the amount of electricity generated by wind farms [17], which positively affects the operation of the Transmission System Operator (TSO) [24].

Power curve-based estimation algorithms can also be successfully applied in wind farm performance monitoring systems [21]. These systems are particularly important due to frequent failures of wind turbines caused by changing operating conditions, which result in increased operating and maintenance costs [1],[19].

Based on the literature [14],[31] it might be concluded that the reference power curve (which is necessary to estimate the output power), provided by the manufacturers, differs significantly from the empirical measurement data. In some cases real data show that a wind turbine has never reached nominal power of the forecasting process. It happens because theoretical power curves supplied by manufacturers assuming ideal meteorological and topographical conditions. In practice, however, wind turbines are never used under ideal conditions [29]. Mainly the wind power forecasting model errors results from the Numerical Weather Prediction (NWP) component [13]. These discrepancies may significantly affect the wind power forecast. Therefore it is important that used model should reflects the real state as well as possible.

There are a number of statistical methods for estimating the power curve [5]. Among them, parametric and non-parametric methods can be distinguished [28]. Parametric methods are based on mathematical models defined on the basis of functions and coefficients describing the power of a wind turbine [22]. In the literature, the following parametric models are distinguished: segmented linear models [18], polynomial regression [12],[6], and models based on probabilistic distributions such as four- or five parameter logistic distributions [28]. The limitation of these methods is their global nature and sensitivity to anomalies occurring in observations. This creates difficulties in the accurate estimation of the power curve in the entire considered wind turbine operation range [29].

The second type of methods for estimating the power curve of wind turbines are non-parametric methods. Compared to parametric methods, these methods are less restrictive, they are also much more resistant to the occurrence of outliers, which makes it possible to model the power curve with greater accuracy in a wider range [29]. Non-parametric methods include neural networks [3],[25],[23], fuzzy logic [27] and data mining methods [20].

Most of methods presented in the literature do not take into account e.g. the wind turbine startup dynamic, which as shown latter in this paper introduce a substantial error. Also only wind speed is considered as input for the methods mentioned, but based on the fact that wind direction changes continuously, it seems rational to include this parameter into an estimation procedure. Moreover, most of the methods do not use measurement data from real-world objects [26] or use data from small turbines [28]. Therefore, the new method based on statistical approach was proposed. Furthermore, calculations are based on real world operation data (90 MW wind farm in north of Poland) and unlike existing methods, the data is downloaded directly from the SCADA system with timestamp of seconds (meanwhile in literature sampling in minutes scale is used). The paper is organized as follows: after the introduction a short description of wind turbines fundamentals is presented. Then field data analysis and error calculations are shown. The next chapter describes a new method of an active power estimation and presents the results of simulations. The last chapter concludes the paper.

Contribution

Wind turbines manufacturers provide nominal (catalogue) curves of a turbines active power, however based on available literature [16],[21],[30] and own observations, it can be noticed that they differ significantly in comparison to data obtained from the existing objects. This is because the power rating of a single turbine unit is given by the manufacturer for certain standard external conditions and at an optimum setting in relation to wind direction and a certain control method. Not only the instantaneous value of the wind but also the dynamics of its parameters (wind direction and speed) play an important role in power generation. As a result, the actual power output may be lower than would be expected for a given wind condition. Those differences are the reason for taking up the subject.

Furthermore, the Transmission System Operator (TSO) is interested in using wind farms to support the frequency control of the high voltage system. To use a wind farm as the system service, TSO needs to know the maximum available active power of a wind farm. Accuracy of the information is crucial to know the exact range of operation and for settlement reasons. To solve the power estimation problem, a method based on a statistical approach was adopted. The algorithm presented in this paper has taken data for learning and verification from the existing object as opposed to many results presented in the literature. One can assume that the estimator can be implemented on PLC (Programmable Logic Controller) hence, it was supposed to have a low computational cost and be relatively straightforward. The proposed method based on the statistical approach fulfils the assumptions made above.

Based on data from the real object, one can notice that not only the speed of the wind is significant for estimation purposes, but wind direction as well. Wind can change its direction and speed rapidly, and it is not always related to changing the gondola direction in the optimal direction to the wind. It causes estimation error, as has been presented in the paper. As shown in the paper the proposed method improves the precision of the estimator by adding a wind direction variable. The next important element additionally included in the proposed method was the dynamics of switching a wind turbine on. That can take place multiple times per day and affects the actual range of the turbine active power. All the above-described features of our algorithm improve the accuracy of estimation in comparison with catalogue curves. They also can be easily implemented on a PLC at the same time. The pilot program run of the algorithm on described windfarm proves its effectiveness.

Power curve fundamentals

Wind turbines active power depends on several variables. The Eq. 1 shows that the factor which influences output power the most is the wind speed v. Because the variable is cubed, even small fluctuation can cause a significant difference in output power P. Air density, which changes during the day or seasons, also has an impact on output power, but it will not be considered in this paper. Parameters such as C_p (resulting from Betz's law) and A are constants for a specific wind turbine.

$$P = \frac{1}{2} C_p \rho A \nu \tag{1}$$

where P is generated power, C_p power coefficient, ρ air density, ν wind speed and A blades area.

Wind turbines have operating limits called the cut-in and cut-out. The first one is also known as the generation threshold. When wind speed exceeds this limit the turbine turns on. Beyond rated power, a turbine controller tries to keep output power constant until wind speed reaches a cut-out value. After that point wind turbine turns off. Turbines are designed so that most energy is generated below the rated wind speed. The manufacturer provides a range where the rated power is generated. In that range both energy and cost are taken into consideration. All mentioned constraints are given by

$$P_w = \begin{cases} 0 & \text{if} \quad v < v_{cut-in} \\ \frac{1}{2} C_p \rho A v^3 & \text{if} \quad v_{cut-in} \leq v < v_r \\ P_r & \text{if} \quad v_r \leq v < v_{cut-out} \\ 0 & \text{if} \quad v \geq v_{cut-out} \end{cases} \tag{2}$$

where:
Pr - rated power,
v - input wind speed,
v_r - rated wind speed,
$v_{cut-out}$ - cut off wind speed,
v_{cut-in} - cut in wind speed.

Eq. 2 can be represented as Fig. 1 which is called a power curve. One can divide it into three areas (I, II, III) based on wind speed values ranges. In the first area (I), below rated power, a turbine works with maximum efficiency to generate as much power as possible for current weather conditions. The second one (II) is a transition area, where the controller keeps rotor torque and noise low. Finally, third area (III) is beyond rated wind speed where output power is limited by a turbine controller. In this area, pitch controller changes the blades pitch angle to maintain certain output power and rotor speed.

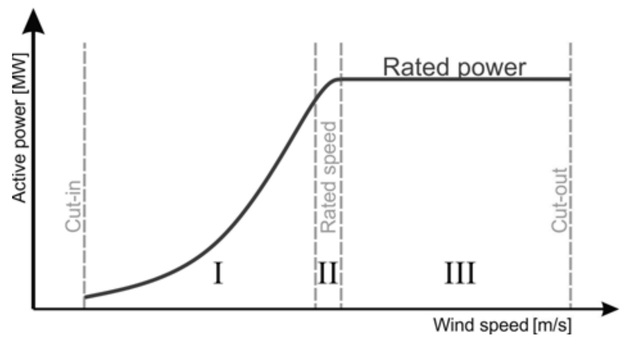

Fig. 1. Wind turbine perfect power curve

The angle of attack is increased by stalling a wind turbine, causing flat side of blades face into the wind. But when the angle is exceeded and air no longer streams smoothly over the blades upper surface, it is called angle critical. The angle of attack decreases when the edge of a blade faces the oncoming wind. The most effective way to limit aerodynamic force is a pitch angle adjustment. It is done at high wind speeds in region III of power curve. Yaw adjustment ensures that the turbine moves, in the horizontal axis, to face into the wind to increase effective rotor area and, as a result, active power. Wind direction can change very quickly, so the turbine may be misaligned with the oncoming wind. This delay causes losses which are approximated with the following Eq. 3.

$$\Delta P = \alpha cos(\epsilon), \tag{3}$$

where ΔP denotes the output power decrease and ϵ the angle of attack.

Field data analysis

In this section the stochastic nature of measured data was analyzed as well data interpolation method was presented for active power curve estimation. After performing the interpolation, close comparison between measured and interpolated values were illustrated. After the estimation process is performed, moving average filter is applied to smooth the results and reduce variance as well as a total estimation error. The data presented in this section: measurements of instantaneous wind speed, its direction as well as wind turbine state were included in the estimation algorithm described in the further sections.

Measurement data

Real-world data were obtained from an existing object located in the north of Poland. It consists of 30 wind turbines of nominal power of 3 MW. All crucial information such as: turbine state, wind speed, wind direction, and output active power, measured on nacelles for every single wind turbine as well as for wind farm as a whole. Most parameters were refreshed in the range from 2 to 5 seconds.

According to Eq. 1, the wind has the greatest influence on the active power generated by a wind turbine. Due to rapid changes in wind speed and direction, power curve estimation is complicated. The dynamics of the turbine itself is also a major difficulty. The same value of wind speed can correspond to various output power values.

The box plot in Fig. 2 visualizes the unpredictable variation of active power as a function of the wind speed of a single turbine selected from the 30 available.

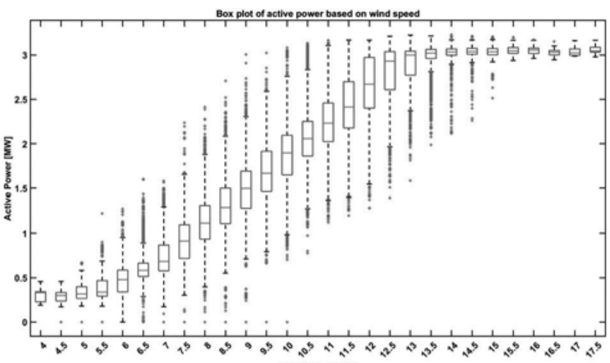

Fig. 2. Box plot of measured active power under the condition of constant wind speed

The figure describes quarterlies of measured output for specific wind speed range of $0.5\frac{m}{s}$ with outliers marked with red crosses. One can notice a significant number of outliers. It is because of the nature of the wind, which behaves in a stochastic manner.

The corresponding measurements for the wind farm are illustrated in Fig. 7. Each point marked in grey color corresponds to the measured active power of the wind turbine for a specific, instantaneous wind speed value. As can be seen the high variance of these measurements causes difficulties in a power curve estimation procedure. The difference in measured power can be up to 1.5 MW for the same value of wind speed.

Furthermore, histograms in Fig. 3 show most common wind speed and direction values for the specific wind farm. Wind direction is measured in regards to turbines themselves. In most cases, the value is nearly zero.

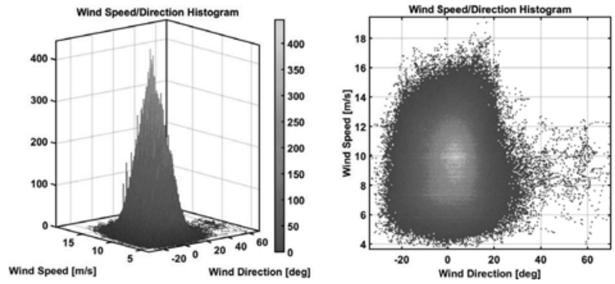

Fig. 3. Histogram of output power based on wind speed and direction

Shown measurements were collected on 10 wind turbines during one day. Measured wind direction values above 10 degree occurs often and leads to underestimation based on the Eq. 3. The accuracy of the estimation depends on the quality of data sets used for training and validation. Separating the samples into the mentioned subsets helps to avoid overfitting the model. Each data set contains measurements collected in three days each. It follows that one dataset contains 259,200 samples of each parameter for a given wind turbine. In a selected period of time, a wind farm was operating in different regions of the power curve. The datasets were also examined for mutual correlation $\rho(A, B)$ (4) to choose the least correlated ones, to ensure different weather conditions

$$\rho(A, B) = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{A_i - \mu_A}{\sigma_A}\right)\left(\frac{B_i - \mu_B}{\sigma_B}\right) \tag{4}$$

where:
A, B - random variables,
μ - expected value,
σ - standard deviation.

Furthermore, each turbine has a state variable which describes whether the turbine is working or not. A wind turbine often changes its state during normal operation. Fig. 4 shows field data obtained from the wind farm.

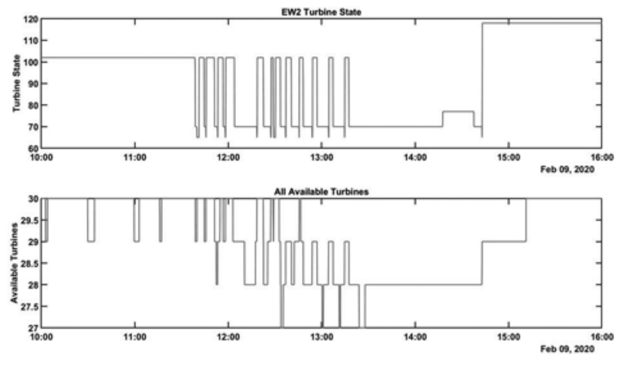

Fig. 4. Wind turbine state changes and amount of all available turbines

Upper subfigure represents state of one of the turbines, lower subfigure shows the amount of all available turbines. Turbine turning on and shutting down is common and can occur even 25 times during the period of 90 minutes. Those changes have an impact on maximum generated power as well as estimation output. As shown in the further sections, dynamic of the start-up procedure should be included in the estimation algorithm to decrease an estimation error during time.

Data interpolation and filtering

The wind farm data were sent event driven at non-uniform time intervals. Interpolation has been performed to obtain the measurements with an equal one-second period. The authors used piecewise cubic Hermite interpolating polynomial to interpolate measured datasets. The method preserves the local extremums of the data, hence no overshooting is introduced [10]. Overshooting could significantly increase an estimation error, as little change in wind speed has a crucial impact on generated power (1).

In turbulence time-scale (considered as a range from 1 sec to 30 min) wind speed changes continuously and rapidly. The datasets were collected from anemometers located on the nacelles and then interpolated. Fig. 5 shows interpolated data from the 10 turbines chosen as exampled from all 30 installed on the wind farm.

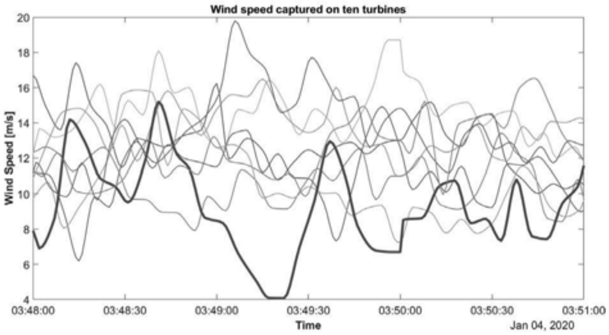

Fig. 5. Time series of interpolated wind speed datasets from the ten turbines chosen from all 30 installed on the wind farm

To decrease rapid variations of the measured data, Moving Average (MA) filter with window of n=15 [sec] had been applied (5) before power curve estimation was performed.

$$\bar{p}_M = \frac{p_M + p_{M-1} + ... + p_{M-(n-1)}}{n} = \frac{1}{n}\sum_{i=0}^{n-1} p_{M-i} \tag{5}$$

where $\bar{p}_M$ denotes a filter output for specific sample M and n is the filter's order. Fig. 6 shows how the used MA filter mitigates the variance of measured data.

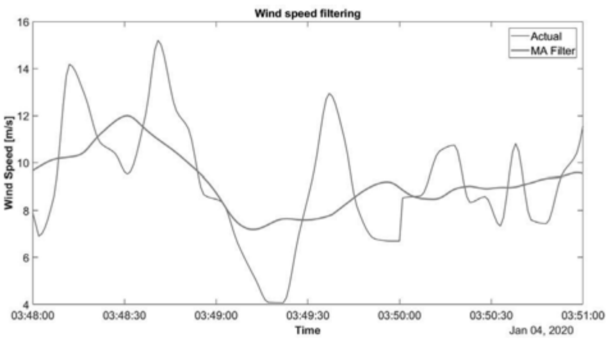

Fig. 6. Measured and MA filtered wind speed input variables

Proposed method and simulation results

One and two variable polynomials of various order were taken as a model for estimation of active power curve. The one variable polynomial considers only a wind speed as an independent variable. The two variable polynomial additionally take into account wind direction as a second independent variable.

Methods used for polynomial fitting are based on the least-squares algorithms [15]. In addition to the classic least-squares method, authors also tested robust least-squares algorithms such as the Least Absolute Residuals methods and Bisquare Weights methods. Those algorithms use iteratively reweighted least-squares algorithm. The methods are less sensitive to non-gaussian distributed measurements called outliers. The first one minimizes the absolute value of residuals resulting in reduced outliers influence on the fit. The second one minimizes the weighted sum of squares of residuals.

After the estimation and aggregation process is performed, prior introduced in Eq. 5 moving average filter is applied to smooth the results and reduce variance as well as a total estimation error.

Also dynamic of turning the turbine discussed further in this paper was included in the presented results.

Estimation quality statistics

To determine the quality of the estimation and to compare the results, estimation quality statistics, based on estimation error were used. The estimation error (6)

$$e_i = \hat{y}_i - y_i, \tag{6}$$

is defined as a difference between estimated $\hat{y}_i$ and measured y_i value. This error is used to compare active power outputs with different polynomials.

In this study statistical measures are used to analyze the final results. These are:

- Root Mean Square Error (RMSE) (7)
- variance of the error (var) (8)
- error value (Error) (9)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} e_i^2} \tag{7}$$

$$var = \frac{1}{N-1}\sum_{i=1}^{N} |e_i - \mu|^2, \tag{8}$$

where μ is the mean of e and

$$\mu = \frac{1}{N}\sum_{i=1}^{N} e_i.$$

$$Error = \frac{RMSE}{P_r} \cdot 100\% \tag{9}$$

which is expressed as a percentage of Root Mean Square Error to rated power P_r.

The following subsection presents a comparative study of proposed methods and polynomials to determine the best approximation model for the power curve based on collected datasets.

Results comparison

An exampled power curves were estimated using one variable polynomial and obtained for different orders (from 4th to 9th) shown in a Fig. 7

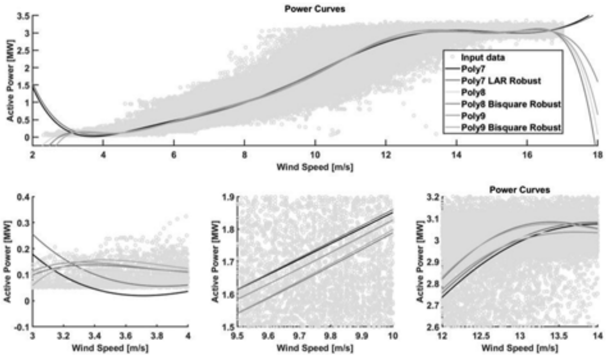

Fig. 7. Model comparison obtained with one variable polynomial

Order	Robust method	var	RMSE	Error	Mean
9	None	3.55	1.97	2.19	-0.57
9	Bisquare	2.93	1.77	1.97	-0.45
9	LAR	2.85	1.74	1.94	-0.44
8	None	3.59	1.99	2.21	-0.59
8	Bisquare	3.05	1.82	2.03	-0.53
8	LAR	2.98	1.8	2	-0.5
7	None	3.59	1.98	2.2	-0.58
7	Bisquare	2.86	1.74	1.93	-0.4
7	LAR	2.85	1.73	1.92	-0.38
6	None	3.76	2.03	2.26	-0.6
6	Bisquare	3.23	1.9	2.11	-0.61
6	LAR	3.24	1.88	2.09	-0.57
5	None	3.87	2.04	2.27	-0.55
5	Bisquare	3.17	1.81	2.01	-0.34
5	LAR	3.24	1.83	2.03	-0.33
4	None	5.24	2.38	2.65	-0.67
4	Bisquare	5.12	2.43	2.7	-0.9
4	LAR	5.19	2.5	2.78	-1.04

Table 1. Quality factors obtained for the different degrees of the one variable polynomial interpolation

Table 1 shows the values of quality factors obtained for the different degrees of the one variable polynomial interpolation.

Increasing polynomials order improves the performance of the estimator. The presence of outliers in measured data is common, which leads to biased results, therefore robust regression methods give better results. Except for very low degrees of polynomials, the error variance is at a similar level. One can notice that the degree parity of the polynomial has a considerable impact on the determined results. Odd order polynomial can better approximate power curves because of its shape. Therefore, the final results for the 7th order polynomial are better than for the 8th.

Eq. 3 denotes that the wind direction influences the value of the generated power. Although output power changes with the cosine of wind direction and has a low impact on power generation, not taking into account that property causes overestimation. Fig. 8 presents one of the models determined by the function of two variables.

Statistical method performance is shown in Table 2 for different surfaces orders and robustness. Variable x of polynomials denotes the wind direction variable, and y the wind speed.

The lowest error was observed for the 5th order surface in terms of RMSE as well as variance and mean value of the errors. Robust methods provide the improvement in estimation performance, as in one variable polynomials. According to the [29] usually, the Bisquare Weights method is preferred

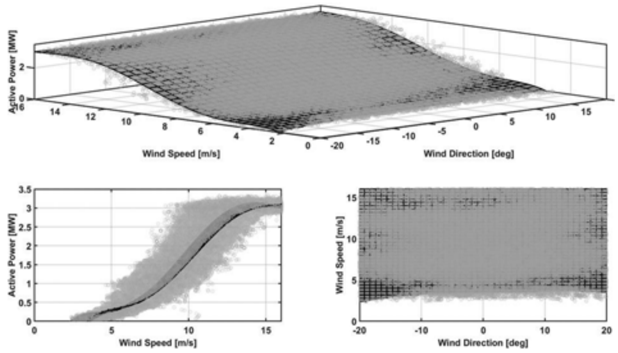

Fig. 8. Model obtained with two variable polynomial

Order x	Order y	Robust method	var	RMSE	Error	Mean
5	5	None	3.2	1.79	1.99	0.02
5	5	Bisquare	2.74	1.66	1.84	-0.01
5	5	LAR	2.85	1.69	1.87	0.02
4	4	Bisquare	4.52	2.19	2.43	-0.51
4	4	None	4.45	2.13	2.37	-0.13
4	4	LAR	4.61	2.24	2.49	-0.65
4	5	None	3.2	1.79	1.99	0.02
4	5	Bisquare	2.74	1.66	1.84	-0.01
4	5	LAR	2.85	1.69	1.88	0.02
5	4	None	4.32	2.08	2.31	-0.08
5	4	Bisquare	4.29	2.12	2.36	-0.46
5	4	LAR	4.35	2.17	2.41	-0.59

Table 2. Quality factors obtained for the different degrees of the two variable polynomial interpolation

over LAR. The parity of selected polynomials order is also important for the same reasons as it was with one variable fitting function.

The above methods for fitting the power curve with one and two variables polynomials have been proposed. Based on them, one can estimate output power generated by wind turbine using input speed and/or direction of the wind.

The power curves may differ among wind turbines on the same wind farm. This is because the individual turbines on the wind farm are spread over a large area with different landforms. One should also notice that air turbulence caused by one turbine can disturb the estimation process on another turbine. Moreover, in the long term run, no real object is stationary. Therefore non-stationary nature of the object must be taken into account if the estimator is implemented in a real object operating for many years. Those impacts were not taken into consideration in this paper.

Results shown in Table 1 and Table 8 were obtained after summing up the estimated power value for each turbine and comparing the output to the real values of total power measured for the wind farm.

Fig. 9 shows the results of aggregated and smoothed active power estimation, in horizon of several hours for three different days.

The first subfigure shows the wind farm working in the range from 40 MW to over 70 MW. The measured power values changes more rapidly and have larger variance comparing to the smoother estimation. In the middle subfigure, the wind farm was operating closer to the rated power, the 10 MW loss in output power was caused by the shutdown of three individual turbines. Also in this case the estimation accurately reproduces the generated active power of all 27 working turbines. The last subfigure shows the three hours of wind farm

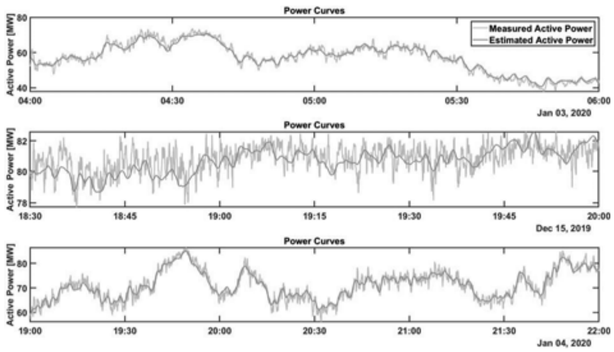

Fig. 9. Measured and estimated values of output power

operation in the upper production capacity range. This figure shows a large variability of the generated power and a good quality of the estimation.

As mentioned before, dynamic of the turbine start-up should be taken into account to obtain satisfying results. First turbine controller waits 120 seconds to begin start-up procedure after turbine state changed. Than it slowly starts up the turbine. When those terms are added to the estimation process i.e. the dead zone and the turbine dynamic, improvement of the estimation to measured response of the system can be obtained.

In the procedure auto-regressive model with an input signal (ARX model) is used in initialization phase, then followed by a search using the nonlinear least squares method minimizing the weighted norm prediction errors [11]. The transfer function determined this way is shown in the Eq. 10, 11, 12.

$$y[n] = -a_1 \cdot y[n-1] - a_2 \cdot y[n-2] + x[n] \tag{10}$$

$$H(z) = \frac{Y(z)}{X(z)} = \frac{1}{1 + a_1 z^{-1} + a_2 z^{-2}} \tag{11}$$

$$\frac{Y(z)}{U(z)} = \frac{0.002361}{1 - 1.974z^{-1} + 0.9495z^{-2}} \tag{12}$$

Fig. 10 shows step responses due to external excitation for the following systems: the first (marked in blue color) is measured real turbines output power, the second (marked in red) is estimated output power without dead-zone and dynamic included.

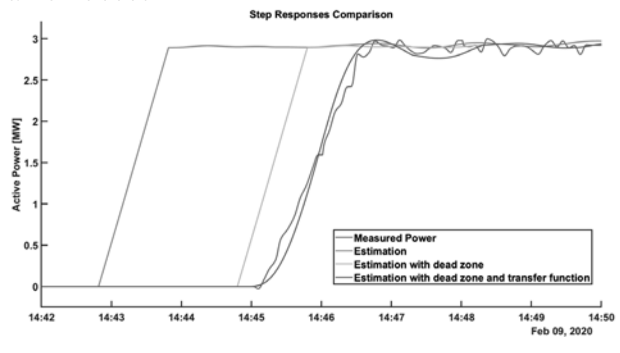

Fig. 10. Wind turbine estimated output during start-up

Response marked in yellow takes into account only dead-zone and the last one (marked in purple) includes second-order dynamic of the system response as well as dead zone mentioned before.

Based on the transfer function (12), one can conclude the main characteristics of the step response. The rise time equals 32 seconds and is determined by the turbine controller that tries slowly start-up the turbine. Obtained transfer shows overshoot above 15% and a settling time of about 160 seconds. Long settling time may raise concerns however, one should remember that the determined transfer function of the system is used only when the turbine controller slowly starts the turbine up. After the response is settled, the dynamic component is no longer used in the estimation procedure.

Every now and then situations, when almost all wind turbines are shut down, occur. As shown in Fig. 11, the wind farm master controller shut down and then restore the turbines to work sequentially.

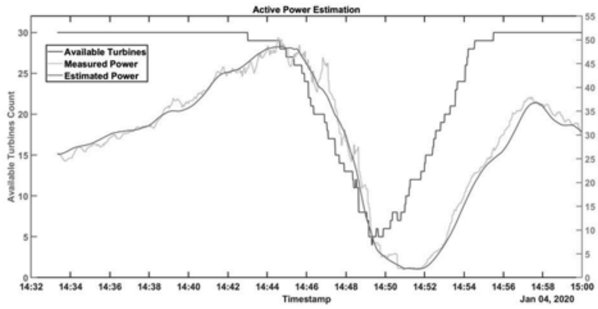

Fig. 11. Estimation of a wind farm after shutting down and turning on some of the generators

During this process power dropped drastically from 50 MW to around 2 MW. A total of 24 turbines working at the moment was shut down. Earlier in this section the start-up dead zone as well as the dynamic response of the turbine, were discussed. Based on Fig. 11 one can see that implementing those components turns out to be necessary to correct the estimation during start-up. Otherwise, the estimation would drastically outpace the measured output power.

Conclusion

The estimation algorithm proposed in this paper was introduced and verified with data obtained from the existing wind farm with a rated capacity of 90 MW. Estimation root mean square error captured over three days, with the measurements sampled every few seconds, never exceeded 2%. The proposed method, in opposition to existing ones, takes into account wind direction and turbine start-up dynamic. The results show that additional estimation inputs i.e. the wind direction and the turbine state, improve the accuracy of estimated power. Another advantage of the method is a low computational cost which allows the algorithm implementation on microcontroller or PLC with ease.

Due to the fact, that the method uses simple polynomial curve and/or surface fitting algorithms, one can use them to find new power curves when conditions such as seasons or location of the turbine change. In long term, those parameters change so it seems reasonable to run a curve/surface fitting algorithm once in a while to correct the outputs.

To determine interpolating polynomial coefficients, data sets downloaded during typical wind farm operations were used. Including the moving average filter turned out to be essential for obtaining good statistical coefficients. The large variance of the input data does not allow the measurements to be used directly. The filter allowed to obtain satisfactory filtration at a quasi-real-time level.

All methods used to determine the power curve were compared to each other using total mean square estimation error. Power estimations that used functions of one variable i.e. wind speed, gave satisfactory results for polynomials of higher orders. The estimation considering both wind speed and direction gave better results. Both approaches allowed for a satisfactory estimation of active power and the choice of one over the other should be conditioned by the possibility of determining polynomials coefficients and the frequency of making adjustments of those coefficients in real-time.

To obtain good estimation output, the additional properties of a wind turbine such as start-up dead zone and the dynamic response of the turbine should be considered. Turbine state changes must be monitored on an ongoing basis and taken into account by the estimator to included two minutes dead zone in the estimation procedure. Moreover, each of the generators should use the corresponding transfer function, which should be included during the turbine start-up. Implementation of those features reduces the total estimation error.

In future research, it seems beneficial to take into account the weather conditions e.g. season of the year, and determine different curve/surface coefficients to reduce the estimation error. Moreover, the different model coefficients for different operating ranges of wind turbines can result in a significant improvement of estimation precision.

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