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Diagnosis of wind turbine systematic yaw error through nacelle anemometer measurement analysis

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ABSTRACT

The power produced by a wind turbine can be considerably affected by the presence of systematic errors, which are particularly difficult to diagnose. This study deals with wind turbine systematic yaw error and proposes a novel point of view for diagnosing and quantifying its impact on the performance. The keystone is that, up to now in the literature, the effect of the yaw error on the nacelle wind speed measurements of the affected wind turbine has been disregarded. Given this, in this work a new method based on the general principle of flow equilibrium is proposed for the diagnosis of such type of error. It is based on recognizing that a misaligned wind turbine measures the wind speed differently with respect to when it is aligned. The method is shown to be effective for the diagnosis of two test cases, about which an independent estimate of the yaw error is available from upwind measurements (spinner anemometer). A data-driven generalization of the concept of relative performance is then formulated and employed for estimating how much the systematic yaw error affects wind turbine performance. It is shown that the proposed method is more appropriate than methods employing wind speed measurements (like the power curve), which are biased by the presence of the error. The results of this study support that SCADA-collected data can be very useful to diagnose wind turbine systematic yaw error, provided that a critical analysis about their use is done.

1. Introduction

Wind turbines at present are the leading renewable energy technology worldwide, due to their advantageous energy density and wind kinetic energy conversion efficiency, and their exploitation is fundamental in the transition to a sustainable energy future [1–3]. The growth of wind turbines installation worldwide almost doubled from 2019 (58 GW) to 2020 (111 GW) [4] and the trend has been further accelerating, which gives immense opportunities as well as risks related to the grid management [5,6].

Wind turbine monitoring is a far from trivial task, due to the stochastic nature of the source and to the complexity of the machine, but it is crucial in order to improve the efficiency of energy conversion and finally diminish the levelized cost of energy. The individuation of systematic errors [7,8] affecting wind turbine operation is an overlooked topic, which should be analyzed more in depth. A systematic yaw error [9] occurs when a wind turbine is controlled to achieve a set point of rotor orientation, which is believed to be front of the wind flow but in fact it is not. This can occur due to wind vane defects, incorrect installation or maintenance, or the aging of the machine. In [10], it is estimated that over 50% of the industrial wind turbines operate with more than 6° of systematic yaw error. Aerodynamic considerations [11] indicate that, in presence of a systematic yaw error γ, the extracted power P is reduced by a factor $\cos^3\gamma$. By assuming for simplicity the $\cos^3$ law, a systematic yaw error of 6° causes an average production loss in the order of 2%. This leads to estimate that, by correcting the systematic yaw error of the wind turbines worldwide, the wind energy production would increase of the 1%.

Supervisory Control And Data Acquisition (SCADA) systems have been historically conceived for allowing remote control of the wind turbines, but they have been evolving into a powerful information source for condition monitoring [12,13]. Actually, SCADA systems store and make available a vast set of environmental, operational, electrical, mechanical and thermal measurements with a typical averaging time of ten minutes. Nevertheless, extracting knowledge from this information is particularly challenging when dealing with systematic errors which regard the rotor.

In line of principle, a wind turbine systematic yaw error can be ascertained by using upwind sensor systems and by comparing the rotor orientation to the upwind wind direction. In fact,

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LiDARs [14,15] or spinner [16] anemometers have been employed at this aim. By a practical point of view, the use of such sensors systems in addition to those already implemented on the wind turbine might be discouraged by their installation cost. Given this, it makes sense to employ the SCADA-collected data (which are typically available to the end user without additional cost) at least as a first advice for directing the installation of LiDARs or spinners to the wind turbines which are more suspected to be affected by the systematic yaw error. The general problem with the use of SCADA data for diagnosing systematic errors related to the rotor is that the anemometer is mounted on the nacelle behind the rotor span [17]. This means that the nacelle anemometer measures the wind perturbed by the rotor in intensity and direction and the undisturbed field is reconstructed through a nacelle transfer function.

On top of this, the literature about SCADA-based detection of wind turbine systematic yaw error has overlooked a further critical point, which is the fact that the nacelle anemometer measurements are affected by the presence of the systematic yaw error [18]. This occurs because, if a wind turbine operates subjected to a systematic yaw error, its nacelle anemometer (being behind the rotor) will be more upwind or more downwind with respect to what happens in normal operation and therefore, for a given free flow wind speed, the nacelle anemometer will respectively measure more or less wind intensity with respect to what would happen normally. The core of the present work is therefore a critical analysis of what the above statement implies and of how the SCADA-based methods for individuating and assessing the impact of the systematic yaw error should be reconsidered.

The structure of the manuscript is as follows. The related work is summarized in Section 1.1, where the innovative contribution of the present study is outlined as well. In Section 2, the test case is described and the method is illustrated. A real-world test case is contemplated, which is a wind farm owned by the ENGIE Italia utility company. In Section 3, the results are collected and the conclusion are drawn in Section 4.

1.1. Related work and contribution to scholarship

The caveat which orientates most studies in the literature is that SCADA-collected direction measurements of a wind turbine affected by a systematic yaw error are very likely indistinguishable with respect to those of a wind turbine operating correctly. The nacelle wind direction and rotor orientation measurements indicate a correct alignment, while this does not occur. This implies that most studies in the literature are based on the individuation of the systematic yaw error through secondary effects and the most straightforward effect is an under-performance (recall the $\cos^3$ law).

An under-performance consists of less power extracted for a certain incoming wind speed. The most common SCADA-based approach for individuating and quantifying an under-performance is the analysis of the power curve, because it is the relation between wind speed (x-axis) and extracted power (y-axis). In this regard, a very interesting study related to the use of the power curve for systematic yaw error detection is [19]. The most noticeable aspect of that work is that a 2.5 MW utility-scale wind turbine (Eolos research station) has been fully controlled by the authors, who have forced the operation under several static yaw errors in order to characterize the different behavior with respect to the normal operation. Actually, a gap in the research is given by the lack of a clear data labeling (with error or not). In this context, the work of [19] is particularly valuable. The data-driven procedure employed in [19] is substantially a fit of the observed power curve in presence of the systematic yaw error to $\cos^3 \gamma$ times the power curve in normal operation. The systematic yaw error is diagnosed also in [20] as an under-performance detected by a data-driven method. A Gaussian Process regression for the power curve is set up, employing operation variables as blade pitch and rotor speed.

Several studies in the literature employ a mixture of analyses, which include jointly the power curve and the behavior of the wind vane measurements. The common assumption is that the best performance of the machine should occur for vanishing yaw error. If this does not occur, it is likely that there is a systematic yaw error, which is consequently estimated as the angle at which the best performance is observed. This line of reasoning is applied for example in [21], where an analysis of the binned power curve is performed upon grouping the data per yaw error intervals of 2°. A similar approach is employed in [22,23]. The difference with respect to [21] is in the power curve model, which is Least-Square B-spline Approximation. In [24], the power curve analysis is applied upon a non-trivial data rejection algorithm that takes into account several features of the machine functioning. In [25], the data are pre-processed appropriately, so that small portions of the power curve are employed for diagnosing and individuating the yaw error.

The same kind of concept is employed in other studies where the target is the power coefficient, rather than the power curve. In [26], the systematic yaw error is individuated by looking at what value of the yaw error the maximum power coefficient occurs actually (measurements) and theoretically, where the theoretical estimate is achieved with a data-driven method that takes into account environmental variables like turbulence intensity and external temperature. In [27], the yaw angle - power coefficient curve is analyzed and the diagnosis is formulated directly from the observed data. The behavior of the yaw angle - rotor speed curve is studied in [28]. The approach employed in [29] instead stands apart somehow, because a wind-farm approach is formulated for diagnosing the systematic yaw error, which is given by the analysis of the distribution of the relative wind direction measurements.

The point of this study is that the above works overlook the fact that the nacelle wind speed measurements are affected by the presence of the yaw error. This implies that it is not completely consistent to compare the power curve of a wind turbine subjected to systematic yaw error to that of a well aligned wind turbine. In this regard, it is worth discussing the recent work in [24]. LiDAR measurements have been employed to diagnose the systematic yaw error on some target wind turbines and to assess its absence upon appropriate intervention on the wind turbines. Therefore, in [24] a clear data labeling is at disposal and the authors elaborate on the SCADA data collected by the wind turbines when operating with and without the systematic yaw error. Through a straightforward comparison of the power curves in presence and absence of the systematic yaw error, it is estimated that less than 10° of yaw error correction provides order of 15% of performance improvement, which is implausible (the $\cos^3$ law gives a 5%). The conclusion drawn in [24] is that there are data quality issues related to the wind turbine nacelle anemometer. Given the line of reasoning of this work, a more plausible interpretation is that, when operating with 10° of yaw error, the nacelle anemometer was more upwind than the normal and then overestimated the wind speed, thus amplifying the apparent difference in the power curve with respect to the case of vanishing yaw error.

At present, there is only one work in the literature dealing with the effects of the systematic yaw error on nacelle wind speed measurements. In [30], the flow equilibrium condition of two nacelle anemometers is employed for individuating the systematic yaw error. The study in [30] raises substantial issues also on the methods based on the characteristic curves of wind turbines as a function of the yaw angle as estimated by the SCADA-collected measurements. Actually, it is argued that the flow distortion induced by the nacelle is disregarded in most studies in the literature.

Based on the above line of reasoning, with this work a research gap is filled regarding the following points:

- **Detection**. A systematic yaw error detection algorithm based on nacelle anemometer measurements analysis is formulated. The points of strength of this algorithm are the consistency following from first principles, the simplicity and the universality (it does not depend on the particular wind turbine model).
- **Assessment**. A method for quantifying the effect of the systematic yaw error on wind turbine performance is formulated, which is the generalization of the concept of relative performance. This method does not employ nacelle wind speed measurements, because those depend on the presence or not of the systematic yaw error. In this work, it is argued that the proposed method provides more consistent results with respect to the power curve analysis.

The selected test case is a further point of strength of this work. Actually, the presence of a systematic yaw error on two wind turbines out of six from an Italian wind farm has been ascertained through an upwind sensor system (spinner anemometer). This means that the data sets are labeled. Furthermore, the systematic yaw error has been corrected and this means that data sets describing the behavior in presence or absence of a remarkable systematic yaw error are at disposal. Summarizing, therefore, the proposed method for detection and assessment of systematic yaw error is shown to be more consistent and effective with respect to the state of the art.

2. Materials and methods

2.1. Definition of systematic yaw error

The yaw error γ is defined as the difference between the wind direction θ_{wd} and the rotor direction θ_{rot}, as indicated in Eq. (1):

$$\gamma = \theta_{wd} - \theta_{rot}. \tag{1}$$

The control system of the wind turbine operates for achieving the set point given by $\gamma = 0$ through the actuation of yaw motors and-or by using the blade pitch control [31] of the turbine [32]. As discussed in detail for example in [32], the critical point for wind turbine yaw control is the measurement or estimation of the wind direction and several possibilities are explored in the technology. The most common is the assumption that the wind direction measured by the nacelle anemometer is the correct one, or at least is in a comprehensible relation with the correct one which can be compensated [33]; the use of more advanced sensor systems like LiDARs has been recently growing [34]; or short term estimation methods based on the operation variables of the wind turbine can be adopted [35]. Whatever the method for estimating the wind direction is, there is a mismatch between the large inertia of the rotor and the wind direction meandering characteristic time. This means that the yaw error γ [36] is a dynamic quantity which changes instant by instant and can be hypothesized to be distributed according to a Gaussian with zero mean and a certain standard deviation σ [21]. There is an important line of research dealing with dynamic yaw error reduction [37–40], which practically means diminishing σ, since the yaw error has a non-trivial impact on aerodynamic characteristics [41]. There are corresponding evidences of the fact that the advance in dynamic yaw control improves the efficiency of wind energy conversion [42,43]. Yet, the yaw error can have also

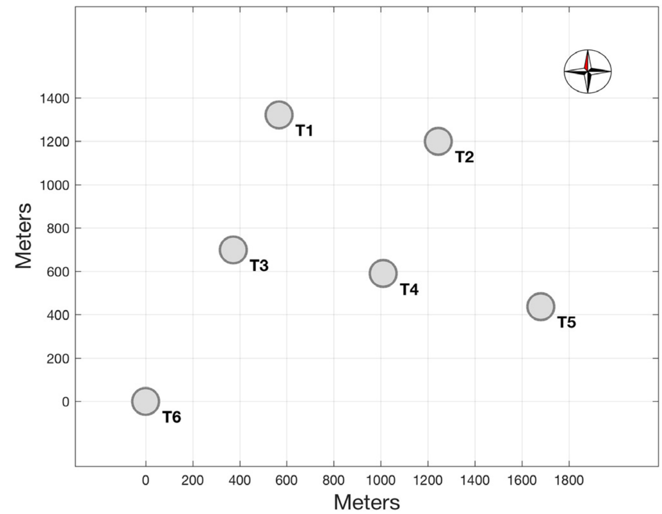

Fig. 1. The layout of the test case wind farm.

a static component, which is typically referred as zero-point shift or systematic yaw error. This means that it can happen that the wind turbine is regulated according to a yaw set point which is believed to be zero, but it is not. Actually, the zero-point of wind vane sensor should align with the rotor shaft in order to ensure the correct measurement of yaw angle, but it can happen that this does not occur, due to inappropriate installation, aging of the machine, wind vane defect. It is as if

$$\theta_{wd} = \theta_{real} + \theta_{err} \tag{2}$$

and then, basing on Eqs. (1) and (2), the expected value of γ becomes θ_{err} instead of zero. Aerodynamic considerations indicate that the power of a wind turbine subjected to a systematic yaw error γ should scale as in Eq. (3):

$$P_{\gamma} = P_0 \cos^3 \gamma, \tag{3}$$

where P_0 is the power which would be extracted under the same conditions with vanishing yaw error. Previous studies about full-scale wind turbines indicate that this is just an approximation and the role of the blade pitch control comes into play [44], but in any case the effect on power production [28] is non-negligible and it can reach some percents of the annual energy production.

2.2. The test case and the data sets

The test case wind farm is composed of six Senvion MM92 wind turbines, each having 2 MW of rated power. It is owned by ENGIE Italia and sited in southern Italy. The layout is reported in Fig. 1.

The peculiarity of the test case is that an upwind spinner anemometer [16] has been installed on these wind turbines and therefore an independent estimate of the systematic yaw error is available. From Table 1, it arises that there has been a period during which the two target wind turbines T3 and T5 have operated (data set D1) with a large yaw error (clockwise with respect to the wind direction), which has been subsequently corrected (data set D2). One of the points of the strength of the present work is therefore the data labeling (D1 with systematic yaw error, D2 without).

Table 1
The data sets and the yaw error estimates provided by the spinner anemometer for the target wind turbines T3 and T5.

Data set	Dates	T3	T5
D1	1st Aug–16th Dec 2020	−14.45°	−12.04°
D2	1st May–30th June 2021	1.13°	0.86°

The measurements at disposal which have been employed for this study are:

- Nacelle wind speed sensor 1 v_1 (m/s);
- Nacelle wind speed sensor 2 v_2 (m/s);
- Power output P (kW).

The data have been filtered on wind turbine operation using the appropriate run time counter collected by the SCADA control system. The wind speed v reported in the SCADA-collected data set is the average of v_1 and v_2, if two sensors are available, and this is indeed the case for the present wind farm. There is no information available about the precise anemometer arrangement, except for the fact that they are expected to be placed at the opposite lateral ends of the nacelle.

2.3. Detection: Comparison against a state of the art method

A state of the art method for diagnosing a systematic yaw error is the analysis of the power coefficient as a function of the wind vane (i.e. yaw error) measurements collected by the SCADA control system. The power coefficient is defined as in Eq. (4):

$$C_p = \frac{P}{\frac{1}{2}\rho A v^3}, \tag{4}$$

where P is the produced power, ρ is the average air density on site, A is the rotor area and v is the wind speed. The yaw error - power coefficient curve is computed for all the wind turbines in the farm through the binning method. Furthermore, the frequency of wind vane measurements is computed and reported for all the wind turbines in the farm.

2.4. Detection: Wind-wind target turbine analysis

Having at disposal data from two wind sensors is a turning point for the diagnosis of a systematic yaw error. Actually, if a wind turbine operates subjected to a systematic yaw error, most of the time one anemometer will be more upwind than in the normal operation and the other will be more downwind. In other words, the relation between v_1 and v_2 will slightly change. If the systematic yaw error is vanishing, the flow streamlines behind the rotor are parallel to the rotor axis. This condition is called flow equilibrium because the difference between v_1 and v_2 depends as weakly as possible on the wind intensity and is expected to be averagely zero [30]. Therefore, by posing a simple linear relation as in Eq. (5):

$$v_2 = k v_1, \tag{5}$$

we expect k to be nearer to 1 in the case of well aligned wind turbines and deviating from 1 when there is a systematic yaw error. In practice, for the considered test case, it should be possible to distinguish the data set D1 with respect to the data set D2 for the two wind turbines T3 and T5, in the form of change of the k coefficient. For further inspection, the average absolute value of the difference between v_1 and v_2 is computed too. This analysis can be carried as well for the other wind turbines in the farm, which act as reference for checking the consistency of the method.

2.5. Detection: Wind-wind reference-target turbine analysis

Based on the above considerations, the occurrence of a systematic yaw error is expected to affect the nacelle wind speed measurement. Therefore, considering that for two wind turbines (T3 and T5) we have a data set where they run subjected to systematic yaw error and one where the error has been corrected, it should be possible to individuate a slight difference in the relation between the nacelle wind speed measurement at the target wind turbines and the nacelle wind speed measured at the nearby reference ones. This can be done by posing once again a linear relation as in Eq. (6):

$$v_{tar} = k_2 v_{ref}, \tag{6}$$

where v_{tar} and v_{ref} are the nacelle wind speeds v at the target and reference wind turbines respectively. This method is proposed using v rather than v_1 or v_2 because in this way it can be applied also for wind turbines having only one wind speed sensor at the nacelle. Substantially, the objective of this analysis for the selected test case is inquiring if k_2 changes for T3 and T5 in D2 with respect to D1 and how.

2.6. Assessment: Comparison against state of the art methods

The standard in the literature for estimating the performance change of a wind turbine from one period to another is the power curve, which goes as follows:

- Compute the average power curve using the method of bins for D1 and D2 data set. This means grouping the data per wind speed bins of 0.5 m/s and averaging the power measurements for each wind speed bin.
- The performance change between D1 and D2 passes through the computation of E_{tar} and E_{ref}, where

  $$E_{tar} = \sum_i P_i f_i$$

  and

  $$E_{ref} = \sum_i \hat{P}_i f_i.$$

  P_i and $\hat{P}_i$ are respectively the average power for the ith bin in the target (D2) and in the reference (D1) data set, f_i is the frequency of the ith bin in the target data set (D2).
- The average percentage performance deviation between D2 and D1 can be estimated as

  $$\Delta = 1 - \frac{E_{ref}}{E_{tar}}. \tag{7}$$

- A subtlety is given by the fact that the power curve depends on several environmental factors (turbulence intensity, atmospheric stability, wind shear and so on [45,46]) which can have a seasonal dependence. If the data sets belong to two different seasons, as is the case for the present work (Table 1), one can have a clearer picture of the performance change of the target wind turbines by renormalizing the Δ estimator with the same quantity computed for a reference wind turbine (Δ_{ref}). One therefore obtains Eq. (8):

  $$\hat{\Delta} = \Delta - \Delta_{ref}. \tag{8}$$

2.7. Assessment: Proposed method

Given that the nacelle wind speed measurements are affected by the presence of the yaw error, the power curve analysis depicted in Section 2.6 has to be revisited. In order to avoid

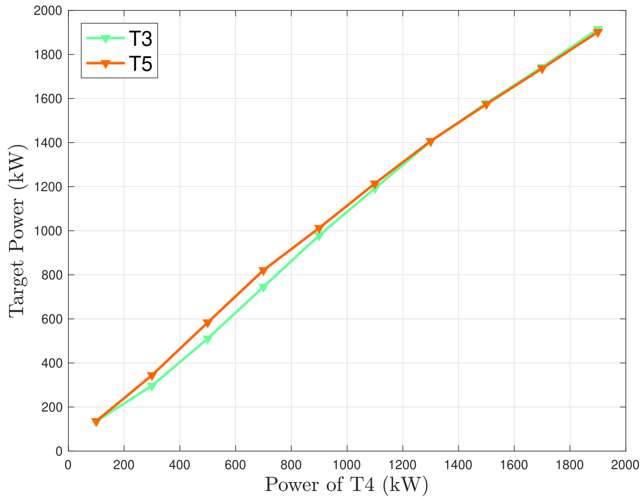

Fig. 2. Power of T3 and T5 as a function of the power of T4 for the data set D1.

bias, in this work a power–power method based on the relative performance of T3 and T5 with respect to the other wind turbines in the farm is proposed.

Such generalization of the concept of relative performance goes as follows:

- Train a model for the power of T3 and one for the power of T5 (indicated as y), using two thirds of the D1 data set. The input variables of each model are selected to be the power of T2, T4 and T6, which constitute a vector $\boldsymbol{x}$. The correlation coefficient between the input variables and the power of T3 and T5 are respectively $(0.92, 0.94, 0.97)$ and $(0.95, 0.97, 0.90)$. It should be noticed that the method does not require to know that the yaw error is absent for the reference wind turbines. It just requires that the behavior of the reference wind turbines does not change, which can be reasonably assumed if no interventions are performed on them. This is the case for the present work for T2, T4 and T6, which have been selected, while T1 has been excluded because it has undergone an intervention.
- Simulate the output of the model for the remainder one third of the data set D1, given the input (using Eq. (14)). The model estimate is indicated as $\hat{y}(\boldsymbol{x}_1)$.
- Do the same for all the data set D2, obtaining $\hat{y}(\boldsymbol{x}_2)$.
- Compute the quantity in Eq. (9) for $i = 1, 2$:

$$\Delta_i = 100 \frac{\sum_{\boldsymbol{x}_i \in Di} y(\boldsymbol{x}_i) - \hat{y}(\boldsymbol{x}_i)}{\sum_{\boldsymbol{x}_i \in Di} y(\boldsymbol{x}_i)} \tag{9}$$

- The quantity $\tilde{\Delta} = \Delta_2 - \Delta_1$ gives an estimate of the performance change between D2 and D1.

The rationale for using the power of the nearby wind turbines as input variables for the power of a target wind turbine can be easily understood also on a qualitative basis, through the plot of the target as a function of one of the reference as in Fig. 2.

The selected model is a Support Vector Regression with Gaussian Kernel. It has been selected basing on a comparative analysis against other typical model structures, which is omitted for brevity. In general its decisive feature justifying its widespread application in SCADA data analysis problems [47,48] in wind energy is its robustness with respect to the presence of outliers. The principles of the Support Vector Regression are as follows. Starting from a linear model as in Eq. (10):

$$y = \boldsymbol{x}\beta, \tag{10}$$

the objective is estimating the coefficients β in order to minimize the norm $\beta'\beta$ compatibly with the residuals between model estimates and measurements being lower than a threshold. The solution can be expressed in terms of the support vectors, which are the coefficients α in Eq. (11):

$$\beta = \sum_{n=1}^{N} \left(\alpha_n - \alpha_n^*\right) \boldsymbol{x}_n \tag{11}$$

and can be computed by minimizing $L(\alpha)$, given in Eq. (12):

$$L(\alpha) = \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \left(\alpha_i - \alpha_i^*\right)\left(\alpha_j - \alpha_j^*\right) \boldsymbol{x}_i' \boldsymbol{x}_j + \epsilon \sum_{i=1}^{N} \left(\alpha_i + \alpha_i^*\right) + \sum_{i=1}^{N} y_i \left(\alpha_i^* - \alpha_i\right). \tag{12}$$

A non-linear Support Vector Regression is obtained by substituting the scalar products between the observations matrix in Eq. (12) with a Kernel function of the observations matrix. A typical selection is the Gaussian kernel given in Eq. (13):

$$G(\boldsymbol{x}_1, \boldsymbol{x}_2) = e^{-\kappa \|\boldsymbol{x}_1 - \boldsymbol{x}_2\|^2}, \tag{13}$$

where κ is the kernel scale. Once a model has been trained, it can be used for predicting, given the input variables, using Eq. (14):

$$f(\boldsymbol{x}) = \sum_{n=1}^{N} \left(\alpha_n - \alpha_n^*\right) G(\boldsymbol{x}_n, \boldsymbol{x}). \tag{14}$$

In this study, the Support Vector Regression has been applied using Matlab upon hyperparameters optimization based on 10-fold cross validation.

3. Results

3.1. Detection: Comparison against state of the art methods

In Fig. 3, the frequency of wind vane measurements for each wind turbine during the data set D1 is reported. From this Figure, it arises that all the wind turbines orientate to a set point which the SCADA reports to be zero, but in fact it is not for wind turbines T3 and T5 (as arises from Table 1). From Fig. 3, it is impossible to clearly distinguish T3 and T5 with respect to the other wind turbines in the farm.

Fig. 4 reports the wind vane - power coefficient curve. Also in this case, it is impossible to distinguish clearly T3 and T5 with respect to the well aligned wind turbines. What this Figure actually shows is the effect of the rotor rotation on the wind, which introduces a sort of rotor blade offset vane [30] in the apparent behavior of the efficiency. Such offset has to be compensated according to the line of reasoning in [33].

The above results indicate that it is questionable to use the wind vane measurements collected by the wind turbine to detect the systematic yaw error.

3.2. Detection: Wind-wind target turbine analysis

In Fig. 5, the average curve of v_2 as a function of v_1 is reported for the data set D1 for the target wind turbines T3 and T5 and for a sample reference wind turbine (selected to be T6). It clearly arises that the behavior of T3 and T5 distinguishes with respect to T6. For T3 and T5, for given v_1, v_2 is slightly lower with respect to what happens for T6. The situation changes upon correction of the systematic error. In the data set D2, represented in Fig. 6, the behavior of the various wind turbines is more similar. This is corroborated by the results in Table 2, where the k coefficient

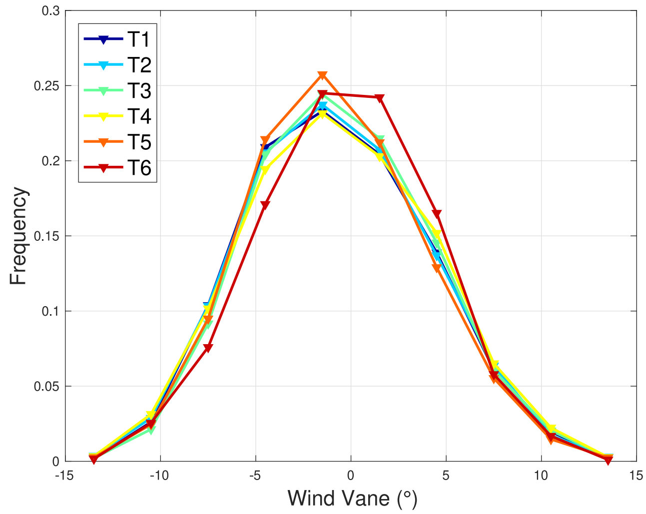

Fig. 3. Frequency of wind vane measurements: data set D1.

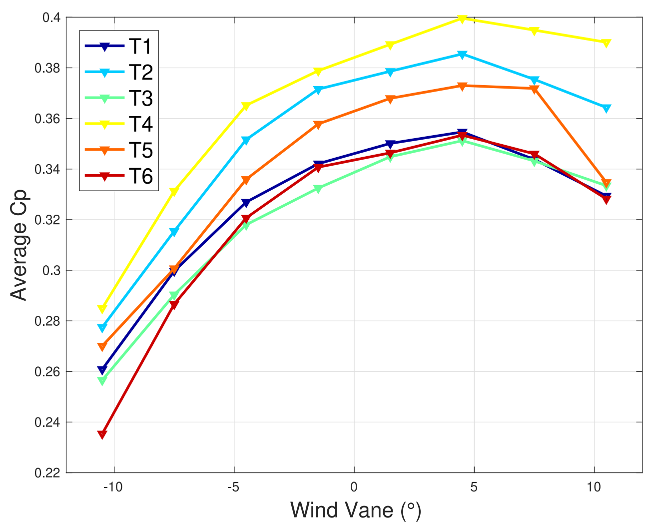

Fig. 4. Wind vane - power coefficient (C_p) curve: data set D1.

is reported for the data sets D1 and D2. The results are reported with 4 digits because the standard error of k estimated by the model is in the order of 10^{-4}. Upon correction of the systematic yaw error (data set D2), the k coefficient for T3 and T5 is in the order of 0.99 while it was respectively in the order of 0.94 and 0.95 in data set D1. For the T6 wind turbine, the coefficient is stably in the order of 1.02, which is reassuring about the consistency of the method (no interventions on T6 and no change in the coefficient). This value is closer to 1 with respect to T3 and T5 in the data D1. From these results, it can be hypothesized that T3 and T5 in data set D2 have even a better alignment than T6. Furthermore, in the data set D1, the deviation with respect to the unity for k is higher for T3 which, according to Table 1, has the higher yaw error. The same kind of conclusions can be drawn from Table 3, where the average absolute difference between v_1 and v_2 is reported for data sets D1 and D2.

3.3. Detection: Wind-wind reference-target turbine analysis

In Table 4, the results are reported for the analysis indicated in Section 2.5. They are reported with 3 digits because the standard deviation of the least squares estimates is in the order of 10^{-3}. T6 is selected as reference and the behavior of T3 and T5 is analyzed for the data sets D1 and D2. Also T4 is included as target wind turbine, in order to verify if it is possible to distinguish it with respect to T3 and T5. The coefficient k_2 is higher in D1 with respect to D2 for the T3 and T5 wind turbines. This means that, for given wind speed measured at the T6 nacelle, in D1 the wind measured at the nacelles of T3 and T5 is slightly higher than in D2. In other words, the effect of the yaw error at T3 and T5 is an over estimation of the wind speed. It should be noticed that the

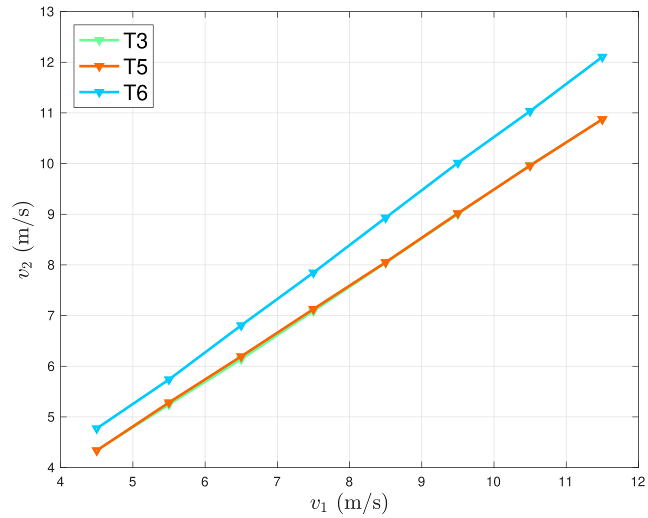

Fig. 5. Average curve of v_2 as a function of v_1 for the data set D1.

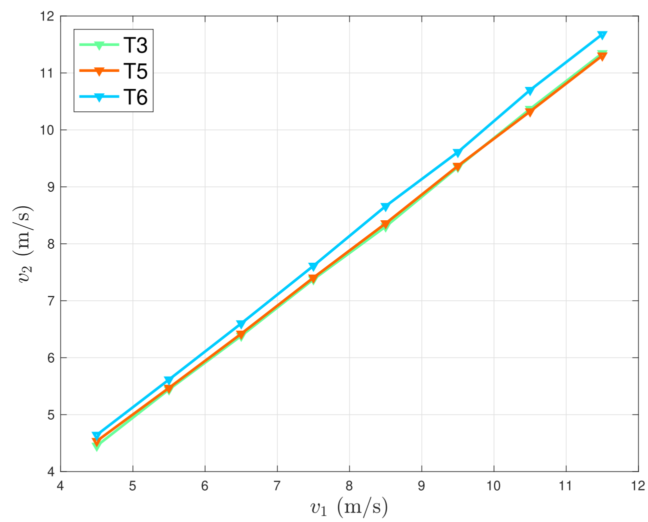

Fig. 6. Average curve of v_2 as a function of v_1 for the data set D2.

Table 2
The estimates of k (Eq. (5)) for the data sets D1 and D2.

Data Set	T3	T5	T6
D1	0.9483	0.9517	1.0215
D2	0.9903	0.9897	1.0241

Table 3
The average absolute difference between v_1 and v_2 for data sets D1 and D2.

Data Set	T3	T5	T6
D1	0.38	0.36	0.23
D2	0.13	0.13	0.22

Table 4
The estimates of k_2 (Eq. (6)) for the data sets D1 and D2.

Data Set	T3	T5	T4
D1	0.963	0.943	0.880
D2	0.932	0.903	0.877

Table 5
The estimates of $\hat{\Delta}$ (Eq. (8)) and $\tilde{\Delta}$.

Metric	T3	T5
$\hat{\Delta}$	4.6%	7.3%
$\tilde{\Delta}$	1.6%	2.5%

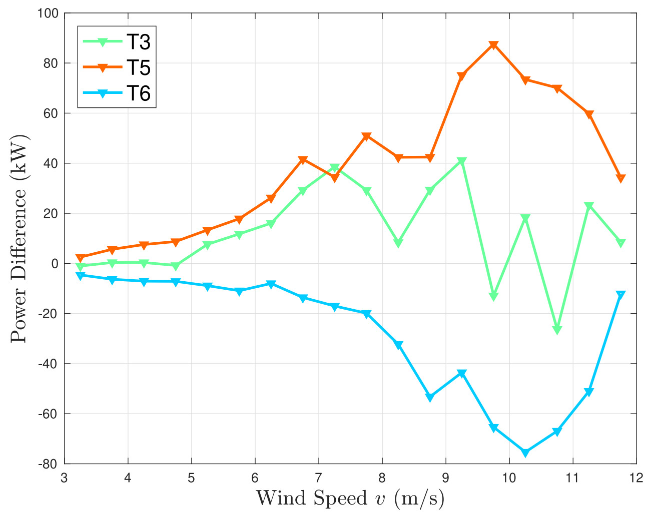

Fig. 7. Average power curve difference between D2 and D1 data sets.

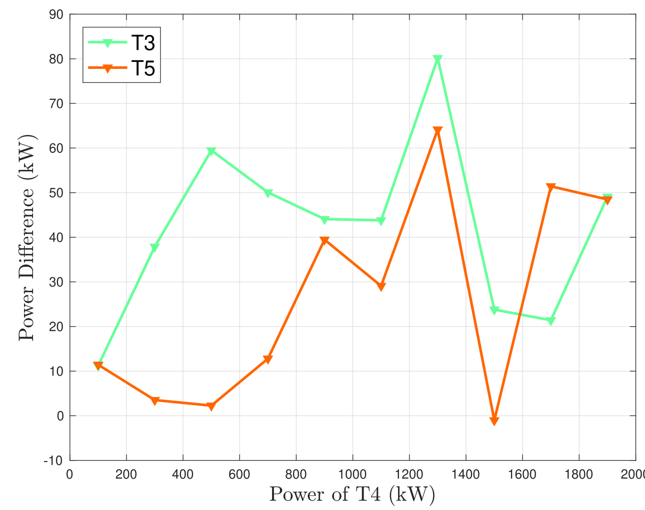

Fig. 8. Power of T3 and T5 as a function of the power of T4, in the form of difference between the data sets D2 and D1.

method proposed in Section 2.4 does not give indication about the fact that the wind speed is under or over estimated due to the presence of the yaw error, while the present method does because it puts in relation the wind at the target wind turbine to the wind at reference wind turbines.

3.4. Assessment: Quantification of the performance change

In Fig. 7, the difference between the power curves computed in the data sets D2 and D1 is reported for wind turbines T3 and T5 and for the reference T6. It appears that T3 and T5 have improved, while T6 even seems to have worsened. This latter behavior of T6 can likely be an apparent effect due to environmental factors. Nevertheless, the procedure indicated in Section 2.7 allows quantifying the difference of the behaviors of T3 and T5 relative to the behavior of T6. The results are reported in Table 5, from which it arises that the average estimate of performance change for T3 and T5 is remarkable (4.6% and 7.3% respectively).

In Table 5, the estimates of $\tilde{\Delta}$ are reported as well. The data-driven method proposed in this work, which employs only power measurements, provides performance change estimates which are in the order of one third of those calculated through the power curve analysis. Those two estimates should be similar if the systematic yaw error did not affect nacelle wind speed measurements but this, as supported with the above analyses, is not the case. The point is that there is a bias in the power curve method and is given by the fact that the nacelle wind speed measurements are affected by the systematic yaw error. These results therefore confirm that, for the considered test cases, the presence of a systematic yaw error led to an over estimation of the nacelle wind speed. Through the power curve analysis, therefore, in this case the effect of apparent under-performance is amplified. Less power is extracted for given wind due to the yaw error, but also more wind intensity is measured due to the yaw error. Therefore, it is not completely consistent to estimate the effect of the systematic yaw error by straightforwardly comparing the power curves. In other words, the quantification of the effect of the systematic yaw error requires a reference which is not affected by the error. Finally, in Fig. 8, the power of T3 and T5 is reported as a function of the power of T4, in the form of difference between the data sets D2 and D1. This provides an unbiased representation of the fact that indeed the performance of T3 and T5 has improved in the data set D2.

4. Conclusions

The present study has dealt with the use of nacelle anemometer SCADA-collected data for the diagnosis and the assessment of the performance impact of wind turbine systematic yaw error. The starting point of this work is the fact that the presence of a systematic yaw error affects nacelle wind speed measurements and this leads to revisit the methods for diagnosis and assessment. Despite being as simple as that, this aspect has never been investigated in deep before in the literature about full-scale industrial wind turbines.

It is therefore questionable to diagnose wind turbine systematic yaw error in the form of under-performance observed from the power curve without taking into account critically the effect of the yaw error itself on the nacelle wind speed measurements. This can be understood through a simple paradox. In presence of a systematic yaw error, the nacelle anemometer of a wind turbine is more upwind or more downwind than in normal operation. If it is more downwind, it measures less wind speed than in normal operation. Therefore, by comparing the power curves with and without systematic yaw error, the latter might even appear better performing, which is a contradiction.

On the other way round, the fact that the nacelle wind speed measurements are affected by the systematic yaw error might be the turning point for the diagnosis. The general rationale is that the presence of a systematic yaw error causes deviations from the flow equilibrium. Based on this, in this work two methods have been concretely formulated. The former is based on the analysis of the relation between the wind speed measured by two nacelle anemometers (if present) at the target wind turbine and the latter is based on the analysis of the relation between the nacelle wind speed measured at the target and reference nearby wind turbines.

As a consequence of the above line of reasoning, also the quantification of the effect of the systematic yaw error should be revisited critically. In this study, the performance change upon a correction of a remarkable yaw error has been estimated using a data-driven generalization of the concept of relative performance, thus employing only power measurements. It is shown that the achieved estimate is more consistent than what would be obtained from a straightforward power curve analysis, which (as above argued) is biased by the effect of systematic yaw error.

SCADA data analysis is fundamental for wind turbine monitoring and in this context it is important to circumscribe appropriately the limitations within which it should be employed. At present, there are no studies in the literature employing the method proposed in this work for the diagnosis of systematic yaw error. This means that there is a limited statistics and that there are no first principles guesses of the relation between the deviations from the flow equilibrium and the amount of systematic yaw error. As in many similar applications, such missing knowledge in the near future will likely be extracted from data, which means from experience. Therefore, the most important further direction of the present work is enlarging the test cases portfolio. As it stands in this work, the proposed method can be very useful for wind energy practitioners as an advice for further inspections and/or installations of upwind sensor systems (like LiDARs or spinners).

CRediT authorship contribution statement

Davide Astolfi: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Ravi Pandit:** Validation, Investigation, Writing – review & editing, Visualization. **Andrea Lombardi:** Validation, Investigation, Supervision, Writing – review & editing. **Ludovico Terzi:** Supervision, Project administration, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

References

[1] P. Sadorsky, Wind energy for sustainable development: Driving factors and future outlook, J. Clean. Prod. 289 (2021) 125779.
[2] L. Chang, H.B. Saydaliev, M.S. Meo, M. Mohsin, How renewable energy matter for environmental sustainability: Evidence from top-10 wind energy consumer countries of European Union, Sustain. Energy Grids Netw. 31 (2022) 100716.
[3] R.K. Samal, M. Tripathy, Cost and emission additionality of wind energy in power systems, Sustain. Energy Grids Netw. 17 (2019) 100179.
[4] P. Scarabaggio, S. Grammatico, R. Carli, M. Dotoli, Distributed demand side management with stochastic wind power forecasting, IEEE Trans. Control Syst. Technol. 30 (1) (2021) 97–112.
[5] A. Coelho, J. Iria, F. Soares, J.P. Lopes, Real-time management of distributed multi-energy resources in multi-energy networks, Sustain. Energy Grids Netw. (2023) 101022.
[6] Z. Hu, B. Gao, R. Sun, An active primary frequency regulation strategy for grid integrated wind farms based on model predictive control, Sustain. Energy Grids Netw. 32 (2022) 100955.
[7] M. Bertelè, C.L. Bottasso, S. Cacciola, Automatic detection and correction of pitch misalignment in wind turbine rotors, Wind Energy Sci. 3 (2) (2018) 791–803.
[8] F. Castellani, A. Eltayesh, M. Becchetti, A. Segalini, Aerodynamic analysis of a wind-turbine rotor affected by pitch unbalance, Energies 14 (3) (2021) 745.
[9] M. Kim, P. Dalhoff, Yaw systems for wind turbines–Overview of concepts, current challenges and design methods, J. Phys. Conf. Ser. 524 (1) (2014) 012086.
[10] H. Pedersen, E.G. Marin, Yaw misalignment and power curve analysis, in: EWEA Analysis of Operating Wind Farms, 2016.
[11] T. Burton, N. Jenkins, D. Sharpe, E. Bossanyi, Wind Energy Handbook, John Wiley & Sons, Chicester, United Kingdom, 2011.
[12] J. Tautz-Weinert, S.J. Watson, Using SCADA data for wind turbine condition monitoring–a review, IET Renew. Power Gener. 11 (4) (2016) 382–394.
[13] R. Pandit, D. Astolfi, J. Hong, D. Infield, M. Santos, SCADA data for wind turbine data-driven condition/performance monitoring: A review on state-of-art, challenges and future trends, Wind Eng. (2022) 0309524X221124031.
[14] D. Choi, W. Shin, K. Ko, W. Rhee, Static and dynamic yaw misalignments of wind turbines and machine learning based correction methods using lidar data, IEEE Trans. Sustain. Energy 10 (2) (2018) 971–982.
[15] L. Zhang, Q. Yang, A method for yaw error alignment of wind turbine based on LiDAR, IEEE Access 8 (2020) 25052–25059.
[16] G. Demurtas, T.F. Pedersen, F. Zahle, Calibration of a spinner anemometer for wind speed measurements, Wind Energy 19 (11) (2016) 2003–2021.
[17] A. Carullo, A. Ciocia, G. Malgaroli, F. Spertino, An innovative correction method of wind speed for efficiency evaluation of wind turbines, ACTA IMEKO 10 (2) (2021) 46–53.
[18] D. Astolfi, R. Pandit, L. Gao, J. Hong, Individuation of wind turbine systematic yaw error through SCADA data, Energies 15 (21) (2022) 8165.
[19] L. Gao, J. Hong, Data-driven yaw misalignment correction for utility-scale wind turbines, J. Renew. Sustain. Energy 13 (6) (2021) 063302.
[20] R. Pandit, D. Infield, T. Dodwell, Operational variables for improving industrial wind turbine yaw misalignment early fault detection capabilities using data-driven techniques, IEEE Trans. Instrum. Meas. 70 (2021) 1–8.
[21] B. Jing, Z. Qian, Y. Pei, L. Zhang, T. Yang, Improving wind turbine efficiency through detection and calibration of yaw misalignment, Renew. Energy 160 (2020) 1217–1227.
[22] Y. Bao, Q. Yang, A data-mining compensation approach for yaw misalignment on wind turbine, IEEE Trans. Ind. Inform. 17 (12) (2021) 8154–8164.
[23] Y. Bao, Q. Yang, S. Li, K. Miao, Y. Sun, A data-driven approach for identification and compensation of wind turbine inherent yaw misalignment, in: 2018 33rd Youth Academic Annual Conference of Chinese Association of Automation, YAC, IEEE, 2018, pp. 961–966.
[24] C. Qu, Z. Lin, P. Chen, J. Liu, Z. Chen, Z. Xie, An improved data-driven methodology and field-test verification of yaw misalignment calibration on wind turbines, Energy Convers. Manage. 266 (2022) 115786.
[25] Y. Pei, Z. Qian, B. Jing, D. Kang, L. Zhang, Data-driven method for wind turbine yaw angle sensor zero-point shifting fault detection, Energies 11 (3) (2018) 553.
[26] J. Yang, L. Wang, D. Song, C. Huang, L. Huang, J. Wang, Incorporating environmental impacts into zero-point shifting diagnosis of wind turbines yaw angle, Energy 238 (2022) 121762.
[27] D. Astolfi, F. Castellani, L. Terzi, An operation data-based method for the diagnosis of zero-point shift of wind turbines yaw angle, J. Sol. Energy Eng. 142 (2) (2020).
[28] D. Astolfi, F. Castellani, M. Becchetti, A. Lombardi, L. Terzi, Wind turbine systematic yaw error: Operation data analysis techniques for detecting it and assessing its performance impact, Energies 13 (9) (2020) 2351.
[29] D. Astolfi, F. Castellani, L. Scappaticci, L. Terzi, Diagnosis of wind turbine misalignment through SCADA data, Diagnostyka 18 (2017).
[30] N. Mittelmeier, M. Kühn, Determination of optimal wind turbine alignment into the wind and detection of alignment changes with SCADA data, Wind Energy Sci. 3 (1) (2018) 395–408.
[31] E.A. Bossanyi, Further load reductions with individual pitch control, Wind Energy Int. J. Prog. Appl. Wind Power Convers. Technol. 8 (4) (2005) 481–485.
[32] J. Yang, L. Fang, D. Song, M. Su, X. Yang, L. Huang, Y.H. Joo, Review of control strategy of large horizontal-axis wind turbines yaw system, Wind Energy 24 (2) (2021) 97–115.
[33] K.A. Kragh, P.A. Fleming, A.K. Scholbrock, Increased power capture by rotor speed–dependent yaw control of wind turbines, J. Sol. Energy Eng. 135 (3) (2013).
[34] K.A. Kragh, M.H. Hansen, T. Mikkelsen, Precision and shortcomings of yaw error estimation using spinner-based light detection and ranging, Wind Energy 16 (3) (2013) 353–366.
[35] N. Karakasis, A. Mesemanolis, T. Nalmpantis, C. Mademlis, Active yaw control in a horizontal axis wind system without requiring wind direction measurement, IET Renew. Power Gener. 10 (9) (2016) 1441–1449.
[36] N. Sheibat-Othman, S. Othman, R. Tayari, A. Sakly, P.F. Odgaard, L.F. Larsen, Estimation of the wind turbine yaw error by support vector machines, IFAC-PapersOnLine 48 (30) (2015) 339–344.

[37] D. Song, Z. Li, L. Wang, F. Jin, C. Huang, E. Xia, R.M. Rizk-Allah, J. Yang, M. Su, Y.H. Joo, Energy capture efficiency enhancement of wind turbines via stochastic model predictive yaw control based on intelligent scenarios generation, Appl. Energy 312 (2022) 118773.
[38] Y. Liu, S. Liu, L. Zhang, F. Cao, L. Wang, Optimization of the yaw control error of wind turbine, Front. Energy Res. 9 (2021) 5.
[39] E.V. Solomin, A.A. Terekhin, A.S. Martyanov, A.N. Shishkov, A.A. Kovalyov, D.R. Ismagilov, G.N. Ryavkin, Horizontal axis wind turbine yaw differential error reduction approach, Energy Convers. Manage. 254 (2022) 115255.
[40] A. Saenz-Aguirre, E. Zulueta, U. Fernandez-Gamiz, J. Lozano, J.M. Lopez-Guede, Artificial neural network based reinforcement learning for wind turbine yaw control, Energies 12 (3) (2019) 436.
[41] S. Wan, L. Cheng, X. Sheng, Effects of yaw error on wind turbine running characteristics based on the equivalent wind speed model, Energies 8 (7) (2015) 6286–6301.
[42] D. Astolfi, F. Castellani, F. Natili, Wind turbine yaw control optimization and its impact on performance, Machines 7 (2) (2019) 41.
[43] A. Puech, J. Read, An improved yaw control algorithm for wind turbines via reinforcement learning, in: Machine Learning and Knowledge Discovery in Databases: European Conference, ECML PKDD 2022, Grenoble, France, September 19–23, 2022, Proceedings, Part V, Springer, 2023, pp. 614–630.
[44] J. Dai, X. Yang, W. Hu, L. Wen, Y. Tan, Effect investigation of yaw on wind turbine performance based on SCADA data, Energy 149 (2018) 684–696.
[45] C.M.S. Martin, J.K. Lundquist, A. Clifton, G.S. Poulos, S.J. Schreck, Atmospheric turbulence affects wind turbine nacelle transfer functions, Wind Energy Sci. 2 (1) (2017) 295–306.
[46] A. Honrubia, A. Vigueras-Rodríguez, E. Gómez-Lázaro, The influence of turbulence and vertical wind profile in wind turbine power curve, in: Progress in Turbulence and Wind Energy IV, Springer, 2012, pp. 251–254.
[47] A. Insuasty, C. Tutivén Gálvez, Y. Vidal Seguí, SCADA data-driven wind turbine main bearing fault prognosis based on one-class support vector machines, Renew. Energy Power Qual. J. 19 (2021) 338–343.
[48] R. Pandit, A. Kolios, SCADA data-based support vector machine wind turbine power curve uncertainty estimation and its comparative studies, Appl. Sci. 10 (23) (2020) 8685.

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Diagnosis of wind turbine systematic yaw error through nacelle anemometer measurement analysis

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