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Editorial

Wind Turbine Drivetrain Condition Monitoring through SCADA-Collected Temperature Data: Discussion of Selected Recent Papers

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Wind energy is going to be the leading renewable source of the next decades. For example, the European Commission has set a target of 50% of electricity production from wind turbines by the year 2050, and this is reflected in the accelerated growth of new installations. The increase in wind power capacity worldwide has indeed doubled from 2019 to 2020, and the trend is going to inevitably accelerate due to the war in Ukraine [1]. One of the main critical points of diffuse wind energy exploitation is the share of the O&M (Operation and Maintenance) costs, which can reach up to 30% for offshore installations [2]. A reduction in such costs is therefore fundamental for further increasing the competitiveness of wind turbine technology. In this regard, in [3], it is estimated that intelligent algorithms can lead to an 8% decrease in the O&M costs and to an 11% recovery of producible energy, which would be otherwise lost. In this perspective, the priority is preventing drivetrain faults, which are associated with the highest amount of downtime and energy loss [4].

Condition monitoring the rotating components of wind turbine drivetrains is a fairly complicated task due to the fact that the machine operation is non-stationary and depends non-trivially on multiple environmental factors. Wind turbines are disseminated with sensors, which for mechanical components are typically of two types: vibration and temperature. The heating and vibrations of a wind turbine drivetrain are two phenomena with very different features. The local accelerations of gears and bearings are signals that depend on instantaneous rotational speed and gearbox geometry. Their frequency content is therefore complex, spanning from a few to thousands of Hz. On the one hand, the comprehension of such signals requires complicated methods and a detailed knowledge of gearbox geometry. On the other hand, the analysis of such kinds of measurements provides in principle a deep insight on incoming damages. The heating of gears and bearings has instead a much slower dynamic, and the general principle of more power, more heat, stands true—whatever the gearbox geometry.

Based on this line of reasoning, it does not come as a surprise that wind turbine component temperatures are employed for condition monitoring in the form of SCADA-collected measurements, with a a typical averaging time of ten minutes [5]; however, the use of such data is affected by the prejudice that only a late-stage indication of incoming fault is achievable [6]. Nevertheless, SCADA data are employed for wind turbine fault diagnosis because they are practical, manageable in size, and available to the end user relatively easily. Scientific research is gradually demonstrating that a judicious use of SCADA-collected temperature data is effective for timely drivetrain fault diagnosis. Given this, the objective of this Editorial is to discuss selected papers that indicate meaningful research directions. According to the author's expertise, the main open questions regarding wind turbine fault diagnosis based on SCADA-collected temperature measurements are related to the following:

- Precise location of the damage;
- Prognosis and application for intelligent O&M;
- Generalization of the results.

1. Literature Review

The standard for the application of SCADA-collected temperatures for fault diagnosis has been set by the study in [5] (391 citations in Scopus; accessed 16 January 2023), which is based on the normal-behavior modeling [7,8] of meaningful internal temperatures, such as gearbox oil temperature, gearbox bearing temperature, and generator winding temperature. The approach of modeling the normal behavior is typical in wind energy applications and is motivated by the fact that the data sets at disposal are highly imbalanced (the vast majority of the data describe healthy operation). Furthermore, since wind turbine drivetrain damages evolve in time, even very slowly, in general it is non-trivial to establish clearly what data refer to healthy or faulty operation. The most adopted method is therefore assuming as normal the operation when there is no clear damage evidence. Once the normal-behavior model is trained with data that are reasonably assumed to describe healthy operation, the fault is therefore individuated by performing meaningful statistical analyses on the time series of the residuals between temperature measurements and model estimates.

In [9], a Gated Recurrent Unit (GRU) Artificial Neural Network (ANN) is employed for modeling the normal behavior of the main bearing temperature as a function of other meaningful temperatures and of environmental variables. A fault prognosis indicator is formulated by employing the Exponentially Weighted Moving Average (EWMA) of the residual between measurements and model estimates. This study touches upon the main critical points that have been summarized above. The temperature of the main bearing is the most used for SCADA-based drivetrain fault diagnosis (see also [10]). In particular, the study in [11] is worth discussing. The low-speed shaft bearing temperature is modeled as a function of exogenous variables (such as wind speed, turbulence intensity, and ambient temperature) through a Convolutional AutoEncoder (CAE), which reshapes the matrices of measurements into images. A fault prognosis indicator is formulated by considering the Image Means Square Error (IMSE). A meaningful discussion contained in [11] is that the fault is detected not only from continuously rising overheating trends until failure but also from heat releases, upon which the target temperature returns back to values below the threshold. A very interesting aspect of that work is that the proposed method allows detecting a case of bearing damage in advance, in addition to a case of gearbox damage. The possible reason for this is discussed in [11] and also in [12], where a similar behavior is observed. In [12], it is hypothesized that a large rotating component, such as the main bearing, releases much heat when in operation and, therefore, it is easier to establish a normal-behavior model and individuate deviations. Furthermore, due to the proximity between the main bearing and the other rotating components of the drivetrain, it is also reasonable to assume that failures that are not strictly related to the main bearing can be detected by monitoring the main bearing temperature. Based on this argument, it is also consistent that for a main bearing damage it is easier to estimate the time to failure, as is performed in [9]. In fact, in [12], it is observed that, if one extends the use of the main bearing temperature for monitoring all of the drivetrain, it becomes more critical to formulate a prognosis indicator.

The approach proposed in [13] is similar to the above studies. The main gear bearing temperature is modeled through a Convolutional Neural Network and the threshold for alarm raising is based on EWMA on the Root Mean Square Error (RMSE) between measurements and model estimates. A noticeable aspect is also that test case 1 in [13] regards a gearbox fault (not a gear bearing fault), which is diagnosed through an analysis of the main gear bearing temperature, similarly to what is performed in [11,12]. The gear bearing temperature is also employed in [14] for individuating incoming gearbox failures. The employed technique, based on Adaptive Threshold and Twin Support Vector Machine classification for time series, is shown to also work if the gear oil temperature is selected as the target, which is different with respect to what is observed in [12].

2. Future Directions

There are several research directions about the above outlined open questions, and there are also interesting first developments. The state of the art is that black-box models applied solely on SCADA data are ascertained to be useful for diagnosing wind turbine drivetrain faults; however, further developments are required regarding the precise fault location and prognosis. It is reasonable to intervene on the model type, the type of employed data, or both.

Regarding the former, an inspiring study is [15]. The idea is to combine normal-behavior modeling with a physics-based model of the heat flow and consequent thermal losses in the drivetrain. The estimated thermal loss acts like an engineering feature for the normal-behavior model, and it is even ranked as the most important feature. This provides a powerful indication of how much information the purely black-box models are indeed missing. Another promising development regards the noticeable growth of explainable Artificial Intelligence (XAI) techniques, which can improve the interpretation of the results. At present, there are no studies applying such techniques for wind turbine drivetrain fault diagnosis and, therefore, this represents a priority research direction.

Regarding the type of data, it would be desirable to go beyond the use of SCADA with ten minutes of averaging time, but without compromising the possibility of employing purely black-box models, which do not need information about the particular wind turbine model and drivetrain geometry. For example, the study in [16] is based on a multi-scale analysis, which starts from the normal-behavior modeling of the gear bearing temperature using SCADA-collected data and then proceeds by individuating the statistical novelty between the suspected target and the reference healthy wind turbines through feature analysis extracted from vibration measurements collected by the industrial Turbine Condition Monitoring (TCM) system. A similar approach is employed in [17], where a normal-behavior model is constructed separately for SCADA-collected temperatures and for the meaningful features of the vibration signals. The error metrics between measurements and model estimations for the SCADA and the vibrations are then fed to a one-class Support Vector Machine classifier. Employing the error metrics for both SCADA and vibration data, a more complex decision boundary can be formed, which allows rating the anomaly level.

Another meaningful development regards taking into account that wind turbine operation is described by variables that are highly correlated between themselves (or, better, are in causal relation, as reported from the first data-driven observations in [18]). Therefore, an improvement in normal-behavior modeling, which might preserve the black-box structure but at the same time be more explanatory, is a multi-output one, as is performed, for example, in [19].

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