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Editorial

Individuation of Wind Turbine Systematic Yaw Error through SCADA Data

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1. Introduction

Much attention in the wind energy literature is devoted to condition monitoring [1] applied to the early fault diagnosis of rotating components. This is motivated by the fact that wind farm operation and management is complex, especially for offshore installations. Nevertheless, more attention is being paid to an overlooked topic, which is the individuation of systematic errors affecting wind turbine operation. Examples of these kind of errors are rotor mass imbalance [2], pitch imbalance [3,4], and the zero-point shift of the yaw. It is comprehensible that these kinds of errors might be considered to have a lower priority because the affected wind turbines can likely operate for years without traumatic interruption. Yet, these errors have a certain non-negligible impact on the efficiency of wind energy conversion for all the operation time and might affect the residue lifetime of the machine, and this motivates the effort to comprehend how they manifest and how they can be fixed.

The control system of a wind turbine operates to achieve a set point of vanishing yaw error, which means that the plane of the rotor should be perpendicular to the incoming wind. The yaw error is, therefore, a dynamic quantity, which can be thought to be distributed according to a Gaussian with zero mean. There are many studies about the design of advanced wind turbine controls for minimizing the dynamic yaw error, taking into account the yaw motion error [5] and the periodical yawing error caused by the flow deviation from the rotating blades [6], but this is out of the scope of the present editorial. Actually, the object of this study is to investigate the static component of the yaw error (also known as zero-point shift), which can be non-vanishing if the wind vane sensor is incorrectly aligned with the rotor shaft. This can occur due to wind vane defects, incorrect installation or maintenance, or the aging of the machine. First-principle aerodynamic considerations indicate that, in the presence of a systematic yaw error γ, the extracted power is diminished by a factor of $\cos^3 \gamma$. In practice, for real-world pitch-controlled industrial wind turbines, the role of the control should be taken into consideration: the systematic yaw error combines non-trivially with the yaw motion error and there is a non-trivial impact on the aeroelastic characteristics [7,8], which turns into energy loss not equally distributed from cut-in to rated, as argued in [9], but the effect is, in any case, remarkable.

The detection of wind turbine systematic yaw error based on supervisory control and data acquisition (SCADA) data is challenging, because the data indicate a correct alignment of the rotor with respect to the incoming wind, while this does not occur. A more robust detection of the systematic yaw error could be achieved by employing further additional upwind sensors, such as LiDARs [10–12] or spinner anemometers [13,14], but these are costly, and different with respect to the SCADA data which are typically available to the

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end user. This motivates the research in advanced data-driven methods for the diagnosis of this kind of error using SCADA data and the objective of the present editorial is a critical discussion of the literature and the indication of meaningful research perspectives.

2. Literature Review

The common ground of the recent studies regarding the detection of wind turbine systematic yaw error is that it is impossible to individuate the error directly from the SCADA data, in the form of the difference between the incoming wind direction and the rotor, and therefore a secondary effect must be targeted. Based on the above line of reasoning, a wind turbine affected by a systematic yaw error underperforms with respect to a wind turbine correctly aligned. Therefore, it is reasonable to diagnose the error by individuating an underperformance. This indeed shifts the problem from impossibility to prohibitiveness. The critical point regarding the detection of wind turbine underperformance is, in general, that the power of wind turbines has a multivariate dependence on environmental conditions and working parameters. Therefore, it is non-trivial to individuate a small under-performance and especially to ascribe it clearly to a certain factor (systematic yaw error rather than another type of problem). For the above reasons, complex data-driven techniques have, in general, been employed for the diagnosis of wind turbine systematic yaw error. It is meaningful to discuss the approaches employed in the literature by dividing them into those based on the analysis of the power curve and those finalized at the individuation of mechanical or operational responses of the machine which are peculiar solely to the systematic yaw error.

As regards the approach based on power curve analysis, the main studies are the following: In [5], a quite straightforward analysis of the binned power curve is employed, upon data pre-processing which consists of grouping per yaw error intervals of 2°. A similar approach is employed in [15,16]: the data are grouped per yaw error intervals and the power curve is analyzed through a Least-Square B-spline Approximation. In the above studies, the systematic yaw error is identified as the measured yaw error at which the best average performance is achieved. In [17], the objective was somehow facilitated by the fact that a utility-scale wind turbine controlled by the authors (Eolos Wind Research Station at the University of Minnesota) was selected as a test case. The operation under static yaw error was forced to the wind turbine and the collected data were analyzed: a data-driven regression for the power curve allowed individuating the error in the form of underperformance. The strength of this work is that the experiment is controlled, which means that the analyzed data sets are labeled. In [18], a Gaussian process regression for the wind turbine power, selecting as input variables the rotor speed and the blade pitch angle, was employed for automatically diagnosing the systematic yaw error in the form of a mismatch between the actual and predicted power, which is superior to a confidence interval estimated directly from the model. In [19], the systematic yaw error is substantially individuated through the analysis of the power curve, upon a non-trivial data rejection algorithm that takes into account several features of the machine functioning. Additionally, in this case, external advice on the presence of the error (which means data labeling) is provided by LiDAR measurements and the post-correction behavior is compared to the pre-correction one. Two methods are employed: the former is the straightforward analysis of the power curve according to International Electrotechnical Commission guidelines and the latter is based on data rejection outside statistical bounds with respect to the nominal power curve. The authors state that the former method provides implausible results and largely overestimates the impact of the yaw error on the power production and attribute this to the quality of the nacelle wind speed measurements collected by the SCADA system. The authors of [19] might have observed, but not clearly recognized, a phenomenon that could allow one to distinguish the systematic yaw error with respect to other kinds of problems causing wind turbine underperformance. In other words, the results of [19] might be implausible because the presence of the systematic yaw error affects the nacelle wind speed measurements. This could be transformed from a problem (difficulty in assessing the performance change) into an opportunity for the diagnosis of this type of error. In summary, the advantage of the above approaches based on the power curve is that they are general, in the sense that, in general, horizontal-axis wind turbines operating with a non-vanishing yaw error underperform. The difficulty in this is that it is not easy to establish a causal relationship between the underperformance and the systematic yaw error because, in principle, there are many reasons (such as other systematic errors or machine aging) why a wind turbine might underperform.

Given this, some attempts have been formulated in the literature for diagnosing the systematic yaw error by individuating phenomena related solely to this kind of error. In [20], 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 such as turbulence intensity and external temperature. A similar approach is also employed in [21,22], which is the analysis of the behavior of the yaw angle–power coefficient (respectively, rotor speed) curve. For the study [22], external advice about the presence of systematic yaw error is provided by a spinner nacelle anemometer. The most innovative aspect of that study is that data before and after the correction are analyzed at a wind farm level and the powers of the wind turbines not affected by the yaw error are used as a reference for modeling the power of the target affected wind turbines. By doing this, it is possible to assess the impact of the systematic yaw error on power production and the results confirm the hypothesis of [9], that the loss is not equally distributed along the power curve span, due to the role of the control. The study in [23] is based on a wind farm comparison of the distribution of the relative wind direction measurements. The advantage of the above-summarized methods is that the connection between the targeted behavior and the error is more solid with respect to the power curve analysis, while the drawback is the loss of generality: for example, the symmetry of the yaw error–power coefficient curve depends on the aerodynamics of the considered nacelle and the approach based on the analysis of the fleet distribution of certain variables might have features which are partially site-specific.

3. Future Directions

From the above discussion of the literature, it arises clearly that the diagnosis of wind turbine systematic yaw error through SCADA data is a complex task for which there is not a well-established method. Despite the success of the state-of-the-art data-driven approach which serves as a low-cost method for systematic yaw error detection and correction, currently, this type of method still lacks generalizability for implementation in utility-scale turbines operating under different field conditions.

For example, it is conceivable that a wind turbine affected by a systematic yaw error is distinguishable with respect to a machine in normal operation because, for a given wind speed, the rotational speed and the extracted power diminish and the tower vibrations increase. Yet, it is as well conceivable that the same kind of outcome also characterizes other types of imperfect operation, such as blade pitch or mass imbalance, or the degradation of the blade pitch actuators. Therefore, it is non-trivial to trace the root cause of manifestations which in general can be associated with more than one type of error. Furthermore, in the literature, a thorough characterization of the response of utility-scale wind turbines in yaw under different environmental conditions (such as wind shear, turbulence intensity, and wind veer) is lacking. Based on this, the critical point is identifying, for various environmental conditions, the operation and structural responses of the machine which can be ascribed specifically to the presence of the systematic yaw error.

Therefore, a general limitation in the literature is that there is a lack of systematic field experimental data (essentially, lack of labeled data) to evaluate the impact of systematic yaw error on various turbine operational and/or structural response variables. For this reason, it is important to stimulate data sharing and joint studies between the academia and the wind energy practitioner communities. Given the above reasoning, there are several valuable research directions to pursue, which should focus on a comprehensive characterization of the turbine operational and structural response changes associated with systematic yaw error.

As argued above, an underperformance is a plausible manifestation of the presence of a systematic yaw error. In practice, the most adopted method for the characterization of the performance of a wind turbine is the power curve, which is the relation between the input (wind speed) and the output (produced power). Consequently, as arises from the above literature review, the data-driven analysis of the power curve is also widely used for the individuation of the systematic yaw error. The advantage of such a method is that it is intuitive because it provides a representation of how much output is extracted for a given input wind speed, but the possible drawback is the lack of comprehension of the causes of a certain operational behavior of the machine. Recently, there have been attempts to include the most important operation parameters as further additional input variables for multivariate power curve models, but these act mainly as black boxes from which it is difficult to extract an interpretation. On the grounds of the above discussion, a desirable objective would be at least to improve the statistical analysis by formulating causality tests [24] on the relation between the power output (diminished with respect to the ideal) and the yaw error, but the general objective is to identify behaviors related to the main operation variables or to the structural response of the machine which can be associated uniquely with the systematic yaw error.

Another aspect that has been up to now overlooked in the literature is the analysis of the effect of the systematic yaw error on the nacelle wind speed measurements. Disregarding the rotor rotation for simplicity, it is conceivable that, if a wind turbine operates most of the time with a non-vanishing yaw error, its nacelle anemometer (or anemometers if more than one) would be systematically more upwind or more downwind with respect to what would happen in normal operation. This implies that the occurrence of a bias in the nacelle anemometer measurements might likely be employed for individuating the systematic yaw error. Indeed, this aspect is addressed in [25] for a Senvion MM92 wind turbine and the flow equilibrium condition between two nacelle anemometers is employed for detecting the yaw error. This line of reasoning also lead to a critical analysis of the methods developed in the literature: if the measurement of the nacelle wind speed changes when the wind turbine is affected by systematic yaw error, the analysis of underperformance based on the power curve should be treated cautiously because the x-axis (wind speed), differently with respect to what is implicitly assumed, is not a reference which is independent of the state of the machine (with an error or not). This observation could explain, for example, why the straightforward comparison of two power curves in [19] (data set with error against data set without error) gives implausible results. In general, it is strongly advisable to have at disposal meteorological mast data as a reference of the environmental conditions on site and to avoid using the wind turbine itself as a probe; this is particularly true when dealing when the systematic yaw error because in line with this principle the presence of the error affects the nacelle anemometer measurements, the working parameters and the structural response of the machine.

On the other hand, the fact that the systematic yaw error plausibly has multi-faceted consequences might become a point of strength for its clear individuation, provided that the data-driven comprehension of the multivariate behavior of wind turbines under different environmental and working conditions improves. Given the rapid development of SCADA-based studies and related data analysis [26], it is realistic that in the near future general methods will be formulated for diagnosing specifically the systematic yaw error, based on the individuation of multiple responses of the machine.

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