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Editorial

Moving towards Preventive Maintenance in Wind Turbine Structural Control and Health Monitoring

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1. Introduction

In recent years, the scope of structural health monitoring in wind turbines has broadened due to the development of innovative data-driven methodologies. These methodologies enable the execution of condition monitoring and fault detection, which can provide support for predictive maintenance across the various components of a wind turbine.

In this Editorial, we present a selection of 10 papers published in *Energies* that contribute to the ongoing research on wind turbine condition monitoring. The papers were divided into three categories: wind fault detection and diagnosis, wind turbine condition monitoring, and wind turbine maintenance. The first category includes papers that focus on the detection and diagnosis of faults in wind turbines, such as those related to bearings, pitch actuator systems, and gearboxes. The second category comprises papers that discuss various aspects of wind turbine condition monitoring, including literature reviews, comparative studies on anomaly detection techniques, and methodologies that predict the remaining useful life of wind turbine components. The third category includes papers that aim to reduce the cost of wind turbine maintenance by developing new maintenance strategies. These papers contribute to the ongoing effort to develop reliable, efficient, and cost-effective techniques for monitoring the condition of wind turbines, with the ultimate goal of increasing their reliability, lifetime, and performance.

2. Wind Turbine Fault Detection and Diagnosis

The study conducted by Castellani et al. [1] presents an analysis of the failures in the bearings of a wind turbine. The novelty of this research lies in its focus on monitoring the vibrations in the wind turbine tower without the need for human interaction, while also ensuring that the developed procedure does not interfere with the normal operation of the wind turbine. The validation of this procedure was carried out on a set of five wind turbines, comprising three healthy structures, one damaged structure, and a recently repaired specimen. The methodology employed in the study involved processing accelerometer signals acquired in the tower of the wind turbines, which underwent several stages, including univariate data cleaning, feature extraction, multivariate data cleaning, statistical analysis, and damage detection based on the Mahalanobis distance. The results of the study indicate that the detectability of damage was successful, as demonstrated by the low number of false alarms in the predictions.

An investigation on the fault detection of a wind turbine pitch actuator system was conducted in [2]. The study employed an algorithm based on the interval observer theory and included three fault stages to authenticate the developed fault detection approach. These fault stages assessed the impact of hydraulic leakage, high air oil content, and pump wear. The study resulted in the development of a fault detection algorithm and a fault classification algorithm. To authenticate these algorithms, 500 experiments were performed, each with a random input. The accuracy values of the detection algorithm exceeded 62%, whereas the classification algorithm had an accuracy value higher than 83%.

In the study conducted by Santolamazza et al. [3], artificial neural networks (ANN) were utilized to detect faults in wind turbines, and SCADA data were used for modeling. The developed methodology consisted of several stages. Firstly, a preprocessing stage was carried out for the removal of abnormal samples, followed by the removal of outliers through the use of a clustering method which evaluated the Mahalanobis distance. Secondly, a model processing stage was carried out, in which the data were split into training, validation, and test sets. Feature selection and tuning of the hyper-parameters of the feed-forward neural network (FFNN) model was also conducted. Finally, a post-processing stage involving an alarm system was implemented to identify any anomalies in the deviations from the real-time baseline value of the output variable. The developed methodology was applied to two critical components of the wind turbine, the generator and the gearbox, with the generator showing the best fault-detection results. The paper also includes Table A1, which summarizes relevant fault detection studies in wind turbines, obtained from the literature. These studies are classified based on their components, methods, real case studies, and approach data type.

In [4], a fault diagnosis methodology of a wind turbine gearbox was developed using both time and frequency domain analysis. The methodology used data collected from accelerometers attached to the gearbox housing. An adaptive Variational Mode Decomposition (VMD) algorithm was optimized with the fast gray wolf optimizer (GWO) to decompose the signal obtained by the accelerometers. Next, a principal component analysis was performed in each domain to obtain a new feature vector. An ELM classifier was trained and tested with classification accuracies greater than 90%. The developed methodology was compared with other classifiers such as SVM, deep convolutional neural networks, a genetic algorithm back propagation neural network, and the ensemble empirical mode decomposition (EEMD) method for signal decomposition. Results indicated that the developed methodology outperformed all compared methods.

In the study by Liu et al. [5], fault indicators were investigated in three components of wind turbines: the converter, the generator, and the pitch system. The study utilized SCADA data obtained from 24 wind turbines of 1.5 MW. The developed methodology involved creating radar charts that varied depending on whether the system was healthy or unhealthy. Three different machine learning classification methods were compared, including the support vector machine (SVM), support vector regression (SVR), and a convolutional neural network (CNN) using ResNet50 structure as the backbone network. The results showed that the CNN achieved the best classification results in all cases, with accuracy values of 97.87% for the generator, 98.03% for the converter, and 98.41% for the pitch system.

3. Wind Turbine Condition Monitoring

In the publication by Maldonado et al. [6], the authors conducted a systematic literature review regarding the use of Supervisory Control and Data Acquisition (SCADA) data for wind turbine condition monitoring (CM). The authors emphasize the economic benefits of utilizing data obtained from the SCADA system, which eliminates the need to install additional sensors or equipment on the wind turbines. The literature review revealed that, among the 102 articles analyzed, 26% were focused on the gearbox failure of wind turbines. The gearbox is considered one of the most critical components, as it contributes to 20% of total downtime in wind turbines. Additionally, the review highlighted other components of wind turbines that have been the subject of different condition monitoring methodologies, including blades, tower, drive train and bearing, yaw system, and various electrical and electronic components. The authors also noted some of the challenges associated with wind turbine condition monitoring, such as the development of non-intrusive and sensorless CM systems, online and real-time CM, standardization of SCADA data, public availability of SCADA data, and the development of an assessment method for monitoring the overall condition of a wind turbine. Furthermore, the SCADA variables utilized for wind turbine condition monitoring include, but are not limited to, environment temperature, wind speed, active power, pitch angle, gearbox temperature, and rotor speed.

In the study by McKinnon et al. [7], a number of anomaly detection techniques were developed based on gearbox SCADA data for wind turbine condition monitoring. The data utilized in the study were obtained from 21 wind turbines, with each turbine providing two months of data. The first month was considered to represent the healthy state, occurring one year prior to the failure, while the second month represented the unhealthy state, occurring one month prior to the failure. The models were trained using various variables, including the temperature and pressure of gearbox components, as well as the generator, rotor, and ambient wind speed. Three different models were compared: the Isolation Forest (IF), One-Class Support Vector Machine (OCSVM), and Elliptical Envelope (EE). OCSVM and IF exhibited an average accuracy of 82%, whereas EE presented a lower accuracy of 77%.

In the study by Velandia et al. [8], the authors investigated the detection of faults in wind turbines. They employed three data preprocessing techniques to improve the performance of a classification task on a highly imbalanced dataset obtained from SCADA data over a period of seven months in a wind turbine. Principal component analysis was used as a dimensionality reduction method, data reshaping served as a data augmentation technique, and random oversampling was applied to deal with the imbalanced characteristic of the dataset. Three different classifiers were compared: RUSBoost, Support Vector Machines (SVM), and k-Nearest Neighbors (k-NN). The results of the research show that the F_1 scores of at least 95% were achieved.

4. Wind Turbine Maintenance

In [9] a data-centric methodology is described. This methodology is designed to enhance the prediction accuracy of the remaining useful life (RUL) of different parts of a wind turbine. This approach contrasts with the conventional model-centric approach, in which the hyperparameters of a machine learning model are adjusted by assessing various feature selection and data preprocessing techniques within a machine learning pipeline. The methodology was validated and trained with data collected from a wind farm between 2016 and 2017. The study focused on diagnosing and analyzing five wind turbine components: the generator, hydraulic group, generator bearing, transformer, and gearbox. Given the skewed nature of the wind turbine dataset, with a significant amount of healthy data and limited fault data, precision and recall metrics were used to assess the classification task. The data-centric methodology outperformed the model-centric approach.

The research described in [10] successfully accomplished the objective of reducing repair costs and the number of repairs in four distinct components of a wind turbine using a support vector machine (SVM) algorithm for condition-based maintenance. The components studied were the rotor, pitch system, gearbox, and generator. The research showed that the generator component incurred the highest maintenance costs. The rotor, on the other hand, presents the best opportunity for cost savings, as its single maintenance cost is relatively higher. One notable contribution of this research is that it includes a comparative scenario analysis versus separate periodic maintenance, demonstrating an improvement in cost savings of 32.5%.

5. Concluding Remarks and Perspectives

The 10 papers described in this Editorial provide a comprehensive overview of current research trends in wind turbine condition monitoring, fault diagnosis, and maintenance. Future research in these areas should focus on the development of more advanced methodologies and the integration of multiple data sources for more accurate and reliable predictions. The integration of machine learning and artificial intelligence techniques can help identify patterns and hidden correlations within the data, leading to more accurate fault detection and condition monitoring of wind turbines. In addition, future research will focus on the development of techniques that address the challenges associated with wind turbine condition monitoring, such as the development of non-intrusive and sensorless condition monitoring systems, the standardization of SCADA data, and the assessment of the overall condition of a wind turbine. With the increasing demand for renewable energy, the need for reliable and efficient wind turbines is paramount, and research in these areas can help further the development of more effective wind turbine systems, improving their performance, extending their lifespan, and reducing downtime and maintenance costs.

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