Fault Diagnosis Methods for Wind Turbines Health Monitoring: a Review

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ABSTRACT

Recently, the rapid expansion of wind energy activity has led to an increasing number of publications that deal with wind turbine health monitoring. In real practice, implementing a prognostics and health management (PHM) strategy for wind turbines is challenging. Indeed, wind turbines are complex electro-mechanical systems that often work under rapidly changing environment and operating load conditions. Although several review papers that address wind turbines fault diagnosis were published, they are mostly focused on a specific component or on a specific category of methods. Therefore, a larger snapshot on recent advances in wind turbine fault diagnosis is presented in this paper. Fault diagnosis approaches could be grouped in three major categories according to the available a priori knowledge about the system behavior: quantitative/qualitative model, signal analysis and artificial intelligence based approaches. Each of the proposed methods in the literature has its advantages and drawbacks. Therefore, a comparison between these methods according to some meaningful evaluation criteria is conducted.

1. INTRODUCTION

Wind power industry continues to show a significant worldwide growth during the last decade. However, due to the competitive environment associated with the power generation industry, costs for operation and maintenance (O&M) of wind turbines need to be reduced (Arabian-Hoseynabadi, Oraee, & Tavner, 2010). Prognostics and Health Management (PHM) is one of the best strategies to achieve such purpose. Indeed, inspection tasks and time based maintenance activities are often expensive and require undesired downtime to be performed (Lu, Li, Wu, & Yang, 2009). Moreover, implementing a PHM policy allows to support system long-term performance through accurate monitoring, incipient fault diagnosis and prediction of impending faults (Kalgren, Byington, & Roemer, 2006). A fault diagnosis function estimates the current system health state from health features or sensors measurements. Whereas, a prognosis procedure seeks to predict when a potential upcoming failure will occur given the current system health state and the future usage conditions (Roemer, Nwadiogbu & Bloor, 2001).

However, a number of challenges remain to be met while performing wind turbines health assessment tasks owing to:

- The complex structure of the wind turbine (Fischer, Besnard & Bertling, 2012)
- The non-linearity and non-stationarity of the aerodynamics of such system (Lu et al., 2009)
- Fault tolerant nature of its control system (Simani, Castaldi & Tilli, 2011).

In order to address these constraints, a better understanding of the multiple failure modes associated with various components and their interactions is needed. In addition, symptoms related to the operating loads, environmental conditions and maintenance scenarios should be distinguished from actual wind turbine performance loss. Then, fault diagnosis and prognosis functions could be reliable.

Although a number of review papers addressing these topics have been published (Hameed, Hong, Cho, Ahn, & Song, 2009), (Sharma & Mahto, 2013), (Azarian, Kumar, Patil, Shrivastava & Pecht, 2011), (García Márquez, Tobias, Pinar

Pérez & Papaelias, 2012), (Nie & Wang, 2013), (Lu & Sharma, 2009) (Sheng, 2011), they are mostly focused either on a particular component (gearbox components, insulated gate bipolar transistors (IGBTs)…) or on condition monitoring techniques and signal analysis tools. Therefore, in this review paper, a larger snapshot of recent diagnosis research works is explored in order to compare the proposed methods according to some meaningful evaluation criteria. Prior to that, a brief description of the wind turbine system and the most common condition monitoring tools is given.

2. WIND TURBINES HEALTH MONITORING

A wind turbine is a rotating mechanical device that converts wind kinetic energy to practical mechanical energy, resulting in electricity production. The rotary part can be either vertical or horizontal. The most recently used wind turbines are horizontal-axis based with two or three blades. These turbines also have a nacelle, which is held up by the tower and contains the gearbox and the generator. The gearbox increases the speed of the low-speed shaft to a suitable value required by the generator. A yaw system, which turns the nacelle and the rotor to face the wind, enables the turbine to capture the maximum amount of energy. According to the type of the generation system, the gearbox and the converter, different wind turbines categories can be distinguished (Kahrobaee & Asgarpoor, 2011). Among them, the variable-speed wind turbines offer advantages such as four quadrant power capabilities, maximum aerodynamic efficiency and reduced mechanical stress (Flórez, 2012). The double fed induction generator (DFIG) is today one of the most popular schemes for variable-speed wind turbines which has been introduced to replace the fixed-speed, squirrel-cage induction generators (Figure 1). In general terms, from the viewpoint of health monitoring, fixed speed turbines have a greater occurrence of mechanical failures (often in the gearbox) while electric failures are predominant in variable-speed turbines. More details about wind turbines configurations and their failures modes could be found in several papers (Fischer et al., 2012) (Arabian-Hoseynabadi et al., 2010), (Kahrobaee & Asgarpoor, 2011).

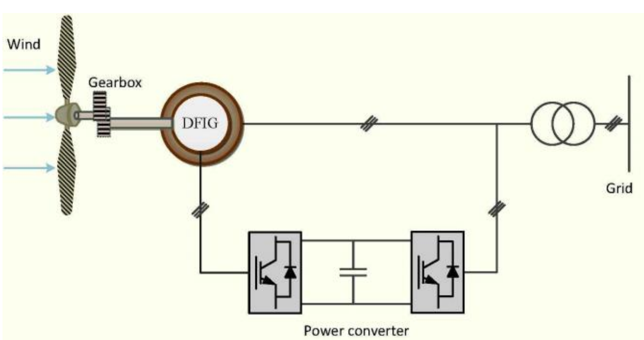

Figure 1. Typical configuration of a DFIG-based wind turbine (Flórez, 2012).

2.1. Condition Monitoring Systems for wind turbines

Among the review papers on wind turbines health monitoring and fault diagnosis, several of them were focused on Condition Monitoring Systems (CMS) tools used for that purpose. A CMS includes a set of sensors, signal acquisition and processing software, cabling and installations that gives continuous information about the monitored component condition. The CMS is used on wind turbines (especially off-shore ones) in order to monitor the most critical components such as gearboxes, generators, main bearings and blades. García Márquez et al. (2012) found that vibration analysis is the most known technology employed in wind turbines, especially for rotating equipment such as gearboxes components and bearings that supports the low speed shaft. Acoustic emission analysis is another condition monitoring tool used for rotating wind turbines components as well as for the blades (Hameed et al., 2009). In addition, oil analysis is typically applied to the gearbox and may have two purposes: (1) guaranteeing the oil quality (by measuring the oil temperature, its contamination and moisture) or (2) monitoring various rotating parts condition/wear (by looking for oil contamination or variation of particulates properties) (Sharma & Mahto, 2013). For more thorough summaries on condition monitoring techniques related to different wind turbines subassemblies, see (Hameed et al., 2009) and (Lu & Sharma, 2009).

Based on the above references, it is worth mentioning that:

- For the drive train components, the variable-speed operation and the stochastic characteristics of the aerodynamic loads prevent the usage of traditional frequency domain analysis techniques. Therefore, time-frequency analysis (e.g. wavelet transforms) is more suitable (Lu et al., 2009),

- The acoustic emission based tools give earlier warning of wind turbines gearbox failure at low-speeds compared to the classical vibration-based ones. However, acoustic emission techniques require higher sampling rates and they may not be a cost-effective solution to the gearbox fault detection (Azarian et al., 2011),

- Despite many research achievements in developing condition monitoring techniques, their implementation in practice still faces some challenges. Indeed, they still suffer from false alarms and they do not demonstrate satisfactory performance in the detection of incipient faults especially those related to electrical/electronic components (Yang, Tavner, Sheng & Court, 2012).

A CMS has the advantage to be accurate in monitoring specific kinds of failures. However, it requires more sensors and equipment to be installed in wind turbines as well as higher data storage costs resulted from a higher sampling rate of the acquired signals. To date, and because of these high implementation costs, such systems are more used for offshore wind turbines where maintenance visits are more complicated (Yang, Tavner, Crabtree & Wilkinson, 2008).

2.2. Towards SCADA data based health monitoring

In comparison with a CMS which is intended only to health monitoring purpose, the Supervisory Control and Data Acquisition (SCADA) system is able to resolve certain supervisory control tasks by automatically starting, stopping, and resetting the turbines in case of small fluctuations (Verma, 2012). Furthermore, SCADA records tend to be a major data source for monitoring wind turbines condition in the last years (Sharma & Mahto, 2013). Indeed, SCADA data might be fault informative. These data are of two types: status codes and operational data. The status data are recorded whenever the system undergoes status changes, whereas the operational data are recorded at predefined time intervals (Kusiak & Verma, 2011). Operational SCADA data include operational variables such as the produced power, the wind speed, some components temperatures and even vibration and oil debris monitoring data in some cases (Nie & Wang, 2013). Thus, SCADA based health monitoring is considered to be a cheaper solution than CMS since no additional sensors are required. However, wind turbines SCADA systems usually limit the amount of data to a number of records (10 min average data) and they are not initially designed for condition monitoring purposes. Then, conventional condition monitoring approaches which are developed for highly sampled CMS data are mostly not valuable and an appropriate SCADA data analysis tool is needed (Yang, Court & Jiang, 2013).

3. WIND TURBINES FAULT DIAGNOSIS APPROACHES

Regardless of used condition monitoring tools, several fault detection and diagnosis methods have been developed. In general and according to the nature of the available process knowledge, these methods can be categorized into three main classes: model-based, signal analysis and artificial intelligence (AI) methods.

- *Model based methods*

For this first broad category, a priori knowledge about the system operation modes is complete enough to be formalized into a quantitative or qualitative model. The quantitative models are in the form of fundamental laws described by mathematical relationships on the system input-output measurements. The quantitative models based approaches are of two categories: parameter estimation, and output observer based approaches.

The parameter estimation based methods use a system identification technique on input/output measurements in order to monitor the evolution of the system characteristic parameters against a nominal parameter set. Output observer (or residual generation) methods use an observer, often a Kalman filter, in order to assess the difference between the actual and the estimated output (reconstructed from the system model and controlled inputs). However, qualitative models use qualitative relationships or knowledge bases to draw conclusions regarding the state of a system and its components (Katipamula & Brambley, 2005). Hence, a qualitative model could be either a qualitative physics-based, discrete event or rule-based model.

- *Signal analysis methods*

Signal analysis methods are based on time and frequency domain analysis without any explicit mathematical model. Only knowledge about suitable fault features is required. Fault features can be derived from raw signals (vibration, acoustic emission, electrical signatures…) in order to evaluate the system operating state. Fast Fourier transformation, cepstrum (spectral representation of signals) and envelope curve analysis are some common approaches. More details about these techniques are given in (Jardine, Lin & Banjevic, 2006).

- *Artificial intelligence methods*

When a process is too complex or poorly known to be monitored through quantitative or qualitative models, and if signal analysis techniques do not allow an unambiguous diagnosis, artificial intelligence (AI) approaches can be used to overcome these limitations. AI based methods learn the complex model exclusively from available historical data (Venkatasubramanian, Rengaswamy, Kavuri & Yin, 2003). Artificial neural networks and clustering/classification techniques belong to this category of methods.

Without concern of exhaustiveness, the present review gives some examples from recent wind turbine fault diagnosis studies in order to illustrate each category of methods.

3.1. Literature review

Different wind turbines components are considered within the reviewed works. Moreover, both CMS and SCADA based monitoring tools could be found. The only differentiator is the category of the fault diagnosis methods used.

Within the quantitative model based fault diagnosis category, Chen, Ding, Sari, Naik, Khan and Yin (2011) put forward an observer-based fault detection and isolation scheme for the wind turbine pitch system and the drive train. They utilized a Kalman filter for residual generation. Then, a generalized likelihood ratio test and a cumulative variance index were applied for residual evaluation. Test data were extracted from a wind turbine simulator proposed within (Odgaard, Stoustrup & Kinnaert, 2009). Another example of an observer based approach implemented using SCADA data is reported in (Guo, 2011). In this paper, the normal behaviour of the generator bearing temperature is modelled based on a nonlinear state estimate technique (NSET). When residuals between the NSET estimates and the measured values exceed predefined thresholds, an incipient fault is flagged. Effectiveness of this approach was evaluated by the analysis of a manual drift added to the historical SCADA data. Simani et al. (2011) performed a parameter identification/estimation based method for converters fault diagnosis. Since the studied component is non-linear and the wind speed measurement is highly noisy, a fuzzy multiple model was considered. Such model consists of a collection of several local affine models, each of them describes a different operating mode. Thus, they used a fuzzy clustering technique in order to determine the regions in which the measured data could be approximated by local models. The effectiveness of such method was shown on a simulated process. On the other hand, Kostandyan and Sørensen (2012) explored a physics of failure model in order to assess the accumulated linear damage for a given load profile. It is applied to evaluate the damage value and predict the wind turbines power electronics reliability.

Regarding the qualitative model based approaches, Echavarria, Tomiyama, Huberts and Van Bussel (2008) developed a model-based reasoner for the overall system. The authors used qualitative physics in order to describe the behavior of the wind turbine in terms of qualitative characteristics changes over time. Such approach allows the possibility to model systems of higher complexity such as wind turbines. Work done by Rodriguez, Garcia, Morant, Correcher and Quiles (2008) has shown that Petri Nets are also suited for system-level modeling and namely for wind turbines fault diagnosis.

Within the scope of this review, signal analysis based fault diagnosis works are the most prevalent in the literature. Classical signal processing techniques were widely applied for studying wind turbines components, mainly the gearbox and the generator components. Indeed, Yang et al., (2008) applied a wavelet-based adaptive filter in order to extract the energy of the generator power signal at prescribed, fault-related frequencies. In addition, the signal non-stationarity was treated by adjusting the filter bandwidth according to the fluctuation of the wind speed. Both mechanical and electrical abnormalities were assessed experimentally on a wind turbine test rig. A similar work on generator fault diagnosis is done by Amirat, Choqueuse and Benbouzid (2010). They highlighted the use of the Hilbert transformation on the stator current data. Vibration signals were also widely used with classical signal processing tools in both time and frequency domain (Zhang, Verma & Kusiak, 2012) (Liu, Zhang, Han & Wang, 2012).

The construction of some SCADA data curves and studying their deviation from a reference one is being more adopted for a global wind turbine health monitoring. This kind of approaches is specific to wind energy domain and can be integrated among AI methods. Kusiak and Verma (2013) studied three operational curves: power curve, rotor curve and blade pitch curve, which plot three measurements against the wind speed. A k-means clustering and Mahalanobis distance were used to extract smooth performance curves by removing outliers without any pretreatment on raw data. The obtained performance curves will be considered as baseline curves to detect fault drifts. In a similar manner, Yang et al. (2013) established several reference plots by extracting correlations between relevant SCADA variables. However, input variables were first preprocessed and normalized relatively to the wind speed or to the generator speed values in order to obtain smooth curves.

With regards to more known AI based approaches, Laouti, Sheibat-Othman and Othman (2011) conducted a fault diagnosis for pitch system sensors and actuators by means of a support vector machine classifier. Fault features were manually constructed and a wind turbine simulator data was used for this purpose. For gearbox fault diagnosis, Kim, Parthasarathy, Uluyol, Foslien, Sheng and Fleming (2011) proposed a fault detection method based on SCADA measurements. They applied principal components analysis and a clustering technique in order to diagnose gearbox faults. Tong and Guo (2013) proposed an improved data-mining algorithm for the extraction of association rules on status codes (considered as fault alarms). The purpose was to extract implied causal relationships between status codes that lead to an effective fault alarm. In such a way, the number of alarms was reduced and then operators' work efficiency improved. Kusiak and Li (2011) proposed to use the occurrence time of certain status codes which are related to the diagnosed faults in order to label the SCADA data. The obtained labeled training data set was then used by several data-mining algorithms (Neural network, standard classification and regression tree (CART), the Boosting Tree Algorithm (BTA), SVM…) in order to predict the diverter malfunction. Work done by Godwin and Matthews (2013) dealt with the development of an expert system for the classification and detection of wind turbine pitch faults. Decision rules were extracted by a decision tree-type rule learning algorithm and then validated by an independent expert. A similar approach could be found within (Yongxin, Tao, Wenguang & Dongxiang, 2012) where a trained decision tree was used in order to construct fault diagnosis rules of a wind turbines gearbox.

3.2. Review results and discussion

Based on this survey, major advantages and drawbacks of each category of wind turbines fault diagnosis approaches are listed hereafter:

- Monitoring data issued from CMS or SCADA systems can be used in implementing model-based and artificial intelligence approaches. However, signal analysis methods are mostly used when accurate and specific fault oriented acquisition system is available, i.e. with CMS.

- Quantitative model approaches, in particular parameter estimation based ones, have the advantage of identifying the abnormal physical parameters rather than faulty signal signatures that are more dependent to the load condition (Lu et al., 2009). However, model-based approaches require a sufficiently accurate a priori knowledge to construct a mathematical or analytic model for the monitored system. This is hard to achieve in case of complex non-linear systems as wind turbines.
- Although qualitative models based approaches require deep knowledge about the wind turbines behavior, they have the ability to monitor the overall system via the causal knowledge and the laws governing the behavior of its subsystems (Venkatasubramanian, Rengaswamy, Yin & Kavuri, 2003).
- Signal analysis based approaches are easier to implement if a sophisticated data acquisition systems and sensors exists. However, successful implementation of such approaches is dependent on the construction of suitable fault-related features and reliable thresholds since subjective and unproven ones may result in wrong alerts (Yang et al., 2013).
- Artificial intelligence approaches achieve multi-dimensional analysis based on the combination of several sensors that monitor the same component. However their performance is highly dependent on the selection of training data set which must represent all operating modes for the wind turbine. In addition, since the obtained models are not usually transparent, the obtained results can be hard to be interpreted and demonstrated.

As a synthesis of this review, some criteria are proposed to compare these three categories of diagnosis methods (Table1). Such comparison could support the choice of the suitable fault diagnosis approach with respect to the initial needs. Chosen criteria for this comparison are the following:

(1) System's non-stationary nature: ability to separate the actual degradation and environmental or load effects

(2) Needed knowledge: ability to construct model without need to a priori knowledge

(3) System level: ability to deal with system hierarchical levels (local component or global system point of view)

Table1 show the rank accorded to each category of methods regarding each criterion. A category is accorded the first rank when it satisfies the best the criterion in question.

Considering the first criterion, quantitative model-based approaches, are the most suitable for dealing with the systems non-stationary nature, especially by using parameter estimation techniques. Signal analysis approaches can also deal with such non-stationarity by adjusting filters bandwidth according to the fluctuation of the wind speed (Yang et al., 2008).

Table 1. Comparison of fault diagnosis methods

	System non-stationarity	**Needed knowledge**	**System level**
Model Based	+ + +	+	+ + +
Signal Analysis	+ +	+ +	+
AI	+	+ + +	+ +

Artificial intelligence approaches are less suited when this constraint should be satisfied. Moreover, in terms of the third criterion, qualitative models are more appropriate for system level monitoring. Artificial intelligence methods can be also used if appropriate health features are afforded.

These results remain broad since they are extracted from a wide range of fault diagnosis approaches from the literature. Thus, such comparison does not substitute an effective implementation and comparison of most major methods with specific fault and real condition monitoring data.

4. CONCLUSION

Fault diagnosis methods developed for different wind turbine components such as gearbox, main bearings and generators are widely proposed. However, other critical wind turbine components such as blades, pitch systems and converters still need more focus. This is because of the -) hard modeling and detection of blades icing, deflection and fatigue and -) actions of the control feedback which compensate the pitch actuators and converter fault effects. In addition, the use of SCADA data for wind turbine health monitoring has led to the development of specific diagnosis methods for wind energy domain. The methods based on the analysis of wind turbine performance clearly separate out pre-failure data from other normal operating data. However, it is challenging to associate a drift in wind turbine performance to a particular failure using only global features as the produced power. Faults characterization requires often measurements about more of specific features related to the components dynamical behaviors. Thus, algorithms based on SCADA signals analysis should be combined with components oriented CMS based signals analysis. This combination helps to better diagnose components related faults.

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