Real-time monitoring, prognosis, and resilient control for wind turbine systems

Zhiwei Gao and Shuangwen Sheng

1. Introduction

Nowadays, industrial systems have become more complex and expensive, with less tolerance for performance degradation, decreased productivity, and safety hazards caused by unanticipated faults, which stimulate an increasing demand for real-time monitoring, prognosis, and resilient control techniques. Recent development of renewable industries, such as wind turbine systems, marine-based energy systems, and photovoltaics energy conversion systems have further stimulated the research and application of the real-time monitoring, diagnosis, prognosis, and resilient control design [1]. Wind power is contributing to more and more portions of the world energy market. However, a deterrent to even greater investment in wind energy is the considerably high failure rates of turbine components [2, 3]. Unexpected wind turbine faults may happen in sensors, electronic control units, electric systems, hydraulic systems, the generator, gearbox, and rotor blades, and so forth, which may cause performance degradation, unscheduled turbine shutdown, and even damaged components in wind turbine systems. As a result, there is a high demand to improve the operation reliability, availability, and productivity of wind turbine systems. Therefore, it is important to detect and identify any kinds of potential abnormalities and faults as early as possible by using real-time monitoring and fault diagnosis, predict the remaining useful life of the components by using data analyses and processing, and implement resilient control and management for minimizing performance degradation and economic cost, and avoiding dangerous situations. This special issue aims to provide a platform for academic and industrial communities to report recent results and emerging research in real-time monitoring, fault diagnosis, prognosis, and resilient control and design of wind turbine systems. After a strict peer-review process, 20 papers were selected, which represent the most recent progress of the real-time monitoring, diagnosis, prognosis, and resilient control methods/techniques in wind turbine systems. The accepted papers can be grouped into the three categories: monitoring and fault diagnosis, prognosis and remaining useful life prediction, and resilient control and optimization of wind turbine systems, as shown in Table 1. We will provide an overview of these papers by following the three aforementioned categories.

Table 1
Categories of selected papers in this special issue

Categories	Monitoring and fault diagnosis for wind turbine systems	Prognosis and remaining useful life prediction for wind turbine systems	Resilient control and optimization for wind turbine systems
Selected papers	[4-14]	[15-19]	[20-23]

2. Monitoring and fault diagnosis for wind turbine systems

The purpose of monitoring and fault diagnosis is to utilize information documented in operation data to detect potential faults, locate the faulty components, and identify/evaluate the severity level so that necessary measures can be taken to prevent an economic loss from an unscheduled shutdown, and to avoid further damage or a complete failure/collapse of the wind turbine system. According to various processing on the information redundancy recorded in the data, and the designer's understanding of these data, monitoring and fault diagnosis for wind turbine systems can be categorized into mode-based methods, signal-based methods, and knowledge-based methods [1]. A model-based approach builds the wind turbine model by using either the physical law method or system identification method, and monitoring/fault diagnosis is then implemented by checking the discrepancy between the model output and the real-time wind turbine output. The signal-based method uses time-domain, frequency-domain, and time-frequency domain approaches to extract the features of the wind turbine system, and monitoring/fault diagnosis is implemented by checking the consistency between the features of the real-time wind turbine system and the known features of the healthy wind turbine. For the knowledge-based method, the implicit relationship among the wind turbine system variables, referred to as the knowledge base, is extracted from the historical data via training or statistical analysis, and monitoring/fault diagnosis is implemented by checking the consistency between the knowledge base and the real-time wind turbine relationship extracted by using online data analysis and processing. In this special issue, there are 11 papers selected, with a focus on monitoring and fault diagnosis, which uses signal-based [4-8], knowledge-based methods [9-13] and mode-based methods [14], respectively.

2.1 Signal-based monitoring and fault diagnosis for wind turbine systems

Based on statistics, induction generators are reported to be one of the major contributors to wind turbine failures. In the paper [4] contributed by Aritigao et al., monitoring and fault diagnosis of a doubly-fed induction generator in an actual in-service wind turbine is investigated through stator current signature analysis via fast Fourier transform during steady-state periods. All the peaks appearing in the spectra are analyzed and the frequency components related to electrical rotor unbalance are successfully identified. The test scenarios for the wind turbine under three various operation conditions are presented to illustrate the effectiveness of the methods used.

Electrical signature analysis-based methods for monitoring and fault diagnosis have received attention, as a result of their ability to diagnose not only electrical faults, but also mechanical faults. In the paper [5] contributed by Shahriar et al., monitoring and diagnosis for mechanical faults, such as rotor imbalance, gear cracks, and other localized faults in wind turbines under the effect of wind turbulence and converter switching, are investigated by using an electrical signal analysis-based approach with the aid of band-pass filtering, Hilbert transform, and discrete Fourier transform. Four typical drivetrain faults are simulated, which reveal how the converter switching and wind turbulence affect the fault detectability of the methods used.

Ice on wind turbine blades may increase the surface roughness and reduce the aerodynamic efficiency, which may lead to an imbalance in the rotor and generate stress on the blades and drivetrain, correspondingly. The wind turbine may not work properly, and may even have to be stopped. Therefore, there is a strong motivation to monitor and diagnose the ice condition on the surface of wind turbine blades. In the paper [6] contributed by Munoz et al., a novel monitoring and diagnosis method is proposed for detecting ice on wind turbine blades by integrating ultrasonic techniques with wavelet transforms and pattern recognition techniques. The proposed monitoring and diagnosis method is demonstrated via three test scenarios: at room temperature, frozen blades without accumulation of ice on the surface, and frozen blades with accumulation of ice on the surface.

Because rolling bearings in a wind turbine gearbox often work under variable-speed and variable-load situations, they are prone to faults. Bearing cracks are a dominant cause, which may lead to a failure of the wind turbine gearbox. As a result, it is paramount to do early fault detection and diagnosis of the bearings. In the paper [7] contributed by Li et al., a multidimension, variation-mode decomposition approach is developed for bearing-crack detection in wind turbines under large driving-speed variations. The proposed method has the capability to deal with multichannel vibration signals under larger speed/load variations. The diagnosis approach is validated by an investigation of bearings with axial cracks in the outer races.

Detecting bearing faults at the early stage can prevent a catastrophic breakdown, save a company time, and reduce the economic cost. The paper [8], contributed by Peeters, is focused on separating the bearing fault signals from the masking signals coming from the drivetrain elements. The cepstral editing procedure is further investigated as an automated procedure for separating these signals by using the real data provided by the National Renewable Energy Laboratory. The analysis of the results shows that the cepstral editing procedure method fits well in the automated vibration analysis schemes, and the method used is effective for bearing fault detection.

2.2 Knowledge-based monitoring and fault diagnosis for wind turbine systems

Knowledge-based methods usually need a large amount of historical data for training and processing. As a result, knowledge-based fault diagnosis and monitoring methods are often called data-driven fault diagnosis and monitoring approaches.

In the paper [9] contributed by Cambron et al., data recorded by the supervisory control and data acquisition (SCADA) system are used for monitoring wind turbine generators. It monitors four indices of a wind turbine including electrical energy produced, tower vibration, nacelle yaw, and gearbox temperature. The diagnosis is implemented by checking the consistency of the indices of a wind turbine with the averaged indices of the remaining wind turbines in a wind farm, with the aid of control charts.

In the paper [10] contributed by Pashazadeh et al., a data-driven fault detection and isolation approach for a wind turbine subjected to sensor and actuator faults is proposed via fusion of a few classifiers. Specifically, multilayer perceptron, radial basis function, decision tree, and k-nearest neighbor classifiers are implemented in parallel, which are then fused together to increase the confidence of the diagnosis decision. The proposed fault detection and diagnosis approach is validated by using extensive simulations conducted based on a FAST wind turbine simulator.

The paper [11] contributed by Dao et al., presents a data-driven monitoring and fault detection method for a wind turbine by using cointegration analysis. The proposed method is illustrated and demonstrated using the experimental data recorded from a 2-MW wind turbine under varying environmental and operational conditions wherein data trends have nonlinear characteristics. The proposed method is simple and fast on computations, which would have good real-time performance for the monitoring and fault detection of wind turbines.

To increase the height of towers for exploiting stronger and more stable wind profiles, a welded-free friction connection seems to be promising for the new generation of wind towers, which requires a reliable monitoring and estimation on the performance of bolts over time. In the paper [12] contributed by Matos et al., a monitoring and identification procedure is presented for a 1-year monitoring of the force and temperature in a prototype. By using data-driven nonlinear identification, a nonlinear Hammerstein-Wiener model is built, which is used to estimate the preload losses of the bolts for 20 years of the tower lifetime.

It is interesting to assess the performance, stability, and reliability of wind turbines under various operational conditions (even faulty conditions) prior to grid connection, which can be performed by a hardware-in-loop setup under anticipated conditions experienced in real life. The test facility will benefit by reducing cost and risk in the design and operation of wind turbine generators. In the paper [13] contributed by Farajzadeh et al., a comprehensive test procedure is developed to test wind turbine generators using a hardware-in-loop setup. In the proposed procedure, a statistical model of the power grid is used and the restrictions of the test facility and system dynamics are considered. Offline and online approaches are both proposed to generate testing data based on Gibbs sampler. The testing data and validation data are compared by using a statistical energy function, which follows a generalized extreme value distribution or a good approximation.

2.3 Model-based monitoring and fault diagnosis for wind turbine systems

A wind turbine is a complex system, composed of several subsystems, such as the blades, drivetrain, generator, and control units, which are driven by random and uncontrolled wind. As a result, it is challenging but important to identify system dynamics across the whole wind turbine operation regime. In the paper [14] by Shao et al., a real-time parameter-varying model is built for a 4.8-MW wind turbine benchmark system. A novel observer is proposed with adaptive parameter tuning for fault estimation based on the proposed wind turbine model. The augmented system approach and the parameter-varying model are integrated for designing this novel fault estimator to simultaneously estimate the concerned faults as well as system states. The algorithm is performed and adjusted online for real-time monitoring and fault diagnosis.

3. Prognosis and remaining useful life prediction for wind turbine systems

Prognosis is a more advanced technique than fault detection and diagnosis, as it can predict the faults/failures ahead of time. The remaining useful life prediction enables an optimal maintenance scheduling to reduce the cost caused by wind turbine damage and unplanned shutdown.

A vibration amplitude of a wind turbine is governed by the amount of the inherent damping in the turbine structure. Therefore, a cost-effective and reliable structural design of wind turbines strongly relies on the accuracy of the employed damping model. As a result, there is motivation to develop a method to effectively estimate/identify the damping of offshore wind turbines. In the paper [15] contributed by Bajric, an automated identification of damping for offshore wind turbine tower vibrations is investigated. The proposed damping identification procedure is validated/demonstrated by using real offshore wind turbine data within a 24-hour period. The estimated damping status would provide useful information for a reliable prediction of the lifetime of offshore wind turbine structures.

In the paper [16] contributed by Jurgen et al., a statistical approach is proposed to predict wind turbine states by using Bayesian inference of wind turbine bearing temperature residuals and Gaussian processes. Evaluated on a limited set of time series, it is proven that the proposed approach can predict bearing failure one month ahead of when the failure occurs, which will help to schedule maintenance and repair before the failure happens. The failure-predictive probability is based on the data available as well as state variables.

In the paper [17] contributed by Djeziri et al., fault prognosis and remaining useful life prediction are investigated for wind turbines subjected to multiple faults. Geolocation principal is used to predict the remaining useful life of wind turbines. Euclidean distances from the normal operation clusters to faulty operation clusters are calculated, and the remaining useful life is computed as the ratio of the Euclidean position and the moving speed of the degradation. The proposed prognosis methods are evaluated via the prognosis horizon and the relative accuracy metrics using real wind turbine data.

The objective of the paper [18] contributed by Lei et al., is to schedule an optimum predictive maintenance based on remaining useful life prediction and power purchase agreements. For multiple wind turbines with remaining useful life predictions, the predictive maintenance priority for every single turbine relies on the operational states of all the other turbines, the amount of the energy delivered, the energy delivery target, the prices, and the underdelivery penalization mechanism defined in power purchase agreements. A case study is provided to determine an optimum predictive maintenance opportunity for a wind farm using power purchase agreement and remaining useful life predictions.

An aging assessment can be regarded as a kind of prognosis method, which can be used to improve the operation and maintenance strategy of wind turbines, and promote wind farm management. In the paper [19] contributed by Dai etc., an aging assessment of a wind turbine is conducted by interpreting wind farm SCADA data. Four data-based wind turbine aging assessment criteria are investigated to assess the aging-resultant performance degradation in wind turbines. Information fusion is then implemented to achieve a reliable aging assessment. The proposed approaches are validated by using the SCADA data collected from an operating wind turbine.

4. Resilient control and optimization for wind turbine systems

Resilient control is an advanced control strategy that is used to help a wind turbine continue to operate with tolerated performance degradation under unanticipated faulty conditions. As a result, resilient control of wind turbines has gained more attention in recent years.

The power converter has been proven to be one of the most fragile parts in wind turbine energy conversion systems, and is responsible for approximately 14% of the total downtime of a wind turbine. Therefore, it is critical to develop resilient control techniques for wind turbine systems subjected to power switch faults. In the paper [20] contributed by Shahbazi et al., real-time, power-switch fault-tolerant operation in a wind turbine system is investigated. An additional power switch leg is used to replace a faulty leg with the aid of a fault diagnosis algorithm for switching faults. The proposed fault diagnosis method and the converter reconfiguration during postfault operation are validated through the field-programmable gate array in the loop approach.

A wind turbine pitch system plays an essential role in regulating pitch angles of the blades so that the wind turbine generator can work at rated speed and produce rated power. When the pitch system is subjected to actuator faults, the pitch system may have slow dynamics that would cause a possible oscillation of the generator speed and power. In the paper [21] contributed by Lan et al., an adaptive, sliding, observer-based, fault-tolerant control strategy is proposed, and the proposed fault-tolerant control method is demonstrated by using a 4.8-MW wind turbine benchmark system.

Fractional-order control theory has received attention recently, which has found many applications in various areas. In the paper [22] contributed by Asghar et al., a fault-tolerant, fractional-order controller is presented for the rotor current reconstruction under faults, and the reconstruction algorithm is based on the measured stator currents and voltages. The proposed fractional-order controller is compared with the conventional integer controller under normal operation conditions, showing that the fractional-order controller has a comparable robustness with a classical sliding mode controller.

Wind turbine optimization may improve system performance and increase power production. In the paper [23] contributed by Santhanagopalan et al., performance optimization for a wind turbine column is investigated for various incoming wind turbulence. Dynamic programming is used to seek an optimal tip-speed ratio and stream-wise spacing of the turbines in a wind farm by using mixed-objective performance indices. Tip-speed ratio optimization is useful for reducing fatigue loads, whereas spacing optimization may lead to an improvement in power production.

5. Conclusion

An overview of the 20 selected papers for the special issue "Real-time monitoring, prognosis, and resilient control for wind turbine systems,'' has been presented, reflecting the most recent progress in the research field. We hope this special issue can further stimulate interest in improving the reliability, availability, and productiveness of wind turbine energy systems from academic societies and renewable industries. More research and practical applications on monitoring, diagnosis, prognosis, and resilient control for wind turbine systems are expected to be explored in the future.

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ZHIWEI GAO, *Guest Editor*
Faculty of Engineering and Environment
University of Northumbria
Newcastle upon Tyne, NE1 8ST, UNITIED KINGDOM

SHUANGWEN SHENG, *Guest Editor*
National Wind Technology Center
National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, Colorado 80401
USA

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