Wind Turbine Faults, Faults Diagnosis and Fault Management Systems: A Review

Dr. Ashwini K. Patil[*1], Dr. Archana Thosar[2]

Assistant Professor, MVPS's KBT College of Engineering, Nashik, Maharashtra, India-422013

patil.ashwini@kbtcoe.org

Professor, COEP Technological University, Pune, Maharashtra, India-422013

agt.elec@coep.ac.in

Article Info

Page Number: 5134 – 5152

Publication Issue:

Vol 71 No. 4 (2022)

Article History

Article Received*: 25 March 2022*

Revised*: 30 April 2022*

Accepted*: 15 June 2022*

Publication*: 19 August 2022*

Abstract

Wind power generation is motivated by environmental concern and exhaustion of fossil fuels. It is gradually becoming an irresistible source to meet the demands of green energy. Wind energy systems are complex structures and vulnerable to many possible faults. The fault detection at initial stage of occurrences of faults can lead to increase the performance of the wind energy systems and reduce the failures. This paper gives the comprehensive review of fault occurrences in wind energy systems, its diagnosis and recent progress in the fault management systems: condition monitoring (CM) systems and fault tolerant control (FTC) systems. The main objective of this study is to realize the existing methods for required levels of efficiency, reliability, and availability in high-capacity wind energy systems.

Keywords: Wind turbine faults, condition monitoring, fault tolerant control, signal based method, model based method

---

I. Introduction

High-capacity wind energy systems (WES) are installed at remote locations. The complicated structure and stochastic wind as input causes various faults in the whole structure, which may result to major failure in the system [1]. If these faults are not detected early, it causes failure which is more acute in case of offshore wind energy systems. To increase the reliability, availability, economy and the most importantly safety, several techniques of fault management systems are used: condition monitoring and fault tolerant control systems. CM system stops the wind turbine at the occurrence of faults whereas FTC can maintain the working condition safely [2]. As the number of wind turbines is noticeably increasing, even a minor increase in efficiency of these wind energy system will increase the collective yield at large.

Most of the wind power industries use CM systems that help to reduce the cost of corrective maintenance by early fault/failure detection [3]. Sensors are used to monitor the parameters like vibration, temperature continuously. The significant change in parameter condition indicates early fault detection which prevents subsequent damage[4]. It leads to shorter downtimes and less revenue losses [5]. FTC system maintains the system function satisfactorily even after the fault appears. This enables detection and replacement of faulty components, thereby reducing the down time cost [6]. FTC systems detect the fault, isolate it and provide an alternate physical or analytical redundant measurement. The common block in these systems is the fault diagnosis [7]. The methods used for fault diagnosis are: signal based, model based, and expert or knowledge-based methods.

This paper gives an overview of wind energy system operation in different wind speed regions, faults occurrence in it, and the fault management systems used in it.

II. Wind energy system control

Wind turbines are classified according to its construction as horizontal axis wind turbines (HAWT) and vertical axis wind turbines (VAWT). Three bladed HAWT yields more electricity and so more popularly used in power industry [8]. It consists of the tower, nacelle, brakes, low-speed shaft, gear box, high-speed shaft, generator, rotor, anemometer, wind vane and yaw mechanism. Kinetic energy of wind is converted by bladed rotor to mechanical energy, transmitted it to generator through brakes, low speed shaft, gear box, high speed shaft and further converted into electrical energy.

Variable speed wind energy system operates, with different dynamics, from the cut-in wind speed to the cut-out wind speed. It splits the wind turbine operation range in two: below rated called partial load region and above rated called full load region, where the captured power must be limited to rated as shown power curve in figure 1 [9].

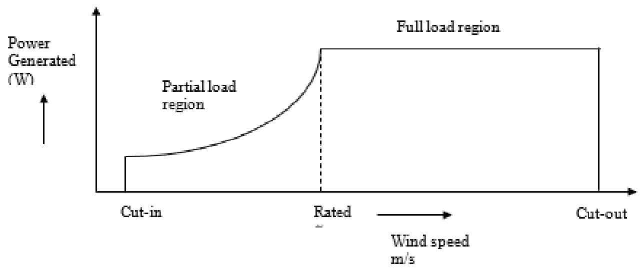

Figure 1. Power generated in different wind region

When wind is low below cut-in wind speed, wind turbines are stopped as it is uneconomical to generate power. The partial load region is where the wind is more than cut-in wind speed and less than rated wind speed, wind turbine should produce maximum achievable power [10]. Generator torque is regulated to get maximum output power.

At rated wind speed wind energy systems generate rated power. Full load region exists from rated wind speed to cut-out wind speed. Power generation is limited to rated power using an aerodynamic power control to avoid the structural and fatigue damage caused by great mechanical loads on the structure [10]. The power controller regulates the generator torque to track the rated generator power. Above cut-out wind speed, the wind energy systems may go in runaway condition and so are stopped.

Stochastic wind is input to the WES causing frequent incipient (due to aging) or abrupt faults. The system has to be stopped if abrupt fault occurs. System can be operational even if incipient fault occurs, with less performance. In the next section the faults in the WES are discussed.

III. Faults in wind energy system

The system failure caused due to the faults occurrence in sensors, actuators and plant faults.

Plant faults and its diagnosis:

The faults in component: rotor hub, blades, tower, drive train, bearings, shaft misalignment, hydraulic systems, generator in WES cause mechanical failures lead to breakdowns. In rotor, asymmetries as well as fatigue, reduced stiffness, crack, increased surface roughness and deformation of blades etc. lead to occurrence of faults. Probable faults in rotor hub and blades are blade corrosion, crack, serious aero-elastic deflection and rotor imbalance [11][12]. Long-term fatigue, pollution, icing leads to cracks on surface or in internal structure of blade which is monitored by using acoustic emission sensors installed on the blade [13]. For higher stable wind, height of tower is raised. Tower is designed in such a way that it should sustain vibrations and hold nacelle at stable condition. The storm, earthquake, lightening may cause failure of tower [14]. Poor manufacturing process, poor raw material used, improper installation, loading, harsh environment lead to structure damages, corrosion and crack. The time and frequency domains analysis of the vibrations of a tower can reveal its health condition [15].

Gearbox in the drive train failures contribute to approximately 20% of the downtime [16]. It is caused due to faults in gear and bearing. It exceeds unacceptable rotor speed. Gearbox failure occurs due to design and material defects, shaft damage, shaft misalignment, torque overloads, surface wear, fatigue, gear damage, bearing damage, broken shaft, high oil temperature and leaking oil [17]. Characteristic vibration frequencies are induced by the bearings faults, which can be analyzed and faults diagnosed [18]. Most gearbox failures start from bearing faults [19]. Using gearbox and generator temperature data and generator speed data, a multiple linear regression model is formed. Faults can be detected by analyzing the stability of regression coefficient using five step Chow’s test [20].

The faults in main shaft affect the shaft rotation and all other rotating parts connected to the shaft. This, in turn, affects the torque transmitted in the drive train and may excite vibrations in the rotor, gearbox and generator at certain characteristic frequencies [21]. Hydraulic system is used for drive motors in blades pitch system, yaw mechanism, and mechanical brake subsystems [22]. In hydraulic system various faults occur, such as, oil leakage and sliding valve blockage. These faults are diagnosed by pressure sensors and level sensors. The abnormal sensor reading indicates a fault in the hydraulic system.

In electric generators and motors the failures are due to electrical faults caused by broken rotor bar, bearing failure, bent shaft, air gap eccentricity, and rotor mass imbalance. The mechanical faults are due to stator or rotor insulation damage or open circuit. The spectrum of the instantaneous power reveals relevant fault-related information than stator line currents [23]. The rotor shaft vibrations caused due to rotor electrical imbalance. Shaft displacement can be an indicator of the fault [24]. Stator electrical imbalance can be diagnosed by monitoring current and power output of the electric machine [25]. The study of variations of the harmonic contents of electrical signals is used to detect the stator electrical imbalance.

Control system faults:

Control systems consist of sensors, controller, transmitters and actuators. Control system faults can be in hardware as good as software. The hardware failure modes include sensor faults, actuator faults, failure of controllers (control board), communication links, etc. The model based methods and the analysis of signals acquired by the control sub-systems are used to diagnose the hardware faults. Software faults are identified by diagnosing codes in the software. Wind turbine control systems are used for avoiding excessive mechanical loads, maximization of energy capture, and power quality [26].

The sensor failure cause more than 14% of failures in wind turbine [16]. Pitch sensor fault causes imbalances in rotor plane. Faults in speed sensor and converter sensor cause deviation of expected output to random output. Pitch actuators are basically of two types: electric and hydraulic. Pitch angles are adjusted by hydraulic actuators through a hydraulic system as it's size can be reduced and it offers rapid response [27]. The converter fault causes low output power. It also causes slow actuation and change in dynamics. Some faults are very serious result in a fast safe closedown of the WES and other can be accommodated by the controller [28].

The next section discusses the various fault management systems.

IV. Fault management systems in WECS: Fault tolerant control and Condition monitoring systems

Recent wind energy control systems are equipped with CM systems. The operating conditions of the wind turbine are monitored using different sensors and faults are detected, isolated and determined. Using available information predictive maintenance is performed. Most CM systems are signal based and utilize e.g., vibration analysis to detect and isolate faults. Various other signal-based approaches utilized in wind turbines are found in [29]. WESs are mostly shut down in case of fault occurrence by using CM system

A fault-tolerant control system prevents component failures from becoming system level failures. However, the control system is allowed to have degraded performance in some cases when exposed to a fault. Fault changes the characteristics of a component and failure causes a component to be completely dysfunctional. Due to limited resources and lack of optimal solutions under real-world constraints, there exist ample scope of research and development [30].

Fault Tolerant Control methods in WECS: There are mainly two types of FTC methods. Signal based control and model based control.

Signal based methods:

These are based on the analysis of measured output signals. An appropriate feature of the measured signals evaluates the operating conditions. These methods are particularly interesting for vibration detection.

Signal based CM systems are numerously available in WES for mechanical and electrical faults in blades, gearboxes, generators and bearings. The algorithms and architectures are implemented based on sensor measurements and efficient monitoring of the machines is done. The faults in gearboxes are analyzed by monitoring the vibration, temperature, lubricating fluid level, and oil cleanliness. The most commonly used is acceleration sensor [31]. The vibro-acoustic analysis is currently popular for diagnosing mechanical faults in gearbox and bearings. The use of discrete wavelet transforms (DWT) reduce noise in highly variable shaft torque and speed signals. The continuous wavelet transforms (CWT) can extract time-frequency features correctly from the highly variable wind turbine signals used for feature extraction [32]. However, a number of transducers are involved in this approach causing high capital cost.

Drive train faults can be detected using generator terminal quantities through current and voltage transformer without using additional sensors [32].

In [33], demodulated current signal of an induction motor driving a multistage gearbox has used for detecting faults using amplitude demodulation and frequency demodulation

The generator and drive train fault detection includes electrical quantities signature analysis (current, power), vibration, temperature and oil monitoring. [34].

The steady-state spectral components of stator (voltage, current, and power) are used for condition monitoring of induction machine to detect turn faults, broken rotor bars, bearing failures and air gap eccentricities [35]. The bearings faults are monitored by vibration. More effectively the stator current signal the first Intrinsic Mode Function (IMF) is used for a generator bearing fault [36].

Limitations of Signal based methods:

The signal based approach use hardware/physical redundancies of multiple sensors, actuators to measure or control a particular variable. Redundant system decides when and where the fault has occurred using voting scheme applied to the hardware. But the hardware redundancy require extra equipment, maintenance cost and additional space to accommodate the equipment.

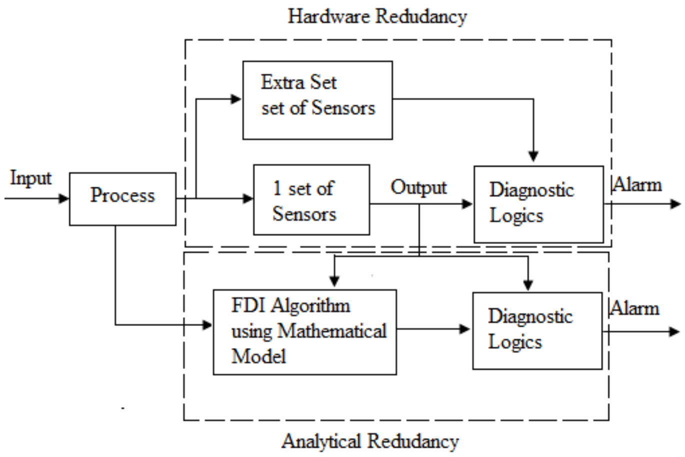

Figure 2. Model based and signal based fault diagnosis

Figure 2 shows hardware and analytical redundancy. In model based approach analytical redundancy is used. As no additional hardware is used, analytical redundancy is potentially more reliable than hardware redundancy. Additional components are not required to realize fault detection and isolation (FDI) algorithm which is a major advantage of model based approach.

The signal based method using vibration signals are generally more versatile. But vibration sensors are not reliable to use as they have a wide variety of dynamic ranges and sensitivities [37].

Model based methods:

In these methods the process parameters are estimated with the help of input-output measurements and plant model. The residuals are generated by comparing the estimated parameters and real parameter sets. These are used as fault indicators. These residuals are used to obtain the desired fault-detection and isolation properties. Model-based techniques require an accurate mathematical model of the process. Different model-based methods are system identification and parameter estimation, parity relation approach, observer based, unknown input observers and residual generation, etc.

Parity relation approach:

In [38] a set membership approach has used for fault diagnosis in wind turbines. Parity equations are formed for the detection of faults. The residual is evaluated by calculating the difference between process output and model output. By checking consistency between measurements and model, the fault is detected. Analyzing the observed fault signatures on-line and matching them with the theoretical ones obtained using structural analysis, the fault isolation algorithm analyzes the fault occurrence. The main drawback of this detection test is that the number of constrains that define grows with data. The decisions are taken using up-down counters based on the fault residuals generated through physically redundant sensors, parity equations and common filtering [39]. Its advantages are fast detection and minimal false alarms without implementation of more complex filtering and detection techniques on residuals. It covers almost all sensors and actuators required in drive train, rotor and pitch system. In [40] a bank of fault isolation estimators employed to determine the particular fault type. An isolation estimator is designed based on a particular fault scenario under consideration. Two sensor measurements are used and threshold is checked for detecting fault.

Fault detection filter using a data-driven model:

A data-driven model extracts data from sensor measurements. The feature from these measurements is fed into a dynamical clustering algorithm. The latter learn process behaviors characterized by clusters. It has ability to update the parameters of these clusters. These parameters are used as health indicators for diagnosing the drive train faults. It consists of five phases: initial processing on sensor measurements, feature estimation, dynamical clustering, health indicators and decision scheme for fault detection and isolation (FDI) [41]. Data-driven design method produces FDI filters directly based on the simulated data from the benchmark model. Fault isolation scheme is developed by using hardware redundancy in the plant. Based on this, a bank of robust data-driven detection filters are designed for the benchmark and implemented, simultaneously. The limitation of this method is the FDI scheme has to be incorporated with controller reconfiguration [42]. In order to enhance the wind turbine diagnosability properties and to optimize the sensor network design, [43] has proposed sensor graph representation of the system. This sensor graph is used to study the diagnosability and evaluate fault tolerance in different cases of sensors distribution.

In [44], the generalized likelihood ratio (GLR) test and the associated statistical fault detection tools are used to detect and isolate faults in the wind turbine benchmark problem. For each of the fault, an accurate detection and isolation of the fault within the stringent time constraints are set. Inaccurate measurement of wind speed, high nonlinearities in the drive train model and correlated process and measurement noises are dealt which are the critical issues.

Closed loop identification technique:

Mathematical model is developed based on closed loop identification technique that includes wind dynamics. Kalman filter is used for residual generation further used for fault detection [45]. The fault isolation is done with the help of dual sensor redundancy. This approach is used for rotor blade moments sensor fault detection large scale wind turbine.

Observer based method:

There are at least four common problems caused by sensors. First, sensors cost can raise the total cost of a control system as the sensors are expensive. Most of the times, the sensors and their associated cabling are very expensive components in the system. Second, sensors and their associated wiring reduce the reliability of control systems. Third, some signals are impractical to measure e.g., the temperature of a motor rotor. Fourth, sensors usually induce significant errors such as stochastic noise, cyclical errors, and limited responsiveness. In this method, observers are designed using mathematical model. Observers design combines the sensed signals with other knowledge of the control system to produce observed signals. These observed signals are accurate, economic and more reliable than sensed signals [46]. Better the designed mathematical model, better will be the reliability and performance of FDI. In order to achieve robustness in FDI, the residuals should be insensitive to uncertainty, whilst sensitive to faults [47].

An important component in modern wind turbines is converter. The generator torque is an important parameter for control point-of-view, but is difficult to measure. The generator measurement normally provides the torque acting on wind turbine generator, as well as measurement of the torque. An unknown input observer is used to estimate the faults in the converter [48] based on benchmark model. In unknown input observer based method, the input parameter is estimated which is not accurately measurable. It increases the robustness.

The FTC scheme based on the estimates of generator speed using bank of unknown input observer is simple and accurate [49]. It uses the healthy sensor measurement for unknown input observer design. It is ensured that even if the healthy sensor measurement used may contain offset, it does not cause the generator speed to shoot above maximum limit. Fault detection and isolation and FTC of wind turbines is obtained using the set-valued observers [50]. But the computational expenses of this algorithm are more. In [51], an approach based on interval observers has used for FDI of wind turbines. Fault detection is proposed using interval observers. The unknown but bounded descriptions of the noise and modelling errors, while fault isolation is based on a row reasoning approach. Polynomial observer is synthesized to estimate fault [52]. In [53], a control law based on a number of interconnected nonlinear observers are proposed. Sliding mode observer (SMO)-based fault detection and isolation (FDI) scheme for wind energy system is proposed in [54]. With this method the actuator faults in pitch systems of the wind turbine are transformed as sensor faults. A reduced order model of the drive train system is constructed to eliminate the effects of unknown aerodynamic rotor torque. In [55] the method based on designing a nonlinear observer using State Dependent Differential Riccati Equation (SDDRE) and a nonlinear model of the 5MW wind turbine has proposed. The care is taken while designing fault detection system that it should be more sensitive to system faults and not to the system noises.

Linear Parameter Varying (LPV):

LPV-based active and LPV-based passive FTC systems proposed in [56]. These methods are used for changed dynamics of the pitch system and loss of the generator speed measurement in full load operation. An AFTC relies on a fault diagnosis system, which is expected to feed information about the faults to the controller. This knowledge makes it possible for the AFTC to reconfigure according to the current state of the system. The active FTC system is slightly superior to that of the passive. But the errors in model may introduce a risk of false positive and false negative diagnosis. Comparatively the false decisions are less likely done by PFTC and the detection is done very fast. These LPV-based design controllers demonstrate that it is possible to add robustness and fault-tolerant capabilities to a nominal LPV controller by utilizing unified linear matrix inequalities (LMI) based design method [57]. LPV systems with the help of recent advances in the set value observers (SVOs) theory used for FDI and FTC methodologies to invalidate dynamic models. The limitation of this strategy is that it depends on the availability of large computational resources [58].

Model predictive controller (MPC):

Model reference adaptive fault-tolerant control is another model based FTC. This control strategy is applied to solve the problem of pitch angle regulation of wind turbines in presence of actuator failures, disturbances and modelling uncertainties for a class of nonlinear systems. This fault tolerant controller does not reply on a prior information regarding the instance of failure, failure pattern or fault size. This method is applied to wind turbine pitch control to alleviate the asymmetric rotor loads without reducing efficiency of the energy capture from wind [59]. The global model predictive controller which is an active FTC proposed to schedule the operation of the components and exploit potential system-level redundancies [60]. In MPC an adaptive internal model combined with a parameter estimation and the mechanism is updated, such as an extended version of Kalman filter. This scheme has been used for pitch system faults [61]. Based on dual multivariable model-free adaptive control strategy, a passive FTC is designed for pitch control in [62]. In [63], model-based predictive controller for FTC is proposed for wind speed sensor fault when the turbine operates in partial load region. Both hardware and analytical redundancy are utilized in this approach. For the wind speed sensor fault, the Least Squares Support Vector Machine (LS-SVM) has proposed for the fault detection and isolation (FDI) unit.

H∞ optimization-based (Frequency domain design for model-based FDI)

An H∞ optimization-based approach for the detection and isolation of faults in a horizontal axis wind turbine using benchmark model is presented in [64]. In this method, primary residuals are first generated from a parity equation approach and then passed onto a robust secondary residual generation or filtering scheme. The robust scheme attempts to remove undesirable cross-coupling between fault-residual pairs and accommodates the strong aerodynamic nonlinearities and modelling uncertainties. Using H∞ tools derived by linear robust control theory the robust schemes are obtained.

In model based methods the perfectly accurate and complete mathematical model of physical system is required which is not easily available. The characteristics of the disturbances and noise are unknown and cannot be modelled accurately. Robustness in a model based approach must be increased by including all possible aspects [65].

Expert systems or knowledge-based methods:

Sometimes a process is too complex to be modeled analytically and a regular signal analysis approach may not yield a reliable scheme, e.g., certain fault combinations have different effects on the system behavior. It is then possible to classify the faulty behavior by using qualitative process knowledge to evaluate relations between measured signals and the current operating conditions.

In application of knowledge-based techniques, a learning process for each individual component of wind energy control system is required for fault detection. In these methods the trends are developed, without necessarily linking cause to fault effects. In [66], the data-driven approach for the identification, fault detection and isolation of a wind turbine model is proposed. In order to detect the faults in the converter and isolate them either to be an actuator or a sensor fault a diagnosis strategy is based on fuzzy prototypes.

Fuzzy techniques are proposed to combine information from different measurements. Event-triggered mechanism based on Takagi–Sugeno (T–S) fuzzy model, is designed for nonlinear control for WES. Using Lyapunov stability theory, the parameter expression of FTC with event-triggered mechanisms is designed which is a feasible solution of linear matrix inequalities. It improves the robustness and reliability of wind energy control system [67].

The "Takagi-Sugeno" (TS) fuzzy model with parametric uncertainties is designed for modelling the nonlinear wind energy control systems and establishing fuzzy state observers for sensor faults [68]. For robust Active Fault Tolerant Fuzzy Control (AFTFC), a multi-observer switching control strategy is proposed.

In [69] the approach for wind energy control system monitoring where the diagnosis is done using neural networks. In [70] the Kalman filter is used for fault detection of the blade pitch system. The Artificial neural network (ANN) builds the predictive model with training, validation and test procedures.

V. Conclusion

This paper has provided the review of the occurrence various faults, its diagnosis methods and fault management systems for wind energy system. The CM systems are useful for predictive maintenance to avoid failure which are abundantly available in the literature. Fault tolerant control systems are considerably less represented in literature as compare to CM systems.

There are numerous signal based methods available in the literature for diagnosing the mechanical faults. Available methods include: Using number of sensors the data is collected and analysed and another method by analysing the generator terminal current and voltage using various techniques which is comparatively more effective and also economic than first.

The model based methods are equally reliable and economic. For that the mathematical model must be accurate and suitable for designing control systems. The model-based fault tolerant control systems used in the literature are

Observer based fault diagnosis and fault tolerant control systems are designed using benchmark model. These fault tolerant control systems are robust, least sensitive to the system disturbances and noises. For designing an observer, the set of healthy sensors are used. For generator speed sensor, even if healthy sensor measurement used consists of offset, it does not cause output to shoot above maximum limit. Using bank of observers, the observer is chosen corresponding to the present fault situation. In wind energy systems the drive train and generator are prone to number of mechanical faults due to misalignment, damaged gear and bearings. Especially in partial load region, the faults cause increased friction due to improper lubrication and irregular maintenance where the shaft speed is variable. At variable rotational speed, these losses vary strongly with torque transmission. Looking at the drive train sensitivity to the faults, it becomes necessary to consider it in the mathematical model.

The sliding mode observer-based fault tolerant control system is based on the observer designing. These are designed for pitch system faults.

Linear parameter varying method is designed effectively for full load region and not for partial load region. Model predictive fault tolerant control systems are used in benchmark model particularly designed for pitch system fault in full load region and for wind speed sensor fault in partial load region.

An H∞ optimization-based approach for the detection and isolation of faults is designed for all the nine faults specified in benchmark model. The limitation of this method is that the detection time required is more.

In the expert or knowledge-based fault tolerant control systems qualitative process knowledge is required. Few papers have presented observer based T-S fuzzy control system.

It motivates to study and develop the model based fault tolerant control system and an accurate mathematical model for designing it. While designing the mathematical model, frequent mechanical faults should be considered so that the design should be robust and efficient.

References

[1] Erich Hau, Horst Von Renauord (2006), "Wind Turbines, Fundamentals, Technologies, Application, Economics", Springer Link.

[2] Habibi, H., Simani, S. (2019), Reliability improvement of wind turbine power generation using model-based fault detection and fault tolerant control: A review. Renew. Energy 2019, 135, 877–896.

[3] Gerber, T., Martin, N., & Mailhes, C (2015) Time-frequency Tracking of Spectral Structures Estimated by a Data-driven Method, Industrial Electronics, IEEE Transactions on, 62(10), 6616-6626.

[4] M. -H. Hsu, P. J. B. Tan and C. -C. Chao(2018) Condition monitoring and fault detection of wind turbines generator, IEEE International Conference on Applied System Invention (ICASI), 2018, pp. 1218-1221, doi: 10.1109/ICASI.2018.8394508

[5] W. Yang (2016) Condition monitoring of offshore wind turbines, DOI:10.1016/B978-0-08-100779-2.00018-0.

[6] MogensBlanke, Michel Kinnaert, Jan Lunze, Marcel Staroswiecki (2016) Diagnosis and Fault-Tolerant Control, 2nd edition, Springer-Verlag Berlin Heidelberg, Printed in Germany

[7] Thomas E., Christo_E. S., Odgaard N., and Brian T J. (2008) Joint Power and Speed Control of Wind Turbines, Technical report, Aaborg University, Department of Electronic Systems.

[8] Sathyajith Mathew (2006) Wind energy, Fundamentals, Resource Analysis and Economics, springeronline.com, © Springer-Verlag Berlin Heidelberg, Printed in The Netherlands

[9] Bianchi, F. D., Battista, H. D., and Mantz, R. J.(2007) Wind Turbine Control Systems: Principles, Modelling and Gain Scheduling Design, Springer. ISBN: 1-84628-492-9.

[10] Dolan, B. (2010). Wind Turbine Modelling, Control and Fault Detection (Master's thesis, Technical University of Denmark, DTU, DK-2800 Kgs. Lyngby, Denmark).

[11] Xudong, W., Shen, W. Z., Zhu, W. J., Sørensen, J. N., & Jin, C. (2009), Shape optimization of wind turbine blades. Wind energy, 12(8), 781-803.

[12] Dimitris Al. Katsaprakakis , Nikos Papadakis and Ioannis Ntintakis(2021), A comprehensive analysis of wind turbine blade damage, Energies, 14, 5974. https://doi.org/10.3390/en14185974

[13] Van Dam, J. V., and Bond, L. J. (2015) Acoustic Emission Monitoring of Wind Turbine Blades, in SPIE Proceedings,Smart Materials and Nondestructive Evaluation for Energy Systems 2015, 94390C. doi:10.1117/12.2084527

[14] Yoshida, S. (2006) Wind turbine tower optimization method using a genetic algorithm. Wind Engineering, 30(6), 453-469.

[15] Kilic, G., & Unluturk, M. S. (2015) Testing of wind turbine towers using wireless sensor network and accelerometer. Renewable Energy, 75, 318-325.

[16] I.P. Girsang, J.S. Dhupia, E. Muljadi, M. Singh, L.Y. Pao (2013) Gearbox and Drivetrain Models to Study Dynamic Effects of Modern Wind Turbines, Presented at the IEEE Energy Conversion Congress and Exposition Denver, Colorado September 15–19, 2013

[17] Tom Bruce (June 2016), “Analysis of the Premature Failure of Wind Turbine Gearbox Bearings”, (A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy) at the University of Sheffield, Mechanical department

[18] Gong, X., & Qiao, W. (2011) Bearing fault detection for direct-drive wind turbines via stator current spectrum analysis. In Energy Conversion Congress and Exposition (ECCE), 2011 IEEE (pp. 313-318). IEEE.

[19] Oyague, F. (2009) Gearbox modeling and load simulation of a baseline 750-kW wind turbine using state-of-the-art simulation codes. Golden, CO: National Renewable Energy Laboratory.

[20] Phong B Dao(2022), Condition monitoring and fault diagnosis of wind turbines based on structural break detection in SCADA data, Applied Energy, Volume 318, 119209

[21] Wilkinson, M. R., Spinato, F., & Tavner, P. J. (2007) Condition monitoring of generators & other subassemblies in wind turbine drive trains. In Diagnostics for Electric Machines, Power

Electronics and Drives, 2007. SDEMPED . IEEE International Symposium on (pp. 388-392). IEEE.

[22] Wu, X., Li, Y., Li, F., Yang, Z., & Teng, W. (2012) Adaptive estimation-based leakage detection for a wind turbine hydraulic pitching system. IEEE/ASME Transactions on Mechatronics, 17(5), 907-914.

[23] Djurovic, S., Williamson, S., Yang, W., & Tavner, P. (2009) Condition monitoring artefacts for detecting winding faults in wind turbine DFIGs. Proceedings of EWEC 2009, Scientific Track-Wind Turbine Electrical System & Component.

[24] Teng W, Ding X, Tang S, Xu J, Shi B, Liu Y. (2021) Vibration Analysis for Fault Detection of Wind Turbine Drivetrains-A Comprehensive Investigation. Sensors (Basel). 2021 Mar 1;21(5):1686. doi: 10.3390/s21051686. PMID: 33804512; PMCID: PMC7957485.

[25] Ragab Abd Allah Mahmoud (2021) Detection and assessment scheme of voltage and current unbalance for three phase synchronous generators using dual numerical techniques based on correlation and deviation percentage concepts , The Journal of Engineering published by John Wiley & Sons Ltd on behalf of The Institution of Engineering and Technology, DOI: 10.1049/tje2.12051

[26] Eltamaly, A. M., & Farh, H. M. (2013) Maximum power extraction from wind energy system based on fuzzy logic control. Electric Power Systems Research, 97, 144-150.

[27] R I Pelin, P D Bârsănescu, I Ţiţa (2018), Hydraulic systems used for pitch control of wind turbines: a literature overview, IOP Conference Series: Materials Science and Engineering, Volume 444, Issue 4, DOI:10.1088/1757-899X/444/4/042013

[28] Vidal, Y., Tutivén, C., Rodellar, J., & Acho, L. (2015) Fault diagnosis and fault-tolerant control of wind turbines via a discrete time controller with a disturbance compensator. Energies, 8(5), 4300-4316.

[29] Hameed, Z., Hong, Y. S., Cho, Y. M., Ahn, S. H., & Song, C. K. (2009) Condition monitoring and fault detection of wind turbines and related algorithms: A review. Renewable and Sustainable energy reviews, 13(1), 1-39.

[30] Precup, R. E., Angelov, P., Costa, B. S. J., & Sayed-Mouchaweh, M. (2015) An overview on fault diagnosis and nature-inspired optimal control of industrial process applications. Computers in Industry, 74, 75-94.

[31] Jack P. Salameh a,b,⇑ , Sebastien Cauet a , Erik Etien a , Anas Sakout b , Laurent Rambault, (2018). Gearbox condition monitoring in wind turbines: A review. Mechanical Systems and Signal Processing, Volume 111, Pages 251-264

[32] Yang, W., Tavner, P. J., & Wilkinson, M. (2008) Wind turbine condition monitoring and fault diagnosis using both mechanical and electrical signatures. In Advanced Intelligent Mechatronics. AIM 2008. IEEE/ASME International Conference on (pp. 1296-1301). IEEE.

[33] Mohanty, A. R., & Kar, C. (2006) Fault detection in a multistage gearbox by demodulation of motor current waveform. IEEE transactions on Industrial Electronics, 53(4), 1285-1297.

[34] Casadei, D., Filippetti, F., Rossi, C., Stefani, A., Yazidi, A., & Capolino, G. A. (2006) Diagnostic technique based on rotor modulating signals signature analysis for doubly fed induction machines in wind generator systems. In Industry Applications Conference, 2006. 41st IAS Annual Meeting. Conference Record of the 2006 IEEE (Vol. 3, pp. 1525-1532). IEEE.

[35] Benbouzid, M. E. H., & Kliman, G. B. (2003) What stator current processing-based technique to use for induction motor rotor faults diagnosis. IEEE Transactions on Energy Conversion, 18(2), 238-244.

[36] Amirat, Y., Choqueuse, V., Benbouzid, M. E. H., & Charpentier, J. F. (2010) Bearing fault detection in DFIG-based wind turbines using the first intrinsic mode function. In Electrical Machines (ICEM), 2010 XIX International Conference on (pp. 1-6). IEEE.

[37] Nandi, A. K., Liu, C., & Wong, M. D. (2013). Intelligent Vibration Signal Processing for Condition Monitoring. Surveillance, 7, 29-30.

[38] Blesa, J., Puig, V., Romera, J., & Saludes, J. (2011). Fault diagnosis of wind turbines using a set-membership approach. IFAC Proceedings Volumes, 44(1), 8316-8321.

[39] Ozdemir, A. A., Seiler, P., & Balas, G. J. (2011). Wind turbine fault detection using counter-based residual thresholding. IFAC Proceedings Volumes, 44(1), 8289-8294.

[40] Zhang, X., Zhang, Q., Zhao, S., Ferrari, R., Polycarpou, M. M., & Parisini, T. (2011). Fault detection and isolation of the wind turbine benchmark: An estimation-based approach. IFAC Proceedings Volumes, 44(1), 8295-8300.

[41] Chammas, A., Duviella, E., & Lecoeuche, S. (2013). Fault diagnosis of wind turbine drive train faults based on dynamical clustering. In Decision and Control (CDC), 2013 IEEE 52nd Annual Conference on (pp. 5650-5655). IEEE.

[42] Dong, J., & Verhaegen, M. (2011) Data driven fault detection and isolation of a wind turbine benchmark. IFAC Proceedings Volumes, 44(1), 7086-7091.

[43] Rouissi, F., & Hoblos, G. (2013) Fault tolerance in wind turbine sensor systems for diagnosability properties guarantee. In Control and Fault-Tolerant Systems (SysTol), 2013 Conference on (pp. 523-528). IEEE.

[44] Kiasi, F., Prakash, J., Shah, S. L., & Lee, J. M. (2011) Fault detection and isolation of a benchmark wind turbine using the likelihood ratio test. IFAC Proceedings Volumes, 44(1), 7079-7085.

[45] Wei, X., Verhaegen, M., & Van Den Engelen, T. (2008) Sensor fault diagnosis of wind turbines for fault tolerant. IFAC Proceedings Volumes, 41(2), 3222-3227.

[46] Teng, J.; Li, C.; Feng, Y.; Yang, T.; Zhou, R.; Sheng, Q.Z. (2021) Adaptive Observer Based Fault Tolerant Control for Sensor and Actuator Faults in Wind Turbines. Sensors 2021, 21, 8170. https://doi.org/10.3390/s21248170

[47] Zhenhai Li, I.M. Jaimoukha (2009) Observer-based fault detection and isolation filter design for linear time-invariant systems, International Journal of Control 82(1):171-182 DOI:10.1080/00207170802031528

[48] Chen, W., Ding, S. X., Haghani, A., Naik, A., Khan, A. Q., & Yin, S. (2011) Observer-based FDI schemes for wind turbine benchmark. IFAC Proceedings Volumes, 44(1), 7073-7078.

[49] Odgaard, P. F., & Stoustrup, J. (2012) Fault tolerant control of wind turbines using unknown input observers. IFAC Proceedings Volumes, 45(20), 313-318.

[50] Pedro Casau, Paulo Rosa, Seyed Mojtaba Tabatabaeipour, Carlos Silvestre, and Jakob Stoustrup (2015) A Set-Valued Approach to FDI and FTC of Wind Turbines, IEEE TRANSACTIONS ON CONTROL SYSTEMS TECHNOLOGY, VOL. 23, NO. 1.

[51] Blesa, J., Nejjari, F., Rotondo, D., & Puig, V. (2013) Robust fault detection and isolation of wind turbines using interval observers. In Control and Fault-Tolerant Systems (SysTol), Conference on (pp. 353-358). IEEE.

[52] Van-Phong Vu, Vsssan-Thuyen Ngo, Van-Dung Do, Dinh-Nhon Truong, Nguyen Vu Quynh, PhucDuc-Hong Bui, Vu The Mai and Ton Duc Do (2020). Polynomial observer based controller synthesis and fault tolerant control for tracking optimal power of wind energy conversion systems, IEEE Access, vol. 8, pp. 150130- 150141.

[53] Corradini, M. L., Ippoliti, G., & Orlando, G. (2015). Sensorless fault-tolerant control of VS Wind Turbines maximizing efficiency in the presence of electrical faults. In Decision and Control (CDC), IEEE 54th Annual Conference on (pp. 682-687). IEEE.

[54] Zhang, J., Bennouna, O., Swain, A. K., & Nguang, S. K. (2013). Detection and isolation of sensor faults of wind turbines using sliding mode observers. In Renewable and Sustainable Energy Conference (IRSEC), International (pp. 234-239). IEEE.

[55] Hwas, A., & Katebi, R. (2014). Nonlinear observer-based fault detection and isolation for wind turbines. In Control and Automation (MED), 22nd Mediterranean Conference of (pp. 870-875). IEEE.

[56] Sloth, C., Esbensen, T., & Stoustrup, J. (2010) Active and passive fault-tolerant LPV control of wind turbines. In American Control Conference (ACC), (pp. 4640-4646). IEEE.

[57] Sloth, C., Esbensen, T., & Stoustrup, J. (2011) Robust and fault-tolerant linear parameter-varying control of wind turbines. Mechatronics, 21(4), 645-659.

[58] Ruinan Zhao and YanxiaShen (2020) Fault detection of WECSs with a delayed input and an unknown part based on SVO", IEEE Access, vol. 8, pp. 121050-121058.

[59] Fan, L., & Song, Y. (2011). Model reference adaptive fault-tolerant control with application to wind turbines. In Control and Decision Conference (CCDC), 2011 Chinese (pp. 1314-1319). IEEE.

[60] Yang, X., & Maciejowski, J. M. (2012) Fault-tolerant model predictive control of a wind turbine benchmark. IFAC Proceedings Volumes, 45(20), 337-342.

[61] Kamal, E., Aitouche, A., & Bayart, M. (2011) Fault-tolerant control of WECS subject to parametric uncertainties and sensor faults. In Control & Automation (MED), 2011 19th Mediterranean Conference on (pp. 126-131). IEEE.

[62] Jianshen Li, Shuangxin Wang (2021) Dual multivariable model-free adaptive individual pitch control for load reduction in wind turbines with actuator faults, Renewable Energy, Volume 174, August 2021, Pages 293-304

[63] Feng, X., & Patton, R. (2013). A model-based predictive control for FTC for wind turbine wind speed sensor fault. In Control and Fault-Tolerant Systems (SysTol), Conference on (pp. 504-509). IEEE.

[64] Pisu, P., & Ayalew, B. (2011) Robust fault diagnosis for a horizontal axis wind turbine. IFAC Proceedings Volumes, 44(1), 7055-7060.

[65] Chen, J., & Patton, R. J. (2012) Robust model-based fault diagnosis for dynamic systems (Vol. 3). Springer Science & Business Media.

[66] Simani, S., Castaldi, P., & Tilli, A. (2011) Data—Driven Approach for Wind Turbine Actuator and Sensor Fault Detection and Isolation. IFAC Proceedings Volumes, 44(1), 8301-8306.

[67] ZhihongHuo and Chang Xu (2022) Event triggered mechanism based robust fault tolerant control for networked wind energy conversion system", Global Energy Interconnection, vol. 5, no. 1, pp. 55-65.

[68] Kamal, E., Aitouche, A., Ghorbani, R., & Bayart, M. (2012) Robust fuzzy fault-tolerant control of wind energy conversion systems subject to sensor faults. IEEE Transactions on Sustainable Energy, 3(2), 231-241.

[69] Raed Ibrahim, Jannis Tautz-Weinert, Simon Watson (2016) Neural Networks for Wind Turbine Fault Detection via Current Signature Analysis. Conference: WindEurope Summit 2016 At: Hamburg

[70] Seongpil Cho, Minjoo Choi, Zhen Gao and Torgeir Moan (2021) Fault detection and diagnosis of a blade pitch system in a floating wind turbine based on kalman filters and artificial neural networks, Renewable Energy, vol. 169, no. 11, pp. 1-13.