Wind turbine power curve upgrades: methods for the assessment and test cases study

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Abstract. The research about wind turbine control and blade design optimization has flourished in the latest years and has provided the opportunity of diffusely updating the technology of operating wind turbines. Due to multivariate dependence of wind turbine power on ambient conditions and working parameters, it is complex to estimate the actual impact of power optimization strategies. This problem therefore calls for devoted operation data mining and statistical techniques, which are explored in the present work. In particular, two test cases of multi-MW wind turbines power upgrades are discussed: the former is a combined aerodynamic and control optimization, the latter is the optimization of the yaw control. The assessment of the upgrades impact is performed through the comparison between the post-upgrade measured production and a model estimate of the pre-upgrade production in the same conditions. The wind turbines nearby to the target upgraded ones are employed as references for the operation conditions and their working parameters are employed for a principal component regression of the power of the target wind turbine. The proposed method is general and, for the selected test cases, it arises that the aerodynamic and control optimization improves the Annual Energy Production of the order of the 3%, while the yaw control optimization provides a 1% AEP improvement.

1. Introduction

Multi-MW wind turbines, having rotor diameter of the order 100 meters, are nowadays a mature technology, widely exploited at the industrial level. This matter of fact poses the question if the latest research developments as regards blade aerodynamics and control optimization can be successfully adopted for retrofitting of this kind of wind turbines and for improving their efficiency.

Many studies in the literature deals with the design of optimized blades and innovative control strategies: for example, the works in [1, 2, 3, 4, 5, 6, 7, 8, 9] deal with vortex generators and passive flow control technology. The work in [10], instead, deals with a novel data driven yaw control algorithm synthesis method based on Reinforcement Learning: the potential power capture improvement is simulated under several wind speed scenarios using the TurbSim software.

Few studies are devoted to the assessment of the actual production improvement provided by wind turbine power curve upgrades, but the topic has been recently gaining attraction for several reasons.

Assessing the performance improvement provided by an update means comparing the production measured after the upgrade against a model estimate of how much the wind turbine
would have produced in the same conditions without the upgrade. This means that a reliable model for the power of the target upgraded turbine is required and this is definitely a non-trivial objective because of the multivariate dependence of power on working parameters and ambient conditions.

Chronologically, the first relevant study tackling this objective is [11]. Two test cases are addressed: vortex generators installation on wind turbine blades and pitch angle optimization. The former test case is addressed through operation data analysis and the latter through the simulation of operation data using a Kernel regression method. Similar methods are employed in [12].

Previous works by the authors have been devoted to this kind of problems and a new point of view has been introduced: namely, employing some references wind turbines for modeling the power of the target turbine. This somehow generalizes the notion of rotor equivalent wind speed [13] to farm equivalent wind field, where the operation variables of references wind turbines are conceptually employed as probes of the on-site conditions. This kind of approach has been employed in [14, 15, 16, 17, 18]: in these works, several test cases have been addressed and several regression models, based on the same principle as above stated, have been employed. A relevant aspect of the methodologies discussed in the previous works [14, 15, 16, 17, 18] and in this work is that they allow overcoming an important critical point of the performance assessment through the power curve: namely, the dependence on the season of the year [19]. This happens because the relation between the operation variables (especially, the power production) of a set of wind turbines in a wind farm is not expected to depend on the season of the year. Therefore, an important point of the proposed methods is that they can be used for assessing a power upgrade after just few months of upgraded operation, while the power curve analysis requires roughly at least one year of data (covering the four seasons).

The objective of this work is discussing two test cases, that have been selected in order to address the main methodological points as regards this kind of study. The former test case is a combined aerodynamic and control optimization: it is based on the installation of vortex generators and passive flow control devices on the blades of a multi-MW wind turbine sited in complex terrain. This test case has been addressed in [17] and in the present work it will be discussed on the grounds of new methodological outcomes. The latter test case deals with the yaw control optimization on a multi-MW wind turbine from a wind farm featuring in total nine wind turbines sited in a flat terrain; the control optimization acts by reducing the response time of the yaw control when the wind direction varies.

A common critical point regards the selection of the most appropriate input variables of the references wind turbines for modeling the power of the target wind turbine. Two are the main aspects: how much variance of the target is explained by each possible regressor and how much is the collinearity between the selected regressors. Several approaches have been employed in [14, 15, 16, 17, 18] and, as regards the present work, a linear multivariate Principal Component Regression (PCR) is adopted. Once this is accomplished, a linear model is shown to be adequate for modeling the power of the target wind turbine and for estimating the power upgrade impact.

Summarizing, the structure of the manuscript is therefore the following: first, the test case and the data sets are briefly described in Section 2; subsequently the methods are discussed in Section 3; the results are summarized in Section 4; conclusions and further directions are sketched in Section 5.

2. The wind farm and the data set
A long standing collaboration between the University of Perugia and the Renvico company (www.renvicoenergy.com) has been established for wind turbine performance control and monitoring and for early fault diagnosis [20, 21, 22, 23].

In the following the selected pilot test cases are shortly described.
2.1. Wind Farm 1
The layout of Wind Farm (WF1) is reported in Figure 1. From the contour lines, it is possible to appreciate the complexity of the terrain. T7 (in red in Figure 1) is the wind turbine that has been upgraded with vortex generators and passive flow control devices. The wind turbines have 2.3 MW of rated power and the hub height is 80 meters above ground level.

![Figure 1. The layout of the wind farm.](image)

All these installed devices produce an increase of the lift on the basis of different principles: the vortex generators delay the airflow separating from the blade surface, the blade tip flow control devices extend the blade chord. It should be noticed that the upgrade involves a control optimization: the rotor revolutions per minute management is improved in order to attain the most appropriate induction level.

The data sets at disposal are the following:

- $D_{bef}$ goes from 01/01/2016 to 01/07/2017 with the standard blade configuration.
- $D_{aft}$ goes from 01/03/2018 to 01/06/2018 with the improved blade configuration and the control optimization.

In particular, for each wind turbine the data available are:

(i) the nacelle wind speed,
(ii) the power output,
(iii) the individual blade pitch angles,
(iv) the rotor revolutions per minute,
(v) the high-speed rotor temperature.

2.2. Wind Farm 2
The layout of Wind Farm (WF2) is reported in Figure 2. The wind turbine undergoing yaw control optimization is T1 and is indicated in red in Figure 2. The hub height is 80 meters, the rotor diameter is 82.5 meters and the rated power is 2 MW.

The data at disposal are organized in two sets as follows:
- The first data set is denoted as $D_{bef}$ from 01/03/2017 to 25/08/2018 prior to the intervention on turbine T1.
- The second data set is denoted as $D_{aft}$ from 01/09/2018 to 01/03/2019 after the yaw control optimization.

The data have ten minutes of sampling time and the available validated measurements for each wind turbine in the wind farm are
- nacelle wind direction;
- power output;
- ambient temperature;
- nacelle position;
- rotor speed;
- generator speed.

3. The method
The objective of this part of the work is formulating a reliable model for the power of the wind turbines of interest (T7 for WF1 and T1 for WF2). This is necessary because the estimate of the production upgrade basically consists of the comparison between the measured power after the upgrade and the model of how much the wind turbine would have produced under the same conditions if the upgrade had not taken place.
The idea for the model formulation is describing the on-site conditions through the measurements and the operation variables at each wind turbine in the farm except the upgraded: all these quantities can in principle be input variables of the model for the power of the wind turbine of interest (denoted as \( y \) in the following). This principle has been adopted, for example, in [17] and in that work the variables selection for the model has been performed through a stepwise regression algorithm. The critical point as regards the application of that kind of regression deals with the fact that some of the possible input variables are very highly correlated.

On these grounds, the Principal Component Regression (PCR) [24] has been selected for this study: sideways, the use of this method for control and monitoring purposes in wind energy has been growing. The procedure goes as follows. Let \( Y_{n,1} = (y_1, \ldots, y_n)^T \) be the vector of measured output (namely, the power of T1) and \( X_{n,p} = (x_1, \ldots, x_n)^T \) be the matrix of covariates. \( n \) is the number of observations and \( p \) is the number of covariates. Notice that it might be appropriate that the \( X \) matrix has been rescaled and different possibilities are currently employed: rescale each column of \( X \) with its standard deviation (with or without having translated the mean of each column to 0), or rescale overall the \( X \) matrix with its maximum. For this work, it has been observed that the results don’t depend sensibly on the normalization of the \( X \) matrix but slightly lowest averages mean errors are obtained when the \( X \) is not normalized and therefore this choice has been pursued.

The ordinary least squares regression assumes that

\[
Y = X\beta + \epsilon
\]

where \( \beta \) are the regression coefficients that must be estimated from the input variables data matrix \( X \) and \( \epsilon \) are random errors. The ordinary least squares estimate of \( \beta \) is given by

\[
\beta_{ols} = (X^TX)^{-1}X^TY
\]

The principal component estimate of \( \beta \) is obtained as follows. Let \( X = UV\Lambda V^T \) be the singular value decomposition of \( X \). This means that the columns of \( U \) and \( V \) are orthonormal sets of vectors denoting the left and right singular vectors of \( X \) and \( \Lambda \) is a diagonal matrix, whose elements are the singular values of \( X \). This allows to decompose \( XX^T \) as:

\[
XX^T = V\Lambda V^T,
\]

where \( \Lambda = diag(\lambda_1, \ldots, \lambda_p) \) and \( \lambda_1 \geq \ldots \geq \lambda_p \geq 0 \).

\( XV_i \) is the \( i \)-th principal component and \( V_i \) is the \( i \)-th loading corresponding to the \( i \)-th principal value \( \lambda_i \).

The principal component regression assumes that a linear relation can be established between the transformed data matrix \( W = XV \) and the target \( Y \). In other words, the principal component regression can be viewed as an ordinary least squares regression between \( W \) and \( Y \).

The usefulness of the principal component regression and its superiority with respect to ordinary least squares regression is that the decomposition in Equation 4 indicates a sort of regularization scheme: namely, the matrix \( W \) can be truncated including a desired number of principal components. This is particularly useful for addressing the problem of multicollinearity of covariates, because when two or more covariates are highly correlated, \( X \) tends to lose its full rank and this implies that \( XX^T \) has some eigenvalues tending to 0. Truncating up to a certain number of principal components means regularizing the covariates matrix in order that it has full rank. It should be noticed that there are critical points also as regards the truncation [24],
because there are arguments supporting that the principal components associated to eigenvalues having low absolute value can carry meaningful information. Nevertheless, for the objectives of the present study it has verified that this is not the case and the decisive point is including at least a certain amount of principal components.

Finally, the principal component estimate of $\beta$ is given as

$$
\beta_{PCR} = V \left( W^T W \right)^{-1} W^T Y,
$$

where it is assumed that the matrices can be truncated to a desired number of columns, i.e. principal components.

The structure of the model for the test case of interest has been selected as follows. The output $Y$ is the power of the target wind turbine; the covariates matrix $X$ is selected to be composed of all the data at disposal (listed in Section 2 for WF1 and WF2) at each wind turbine, except the target ones. This has been done because it is likely that the aerodynamic and control optimizations change the relation between operation parameters and power output.

The selection of an adequate number of principal components for the regression is performed through $K$-fold cross-validation [25]. The procedure goes as follows: divide $D_{bef}$ randomly in two fractions, where $(K - 1)/K$ of the data are used for training and the remaining $1/K$ are used for validation. $K = 10$ is selected for this study. The training data are therefore employed for estimating $\beta$ through principal component regression (Equation 5) and the model estimate of the validation data is given by

$$
\hat{Y}_{valid} = X_{valid} \beta_{PCR}
$$

This procedure is repeated for each fold selection. The Mean Square Error ($RMSE$) is selected for the estimating the regression error. It is defined as

$$
RMSE = \left( \frac{1}{n_{valid}} \sum_{i=1}^{n_{valid}} (\hat{y}_i - y_i)^2 \right)^{1/2},
$$

where $n_{valid}$ is the number of observation of $X_{valid}$. The $RMSE$ values are subsequently averaged on the folds selection and therefore, for a given number of principal components included in the regression, a unique metric for estimating the quality of the regression is obtained.

Selecting an adequate number of principal components for the regression is fundamental in order to avoid the over-fitting of the model. This is achieved as follows:

- a stepwise regression algorithm is run, where the PCA-transformed covariates matrix is selected as input;
- the $p$-value for the $F$-statistics is selected to be less than $10^{-10}$ because, doing this, robust models are selected;
- a $K$-fold cross-validation is run and the number of selected principal component selected regressors is observed.

Doing this, it arises that the number of principal components to include in the regression should not exceed 10 for WF1 and WF2.

4. Results

The data sets at disposal are employed as follows:

- $D_{bef}$ is randomly divided in two subsets: $D0 \left( \frac{2}{3} \right.$ of the data set) and $D1 \left( \frac{1}{3} \right.$ of the data set). $D0$ is used for training the model and constructing the weight matrix $\beta_{PCR}$, $D1$ is used for validating the model.
• $D_{aft}$ (also named D2 for simplifying the notation in the following) is used to quantify the performance improvement.

The upgrade can be estimated as a change in the behavior of the residuals for the D2 data set, with respect to D1. This should happen because the model is trained with pre-upgrade data and is employed to simulate one pre-upgrade data set (D1) and one post-upgrade data set (D2). Namely, the residuals between measurements and model estimates should averagely be 0 for the data set D1, while they should be higher than 0 for the data set D2 (because the measured power should be higher than the power simulated according to a model trained with the pre-upgrade behavior). In the following, the procedure is reported for verifying if this is the case (and with what statistical significance) and for quantifying the upgrade.

Therefore, consider Equation 8 with $i = 1, 2$.

$$R(x_i) = y(x_i) - \hat{y}(x_i).$$

For $i = 1, 2$, one has that the mean residual is

$$\delta_i = \frac{1}{N_i} \sum_{x \in D_i} y(x) - \hat{y}(x)$$

and the mean absolute residual is

$$\bar{\delta}_i = \frac{1}{N_i} \sum_{x \in D_i} |y(x) - \hat{y}(x)|,$$

where $N_i$ is the number of measurements in data sets D1 and D2 respectively.

Since the measured $y$ and estimated $\hat{y}$ powers have all the same time basis (ten minutes), the quantity

$$\Delta = \Delta_2 - \Delta_1,$$

where

$$\Delta_i = 100 \times \frac{\sum_{x \in D_i} (y(x) - \hat{y}(x))}{\sum_{x \in D_i} y(x)}$$

is a percentage estimate of the energy improvement provided by the upgrade.

The above procedure has been repeated several times, by varying the random selection of D0 (and consequently of D1). The repetitions have been performed until the standard deviation of the $\Delta$ estimates (obtained for the different runs of the procedure) has become stable: as a rule of thumb, it can be said that 30 repetitions are sufficient. For each of these 30 runs of the model, $\Delta$, $\delta_i$ and $\bar{\delta}_i$ have been computed.

4.1. WF1: results

The results for the $K$-fold cross-validation are reported in Figure 3 and it arises that the $RMSE$ decreases non-negligibly up to the inclusion of 10 principal components. For this reason, 10 principal components have been selected for the regression.
Figure 3. Average $RMSE$ as a function of the number of principal components included in the regression: WF1.

In Figure 4, the power of T7 during D1 and D2 is plotted against the first principal component of the covariates matrix of data set D0. From Figure 4, the performance improvement during D2 with respect to D1 is clear.

Figure 4. Power of T7 during D1 and D2 is plotted against the first principal component of the covariates matrix of data set D0.

The statistical behavior of the residuals between measurement and model estimation is reported in Table 1.
Residual | $\bar{\delta}_{ave} (\text{kW})$ | $\delta_{ave} (\text{kW})$
---|---|---
$R(x_1)$ | -2.2 | 100.0
$R(x_2)$ | 36.9 | 103.6

**Table 1.** Statistical behavior of the residuals between measurement and estimation, for the different random choices of the D0 and D1 data set: WF1.

From Table 1, it arises that the upgrade can be detected as an average increase of about 37 kW while the average energy improvement is computed to be $\Delta = 2.9\%$. In other words, the estimate is that, since the T7 has been optimized, it has produced the 2.9% more than it would have done without the upgrade with a standard deviation $\sigma_{\Delta} = 0.2\%$. Finally, in order to appreciate how the aerodynamic and control upgrade changes the power production, it is possible to report a plot like the one in Figure 5: $R(x_1)$ and $R(x_2)$, computed on a sample model run, are displayed. The data are averaged in power production intervals, whose amplitude is 10% of the rated.

![Figure 5](image)

**Figure 5.** The average difference $R$ between power measurement $y$ and estimation $\hat{y}$ (Equation 8). Data sets: D1 and D2. Sample run of the model. WF1.

As an aside, it is interesting to notice that the upgrade has been installed in two steps, as discussed in [17]: first, the aerodynamic part has been installed and, after some months, also the control part has been installed. The study in the present work deals with the operation after the installation of the whole upgrade, but it is possible also to study the two periods (only aerodynamic upgrade, full upgrade): doing this, by difference, it is possible to estimate separately the effect of each upgrade. The result is that the aerodynamic upgrade provides an improvement of the order of 2% AEP and the control upgrade guarantees a +1% AEP. This is compatible with other estimates about the impact of control upgrades [15].

### 4.2. WF2: results

The results for the $K$-fold cross-validation are reported in Figure 6 and it arises that, if the number of principal components is higher or equal than 5, the average $RMSE$ is basically stable. For this reason, 5 principal components have been selected for this study.
In Figure 7, the power of T1 during D1 and D2 is plotted against the first principal component of the covariates matrix of data set D0. From Figure 7, the performance improvement during D2 with respect to D1, albeit weak, is clear.

The statistical behavior of the residuals between measurement and model estimation is reported in Table 2.

| Residual | $\delta_{ave}$ (kW) | $\delta_{ave}$ (kW) |
|----------|---------------------|---------------------|
| $R(x_1)$ | -0.2                | 78.0                |
| $R(x_2)$ | 8.2                 | 85.2                |

Table 2. Statistical behavior of the residuals between measurement and estimation, for the different random choices of the D0 and D1 data set: WF2
From Table 2, it arises that the upgrade can be detected as an average increase of 8 kW in the difference between measurements and model estimates. The average energy improvement is computed to be $\Delta = 1.0\%$. In other words, the estimate is that, since the yaw control of T1 has been optimized, T1 has produced the 1.0% more than it would have done without the upgrade with a standard deviation $\sigma_\Delta = 0.1\%$. Finally, in order to appreciate how the yaw control upgrade changes the power production, it is possible to report a plot like the one in Figure 8: $R(x_1)$ and $R(x_2)$, computed on a sample model run, are displayed. The data are averaged in power production intervals, whose amplitude is 10% of the rated.

![Figure 8](image.png)

**Figure 8.** The average difference $R$ between power measurement $y$ and estimation $\hat{y}$ (Equation 8). Data sets: D1 and D2. Sample run of the model. WF2.

5. Conclusions and further directions

MW-scale wind turbine technology is continuously evolving and a common practice in the wind energy practitioners community is refurbishing wind turbines operating since a certain number of years through the latest updates as regards aerodynamics and control.

A critical point is given by the fact that the actual efficiency of wind turbine power upgrades can mismatch with respect to the theoretical estimation formulated in the design phase of the technology update. This fact calls for the importance of test case studies as regards the operation assessment of wind turbine power upgrades. An order of magnitude estimate is that control upgrades typically provide a 1% improvement of the AEP, while the improvement can be higher when the optimization regards the blade aerodynamics: this implies that a power upgrade can be detected with performance control and monitoring techniques that are capable of distinguishing the order of the percent of the AEP. This is definitely a non-trivial task, due to the multivariate dependence of the power of a wind turbine on ambient conditions and working parameters.

This work has been devoted to two test cases discussions: the former is a combined aerodynamic and control optimization, the latter is a yaw angle control optimization. Both test cases deal with MW-scale wind turbines sited in Italy.

Three are the main methodological contributions of the present work:

(i) the idea that the upgrade can be estimated by comparing the post-upgrade measured production against a model estimate of the pre-upgrade power of the target wind turbine in the same conditions;
(ii) the idea that the nearby wind turbines can be used as probes of the external conditions (generalizing the concept of rotor equivalent wind speed to farm equivalent wind field) and their working parameters can be used as input variables for the model of the power of the target wind turbine;

(iii) the criterion for the model selection. Basing on previous studies from the authors [17], it has been argued that a linear model can be adequate for the objectives, but a critical point arises: namely, the working parameters of nearby wind turbines can be remarkably collinear and this can affect the effectiveness of the linear regression. For this reason, in this work, principal component regression and it is shown how to apply it to this kind of problems.

As regards the selected test case, the results are the following: the aerodynamic and control upgrade is estimated to provide the 2.9% of AEP improvement, while the yaw control optimization is estimated to provide the 1% of AEP improvement. On the grounds of the above results and of a cost analysis (which is omitted for privacy of the wind farm owner and manufacturers), it can be stated that the power upgrades considered in this work resulted being profitable for the wind farm owner. In general, the policy of Renvico is installing only power upgrades that are estimated being profitable (and the estimate is confirmed or confuted by studies like this), in compliance with the incentives mechanism.

The main further direction of this kind of studies is including in the analysis how the residual useful lifetime changes, according to the dynamics of the refurbished wind turbine.

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