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Editorial

Editorial on the Special Issue "Wind Turbine Monitoring through Operation Data Analysis"

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1. Introduction

Horizontal axis wind turbines likely constitute the most promising renewable energy technology worldwide and their exploitation has been recently accelerating due to energy transition policies. On one side, the large rotor size of the new installations poses scientific and technological challenges; on the other side, a huge fraction of the already operating wind turbines is reaching the end of expected lifetime (with peaks in the order of 50% in some European countries such as Germany, Denmark, or Spain), posing complex issues to wind energy practitioners about decommissioning and/or repowering.

In this context, there is increasing importance regarding the data collected by wind turbines Supervisory Control. Furthermore, Data Acquisition (SCADA) systems contain information that is fundamental for practical purposes of performance monitoring and fault diagnosis and for the scientific objectives related to the comprehension of the interaction between the machine and the environment. Actually, SCADA-collected data sets include environmental measurements (such as wind speed and direction and ambient temperature), operation variables of the machine (such as blade pitch angle or rotational speed), internal temperatures collected at meaningful sub-components, electrical parameters such as voltages and currents, and so on.

It is often said that through SCADA data it is possible to do reverse engineering. This claim is partially true, in the sense that it is correct that it is critical to employ SCADA data for detecting the root cause of a behavior; nevertheless, their judicious exploitation is extremely valuable for formulating coherent hypothesis about the behavior of the machine.

Basing on this premise, the scientific literature about wind turbine SCADA data analysis typically has a twofold point of view:

- Methodological: focused on the development of innovative algorithms, which typically are based on machine learning;
- Applied: focused on the identification of meaningful fields of investigation.

The articles published in this Special Issue resemble the above twofold approach because they provide methodological innovations applied to timely topics in the literature and in the wind energy practice. In Section 2, a brief summary of the research contributions of the papers is provided in chronological publication order. In Section 3, some brief conclusions are drawn and further research directions are indicated.

2. A Short Review of the Contributions in This Issue

The study in [1] deals with an important topic in wind energy practice, which is the analysis of systematic errors affecting wind turbine operation. Actually, the presence of a systematic error (which can be related, for example, to the yaw or pitch) causes producible energy losses for all the operation times of the machine and can impact the operational lifetime. There is therefore a relevant practical urgency in identifying how to diagnose systematic errors in wind turbines; however, this is a complex task because it is not possible to employ SCADA data straightforwardly—the only possibility is identifying the possible secondary effects. In [1], the systematic yaw error of wind turbines is studied based on a real-world experience. The study is a collaboration between academia (University of Perugia) and a utility company (ENGIE Italia). Two are the main innovative points of the study:

- The secondary effect of the yaw error, which is considered the decrease in rotor speed for a given wind speed;
- The effect on energy production of the systematic yaw error is quantified through the analysis of data before and after the error correction.

In particular, the quantification of the effect of the systematic yaw error is pursued by generalizing the concept of relative performance. The fact that in a real-world environment wind turbines are grouped in fleets allows for employing the operation variables of the wind turbines near the target as a reference for the behavior of the target wind turbine. Translating this concept into the language of machine learning, this means that there is an abundance of features (which can be selected through algorithms) for modeling the power of a target wind turbine in a farm.

The investigation object of [2] is that wind turbines performance declines with age. There are no theoretical estimates in this regard and the only possibility is learning from experience, which means data. Most of the previous studies on this topic dealt with cumulative data (for example the annual capacity factor) of the highest possible number of wind turbines. The approach of [2] is opposite and considers a limited number of test cases, but employs the information source that has the maximum possible amount of detail in order to quantify the aging trends and possibly interpret them. In [2], a Vestas V52 located at the Dundalk Institute of Technology is studied through the analysis of ten years of SCADA data. The performance decline with age is visualized and quantified through qualitative and machine learning analysis of wind turbine operation curves dealing with the rotational speed and the blade pitch. It it shown that the worsening performance manifests mainly as diminished power for a given rotational speed and the amount of producible energy loss can be relevant.

The work in [3] deals with data-driven models for wind turbine power curve analyses. Specifically, the power curve is the most straightforward analysis tool for wind turbine performance evaluation because it is the relation between the input (wind speed) and the output (power), but its comprehension is far less intuitive than it could be expected. In reality, there is at least one major issue each regarding the input and the output:

- The wind intensity (input) is measured behind the rotor span and the free stream speed is estimated ex post through a nacelle transfer function;
- The power (output) has a multivariate dependence on environmental conditions, working parameters, and health state of the machine.

Therefore, theoretical wind turbine power curves are a line in a plane, while real-world ones are clouds of points that need to be interpreted in order to understand the machine performance. Based on this, the idea of [3] is employing multivariate models for the power of wind turbines and including in the possible covariates such as the minimum, maximum, and standard deviation of the measurement channels that are averaged by the SCADA systems on a ten-minutes time basis. The input variables are selected through an automatic features selection and, from the analysis of multiple test cases, it is shown that one size does not fit all and the most appropriate input variables depend on the technology of the wind turbine.

The study in [4] deals, similarly to [2], with wind turbine performance declining with age. The test case is the Mitsubishi MWT-1000A wind turbines located at the Shinan wind farm in South Korea. The peculiarity of the study is that the authors employ SCADA data and LiDAR data simultaneously, thus circumventing the issue of wind speed data quality issue. By calibrating LiDAR and SCADA data, the nacelle transfer function is derived and it is therefore possible to reliably employ the power curve degradation as an indication of the performance worsening with age. A four-year analysis is conducted and the achieved estimate is that the test case wind turbines worsen their performance at a rate of 0.52% per year, similar to what is reported in the literature for this size and technology.

The approach of [5] is mainly methodological. The objective is the comprehension of the operational behavior of a wind farm that can be arbitrarily complex. The general idea formulated by the authors is employing discretization methods. Two of them are contemplated:

- A layered integration approach based on endogenous and exogenous parameters;
- A circular binning that leverages the periodicity of the angular variables.

In [5], the authors support, based on real-world data sets analysis, that a judicious data preparation and discretization is fundamental for advanced analytics on time series data of multiple machines. In particular, they show that such an approach is powerful for the individuation of operating trends and anomalies.

The study in [6] deals with classification of wind turbine operation based on SCADA data. The main ingredients are data preprocessing, feature selection, and clustering. The features are selected based on the Pearson correlation coefficient with the power, which is collected with an averaging time of 30 s. The clustering is performed through the *k*-means algorithm, whose application is explored in conjunction or not with a preliminary clustering which, similar to the line of reasoning in [2], is based on the principles of wind turbine operation. Actually, five operation phases can be retrieved:

- Shutdown phase;
- Startup phase;
- Maximum wind energy tracking phase (which corresponds to Region 2 in the nomenclature of [2]);
- Constant speed phase (Region 2 1/2 according to [2]);
- Rated power phase.

The analyzed target is the false alarm classification rate of the anomalous vibration of an operating wind turbine.

3. Conclusions

The Special Issue "Wind Turbine Monitoring through Operation Data Analysis" has collected six published papers with relevant scientific developments about methods and applications of wind turbine SCADA data analysis.

It is important to continue advancing research about this research topic. In our opinion, some promising aspects that should be investigated in the near future include (but are not limited to) the following:

- The integration of multiple data sources with different time scales;
- The use of time resolved data with sampling time in the order of the second;
- A deeper comprehension of the root causes of wind turbine performance in relation to the state of health of the main subcomponents;
- A relevant test case of statistics for SCADA-based fault diagnosis methods.

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