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Editorial

Artificial Intelligence for Wind Turbine Condition Monitoring

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The global energy system is undergoing an undeniable change. In the wake of the Ukrainian invasion, it is clear that mass acceptance and utilization of renewable energy is the answer to increased energy independence and halting climate change [1]. Renewable-based electrification will be essential in order to achieve climate neutrality in Europe by 2050, and wind energy will be of the utmost importance in achieving this objective; it must come to represent 50% of the energy mix [2]. However, the levelized cost of electricity (LCOE) is the primary obstacle to the growth of the wind industry. The LCOE of a wind park is calculated by integrating many elements, with operation and maintenance (O&M) costs accounting for a considerable share (20–30%) [3]. Therefore, improving maintenance practices is essential.

Any industrial-sized wind park might experience annual financial losses of millions of euros due to downtime and component replacement costs. As a result, it is critical that the wind sector transitions from corrective maintenance (repairing components after they fail) and preventive maintenance (scheduled at regular intervals without considering the asset's current condition) to predictive maintenance (scheduled as needed based on the state of the asset). Digitalization and artificial intelligence (AI) are crucial technologies in this approach for improved exploitation of information in enormous amounts of data from various sensors obtained from assets. The overall goal is to identify alterations in the situation that deviate from normal operation and bespeak the development of a defect.

Within this framework, in this editorial, "Artificial Intelligence for Wind Turbine Condition Monitoring", a review of ten highly cited articles that have recently been published in this journal is provided, addressing a wide variety of technical and scientific concerns on the topic of wind turbine (WT) condition monitoring (CM).

CM is a broad field of study that has been effectively applied to a broad range of problems. Nevertheless, its postulation to complex systems such as WTs, which are megastructures that operate in a variety of operational and climatic circumstances, as well as in hazardous settings (such as offshore), remains a difficulty. The excellent review paper [4] provides an in-depth examination of existing CM and fault diagnosis methodologies in three areas: energy flow, information flow, and an integrated (O&M) system. The angle of energy conversion of the WTs is used to assess the properties of each component in the energy flow. WT fault and control information is carried through the information flow. This review paper also proposes an integrated WT (O&M) system based on electrical signals. It is clear that, on the one hand, vibration signals are important information carriers of fault parameters. On the other hand, the use of only SCADA data for CM has recently derived a lot of attention. In the following paragraphs, these two areas of research are reviewed.

On the one hand, CM strategies based on vibration signals have been studied with outstanding results. For example, in [5], a new approach is proposed to diagnose drivetrain bearing degradation: vibrations are recorded in the tower rather than in the gearbox. The test case covered is a wind park that has six wind turbines with a rated output of 2 MW each. In winter 2019, a measurement campaign was carried out and vibration measurements were taken in five WTs in the park. Three WTs were healthy when tests were performed, one WT had recently recovered from a planetary bearing defect, and one WT was experiencing a high-speed shaft-bearing fault. Healthy WTs are chosen as references and damaged and recovered WTs as targets: vibration measurements are processed in the feature space using a multivariate novelty detection algorithm. The use of this approach is supported by univariate statistical tests on the selected time-domain characteristics, as well as a visual evaluation of the dataset using principal component analysis (PCA). Finally, the abnormal state of the damaged wind turbine is detected using a novelty index based on the Mahalanobis distance. Notably, the authors of [6] suggested a unique system for detecting multiple levels of rolling bearing faults in varied operating situations. First, the variational mode decomposition was used. Second, in the time domain, statistical characteristics were computed and extracted. Meanwhile, the complexity of the vibrational signal in the time series was estimated using a permutation entropy analysis. Subsequently, feature selection approaches were used to increase identification accuracy while reducing computing overhead. Finally, the rated feature vectors were used as inputs to machine learning (ML) algorithms to determine the state of the bearing flaw. The suggested technique was tested in the various regions of operation of WTs.

On the other hand, the most recent innovations tend to require expensive, specially fitted sensors, which are not economically practical for wind parks that are currently in service, much less if they are approaching the end of their lives. Data-driven predictive maintenance approaches grounded in current supervisory control and data acquisition (SCADA) data (found in all industrial-sized WTs) are a viable cost-effective option in this area. Because SCADA data were originally designed for sole operation and control, using them for predictive maintenance is a significant challenge. In [7], a systematic review of the literature is given with the objective of evaluating the application of SCADA data and how AI approaches can transform SCADA data into information that can be utilized to detect WT faults early. This review emphasizes the problem of inaccessible WT SCADA data for research and the need for standardization. Furthermore, [8] identifies the frequent problems encountered by researchers working in the fields of CM and reliability analysis. Standards and policy efforts aimed at alleviating some of these issues are described, along with a review of their suggestions. The key outcome of this research is that unified standards for turbine taxonomy, alarm codes, SCADA operating data, and maintenance and fault reporting will greatly benefit the industry. Regardless of these challenges, recently, the subject of utilizing SCADA data for predictive maintenance aims has led to notable contributions, such as those reviewed in the following paragraphs.

One of the most important aspects of wind turbine failure prediction using SCADA data is selecting the optimal or nearly optimal set of inputs that may be used by the failure prediction algorithm. The ideal set of inputs acquired by exhaustive-search rules is not realistic in most scenarios due to a large number of available predictors. To demonstrate the practicality of the prediction and select the best set of variables from more than 200 variables recorded by the SCADA of the wind park, the work in [9] presents a detailed study of automatic input selection rules for the prediction of wind turbine failures, as well as a reference-exhaustive search-based quasi-optimal algorithm. The article uses a k -NN classification method to assess performance. The conditional mutual information feature selection approach was found to be the best automatic feature selection method, whereas the mutual information feature selection method was found to be the worst. The experiments were derived from measurements conducted over a year corresponding to the gearbox and transmission systems of the wind turbines in production.

Real SCADA data from an operational wind parks lead to a highly imbalanced dataset, with a majority class of healthy data and a minority class with few samples of faulty data. In [10], when using a highly imbalanced dataset, three data preprocessing algorithms were proved. PCA for data modeling and reduction; a random oversampling technique used to tackle the imbalanced data problem; and the data reshaping technique for data augmentation are among these strategies. When training the ML algorithms, a time split was used to avoid corrupting the dataset's time structure and to prevent data leakage.

The assemblage of these preprocessing techniques shows excellent performance, as results showed F1 scores of at least 95%.

Normal behavior models have also been used successfully. For example, in [11], a general health monitoring system is provided for wind turbines. The suggested framework first separates the turbine operation into several sub-operation conditions using the clustering technique, and then constructs a normal behavior model for each sub-operation state. An efficient deep belief network is presented to model normal behavior. This improved modeling technique can capture complicated nonlinear relationships between multiple monitoring variables, which helps to improve prediction performance. To verify the suggested technique, a case study of main bearing defect detection utilizing real SCADA data is performed. Further notable findings are presented in [12], in which a novel CM method for WTs is based on long-short-term memory (LSTM) networks. Long-term dependencies hidden within a sequence of measurements can be captured by LSTM networks and used to improve prediction accuracy. Finally, CM is achieved by comparing the predicted values with the actual measurements from the SCADA data.

Another active area of research is anomaly detection. In [13], three anomaly detection models were compared for operational wind turbine SCADA, namely: one-class support vector machine (OCSVM), isolation forest (IF), and elliptical envelope (EE). The paper describes a novel CM method that requires only two months of data per turbine. A year separated these months, the first of which was healthy and the second of which was unhealthy. The number of anomalies is compared, with a higher number in the unhealthy month being considered correct. In general, for all configurations considered, IF and OCSVM had an average accuracy of 82%, compared to 77% for EE.

Finally, in the near future, attention will be focused on WT digital twins (DT). A DT is a current representation, or model, of a real WT in use. It might be a component-level model that shows the actual WT state and incorporates pertinent historical data. DTs can be physics based (based on fundamental principles), data driven (using AI or statistical techniques, for example), or a combination of the two. The models represent the current environment, age, and configuration of the operational asset, which often requires streaming of WT data into tuning algorithms that can employ AI approaches. Once the DT is online and up to date, it can be used to predict future behavior.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence.
CM	Condition monitoring.
DT	Digital twins.
EE	Elliptical envelope.
IF	Isolation forest.
LCOE	Levelized cost of energy.
LSTM	Long-short-term memory.
ML	Machine learning.
OCSVM	One-class support vector machine.
O&M	Operation and maintenance.
PCA	Principal component analysis.
SCADA	Supervisory control and data acquisition.
WT	Wind turbine.

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