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Condition Monitoring of Wind Turbine Gear Box

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Abstract: *This paper presents that how visibility of maintenance personnel can be increased on developing maintenance issues by exploiting collected data and maintenance capabilities in the form of onboard SCADA system. The paper focuses on developing a data driven model which is capable of describing the fault free behaviour of main bearing temperature signal.. Then using developed model, the difference between the estimated main bearing temperature and observed main bearing temperature which is called residual is used to detect the presence of a potential incipient fault detection.*

Keywords: *Wind energy, Gear box maintenance*

1. Introduction

Condition based maintenance has been described as a process that require technologies and people skills that integrates all available equipment condition indicators to make timely decisions about maintenance requirement of important equipment. Today most of the maintenance actions are carried out either by preventive maintenance or corrective maintenance approach. The preventive maintenance generally have fixed intervals to prevent the components from failure where as corrective maintenance is performed after a fault or breakdown has occurred. But these approaches proves very costly in many cases due to loss in production, cost of keeping spare parts , quality deficiencies etc. Condition based maintenance involves the measurement or monitoring of specific parameters which directly corresponds to machine. The main difference between preventive maintenance and condition based maintenance is that condition based maintenance uses various methods of monitoring for checking the condition of the machine to determine the actual mean time for failure where as preventive maintenance depends upon industrial average life statistics. Condition based maintenance has three complimentary levels of implementations:

i. Data acquisition step, to obtain data relevant to system health.

ii. Data processing: Data processing analyze the data for interpretation, also known as Diagnosis.

iii. Maintenance decision making step, to implement best optimum maintenance policy (Prognosis).

The maintenance of critical plant and machinery is a major expense for manufacturers and operators. Maintenance practices have traditionally employed one of two philosophies; preventative or corrective. Preventative maintenance involves performing regular scheduled maintenance to maintain equipment in good health and avoid in-service equipment failures. Corrective maintenance involves running equipment until it fails and then taking remedial action. Both approaches have drawbacks. Preventative maintenance is expensive to perform and the serviceable life of equipment and components is not maximized. Corrective maintenance maximizes the serviceable life of equipment but risks damage to other equipment when failures occur. Regardless of which approach is taken, unexpected equipment failures result in equipment downtime, and thus the necessary maintenance will always be *reactive*. Consequently, the resulting equipment downtime will be prolonged while the necessary spare parts, personnel, and equipment, necessary to carry out the required maintenance, are organized.

2. Literature Review

Palle Christensen and Gregor Gie bel (2001) [1] introduces a new condition monitoring tool which provide a fully automatic supervision and control of the wind farm on internet and data can be accessed with common interface for all form of data from farm.

T Holroyd (2001) [2] constructed a test rig to seeded the defect of varying sizes on outer races of bearing. A comparison has been done between AE (Acoustic Emission) and vibration analyses. It was concluded that AE not even detect earlier faults but can also provide indication of defect size.

N. Jamludin et al. (2001) [3] present a work in which they apply the stress waves analyses to detect early stages damages of bearing at a very low speed i.e. 1.12r/min.

Shjn Dander (2002) [4] presented a work in which they access the use of time domain model based fault detection and identification (FDI) method for application to a horizontal axis wind turbine (HAWT) that uses pitch to vane control. They use two approaches, the system identification approach and observer based approach using the kalman filter. They construct a horizontal axis wind turbine model and use the simulation to test various approaches. Two algorithms based on kalman filter are presented which provide a reliable estimate of the wind speed by including it in an augmented system state.

T.W. Verbruggen (2003) [5] develop a inventory of available condition monitoring techniques and selecting a set which has added a value for wind turbines. The area for further development of sensors, algorithm for data analyses were investigated.

L. Mihet-Popa et al (2003) [6] proposed a technique based on steady state analyses and applied to induction generators. This technique identify interturn stator fault and rotor asymmetries.

L.W.M.M. Rademakers et al. (2004) [7] they present a condition monitoring system for fiber optic blades. They installed the system on a NORDEX turbine for about one year to get operational experience with it to optimize and extend the algorithm. The data is stored on turbine module with back up at ECN. Based on this historical data algorithm were tested before implementing on any turbine system.

Giurgiutiu, V & Cuc, A. (2005) [8] presented a damage detection method which was based on ultrasonic rely due to propagation and reflection of elastic waves within the material. They identify local damages and flaws via blade field disturbances. They propose the use of piezoelectric transducer in place of conventional non destructive transducer because piezoelectric transducer can act both transmitter and receiver of ultrasonic waves.

Douglas H. (2005) [9] presented a work in which a steady state technique has been applied e.g. Motor Current Signature Analyses (MCSA) and Extended Park's Vector Approach (EPVA) and a new technique which was combination of EPVA and discrete wavelet transform and statics to detect the turn faults in doubly fed induction generators (DFIG). The proposed technique shows that steady state technique is not effective when DFIG's operate under transient condition but stator turn faults can be detected under transient conditions.

Christopher A. Walfard (2006) [10] highlights the relevant issues of reliability for wind turbine power generation projects. They identify the cost elements associated with wind farm operation and maintenance. Causes of uncertainty in reliability estimation of wind turbine was also discussed.

C. Walfard, D. Robert (2006) [11] present a work in which they conduct a cost benefit analyses and estimates that cost liability for failure of wind turbine after four to five years is $75,000 to $ 2,25,000 per event for megawatt scale turbine.

R.W. Hyers et al. (2006) [12] compare the condition monitoring in wind turbine with monitoring and prognosis in helicopter gearboxes. They evaluate the state of art of electronic control and power electronics and compare with state of art in aerospace.

Jesse A. Andrawus et al. (2006) [13] apply the RCM approach to horizontal axis wind turbine to detect various failure modes and their causes and effects on system operation. The failure consequences are estimated in term of financial terms by evaluation. Over the whole life cycle of wind turbine the CBM activities are identified and assessed to maximize the return on investment in wind farms.

David Mc Millan and Grahm W. Ault (2007) [14] measure the benefits of condition monitoring quantitatively. They construct a probabilistic model which uses various methods including discrete-time Markov Chains, Monte Carlo method and time series modeling.

Ayetullah Gunel et al. (2007) [15] present a new technique i.e. fluid condition monitoring system in which temperature of oil filter and cooling subsystems are monitored with various sensors. The other parameters such as absolute pressure drop across the filter, dielectric constant and viscosity are also monitored to analyze oil degradation. The data was recorded for two years for two turbines. Then filter lifetime can be predicted by processing the recorded data with statistical and semantic method. The combination of statistical and semantic method make the technique hybrid.

Michael Wilkinson et al. (2007) [16] develop a electomechanical test rig for assessment that which sensor and fault detection algorithm should be used in a condition monitoring system for operational wind turbines. The test rig has been driven at variable speed to investigate the behavior of wind turbine. A number of fault detection algorithms have been tested on each sensor signal.

Edwin Wiggelinkhuizen et al. (2007) [17] set up a wind farm of five turbines and several condition monitoring systems has been installed. Traditional measurement systems are also used. A algorithm has been developed which can be integrated with a SCADA system.

German Wind energy Association (2007) [18] highlights the objective and condition monitoring intervals according to the wind turbine size in megawatt. They highlight the technical experts qualification required for CM plan, inspection requirements, maintenance requirements and technical control system requirements.

Michael R. Wilkinson (2007) [19] constructed 30 kW test rig which have the same feature as wind turbine drive train, for signal processing technique necessary for variable speeds and high torque variation application. The faults are detected by investigating various approaches of condition monitoring on this test rig, and measuring torque, speed and shaft displacement and gearbox vibrations.

R. Andrew Swartz et al. (2008) [20] deployed wireless sensor technology on two wind turbines to construct better models of wind turbine dynamic behavior and response to loading.

Scott J. Johnson et al.(2008) [21] presented a report in which they introduces a number of active techniques which can be used for control of wind turbine blades. They apply active flow control (AFC) to wind turbine performance and loads. A special focus was given on actuators and devices and flow phenomena caused by each device.

Mike Woebbeking (2008) [22] performed various kind of inspections at turbines. The inspection include periodic monitoring, operation and maintenance surveillance, inspection after commissioning of wind turbine etc. The results shows that 26% of defects and damages are due to gearbox, 17% from generator and 13% from drive train.

Asif Saeed (2008) [23] implemented various conventional and latest techniques of condition monitoring including signal processing methods for vibration analyses for early fault detection. As a result of the study, infrared thermography is applied as an online condition monitoring for wind system as a retrofit design to increase performance of early detection system.

William A. Vachon (2008) [24] presented a work which focuses on joint wind project involving IMLD and IpsWich school District (ISD). They install a single MW scale wind turbine generator and the output of the generator is shared in proportion according to funds provided by each party, and value of power delivered to each party reflect the projected time of use of costs. Thus goal of the study was to project the economics of the project.

E Lie-Ahmar et al (2008) [25] presented a work which investigate specific transient techniques suitable for electrical and mechanical failures in an induction generator based wind turbine. An experimental set up of 1.1kW has been constructed and investigations shows that proposed technique can diagnose failure under transient condition.

Cattin Rene et al. (2009) [26] concludes some results from turbines working in ice regions. They revealed that in cloud conditions the air temperature can be used as an indicator for detecting icing conditions. They point out that there is no ice detector in market which can measure icing reliably. The results of Enrcon E-40 turbine shows that the ice detection via power curve can be a better method except for light icing and in case of low wind speed. They point out that it is not possible to melt ice during one heating cycle specially at leading edge of blades thus heat transfer to leading edge should be optimized.

Yassine Amirat et al. (2009) [27] discussed different types of faults, Their generated signature and their diagnostic scheme by keeping in mind the need for future research.

T. Barszczet et al. (2009) [28] states that there is lack of sufficient data to perform training of method, thus some new states should have created, when there is data different from all known states. Thus they apply Neural Network approach because Neural is a proper tool for classification of operational states in wind turbine and is also capable to recognize new states.

R.F. Mesquita et al. (2010) [29] apply the Neural network to analyze all the wind turbine information to identify possible future failure, based on past data of turbine. They show that neural network is a valid tool to make an early detection of failure in some wind turbine equipments.

Emilio Miguelanez et al. (2010) [30] presents the role of SeeByte's RECOVERY system within the wind industry, specially focus on offshore turbines. Systems of today gives false alarms most of the time which results in incorrect diagnosis and unnecessary intervention and important warnings are ignored. A RECOVERY system has been developed to guide the fault detection process and better automate knowledge discovery to improve diagnostics. The diagnostics concept is represented on the basis of system observation design pattern. This holistic system improve the diagnostic correctness by taking care of events and sensors values for complete turbine system. Thus it reduces the no-fault-found situations.

Bincheng Jiang (2010) [31] analyze the dynamic performance of drive train in wind power station and dynamic behavior of gearbox under normal and transient load conditions has been studied to investigate the reasons of drive train misalignment in future work. A 1-D torsional multibody dynamic model of the drive train taking into account the effect of aerodynamic force and excitation has been developed.

Wenxian Yang et al. (2010) [32] presented a CM technique in which generator output power develop a fault detection signal. A algorithm is used which uses continuous wavelet transform. Adaptive filters are used to track the energy in prescribed time-varying fault-related frequency bands in power signals. The generator control the central frequency and band width is related with speed fluctuations. Using this technique faults can be detected with low calculations time.

Yassine Amirat et al. (2010) [33] proposed a new fault detector which is based on amplitude demodulation of the three phase stator. They proves by simulation that this low complexity method can be well applied for stationary and non stationary behavior.

Richard Dupuis (2010) [42] explains that how bearing and gear rolling elements fails by surface fatigue mode and also study the characteristics of debris produced by failure mode. Their work present that how the accumulated debris damage limit can be counted on the basis of gear geometry. They develop an effective PHM technique by presenting actual data obtained from seeded fault bearing and gear test.

Zhi Gang Tian et al. (2010) [34] develop a optimal CBM defined by two failure probability thresholds values at wind turbine level. The CBM decisions can be made by calculating failure probability values on the basis of condition monitoring and prognostic data. The cost of CBM technology is evaluated by simulation.

F.D. Coninck et al. (2010) [35] constructed a back to back gearbox setup which is one of the largest in world. The complexity of dynamics was tackled by the concept of load cases. Each load case represent different turbine behavior. A control architecture was developed to handle the complex interactions between mechanical dynamics and electrical controller of test rig. The test rig is fit for experimental validation of dynamic load situation models.

Bodil Anjar et al. (2011) [36] conducted a feasibility study and they investigate the possibilities of using thermal condition monitoring of the systems and components in wind turbines. They conclude that thermography is suitable for monitoring electrical systems, transformers and also for fire detection and fire extinguishing. The IR cameras can be mounted on a pan tilt unit for continuous monitoring. They show that as the size of wind power plant increases the cost for downtime and repair also increases.

Shuangwen Sheng (2011) [37] present a study work which focuses on results obtained by various CM techniques from a damaged Gearbox Reliability Collaborative (GRC) test gearbox. The study shows the capabilities and limitations of each technique. The results from a test gear box under healthy condition are compared with damaged gearbox. A fieldtest of one GRC gearbox shows that damaged gearbox experienced two unexpected oil losses which damage its internal components. The damaged gearbox is reset by using different CM techniques which help in evaluating the different CM techniques.

Pratesh Jayaswal et al. (2011) [38] present a work in which they acquired the vibration signals of bearings and analyzed them with the help of vibration analyses techniques. In present work they detect the earlier fault in bearing using vibration monitoring. By study the FFT spectrum of bearing vibration signal they access the condition of bearing.

Peng Guo et al. (2011) [39] proposed a new technique Autoassociative Kernel Regression (AAKR) which is used to construct the normal behavior model of gearbox temperature. The measurement temperature become significant, when residual between AAKR estimates on incipient failure of gearbox. To detect the changes of the residual mean value and standard deviation in timely manner a moving window statistical method is used. As one of these parameters exceeds the predefined value the incipient failure flagged.

Secil Vorbak Nese et al. (2011) [40] constructed a model of three blades horizontal axis turbine and fault due to possible blade deformation was studied. By applying Continuous Wavelet Transform (CWT) approach a comparison is done between generator rotor speed and torque for healthy and damaged blades.

Peng Gua (2012) [41] used the history data of Supervisory Control and Data Acquisition (SCADA) system and analyzed this data for detecting the failure of turbine generator bearing. A new condition monitoring method based on Nonlinear State Estimate Technique (NSET) is proposed which is used to construct the normal behavior model of generator bearing temperature. When the generator bearing has an incipient failure the residual between NSET model estimates and measured generator bearing temperature will become insignificant and when residual exceeds the thresholds, an incipient failure is flagged.

Wenxian Yang et al. (2012) [42] proposed that reliability centered maintenance is best for offshore wind turbines which include preventive and predictive maintenance techniques enabling wind turbine to achieve high availability and low cost of energy. They present the wind industry with a detailed analyses of the current challenges with existing wind turbine condition monitoring technology.

Simon Gill et al. (2012)[43] used the operational data from wind turbine to estimate bivariate probability distribution functions representing the power curves of existing turbines. Hence deviations from expected behavior can be detected. They proposed application of empirical copulas to reduce the complexity between active power and wind speed which was either impossible to approximate by any parameterized distribution.

Bill Chun et al. (2012) [44] addressed that cost of manufacturing, logistics, installation, grid control and maintenance of offshore wind turbine is high. They apply Prognostics and system Health Management (PHM) to enhance the cost effectiveness of the maintenance strategy.

Michael Wilkinson et al. (2013) [45] proposed that operational costs get greatly reduced by monitoring the condition of major components in the drive train. They conduct the validation study on this method using five wind farms and conclude that a good detection accuracy and high detection rate is possible.

Dr. Shaik Nafeez Umar et al. (2013) [46] apply acoustic emission technique for condition monitoring of wind turbine and they conclude that AE technique can be successfully applied for condition monitoring of low speed rotating components. They observed that technique is able to detect very small energy release rates due to incipient failure at starting stage.

Schlechtingen, Meik (2013) [47] present a system for wind turbine condition monitoring by using adaptive Neuro-Fuzy interference systems (ANFIS). To fulfill the purpose a normal behavior model for common SCADA are developed to detect abnormal signals.

Van Horenbeek, Adriaan et al. (2013) [48] state that it is difficult to implement condition monitoring system due to uncertain parameters. They take into account the performance of the condition monitoring system itself which had been neglected in most of available literature. The modeling is done on the base of P-F curve for for different failure modes and then implemented on turbine gearbox. The case study proves that condition monitoring system is beneficial as compare to other maintenance strategies and benefit depends directly on performance of CBM.

3. Condition Monitoring of Wind Turbine

A Change in process parameter is an indicative of a developing failure [14]. A modern condition monitoring system consist of sensors and a processing unit which continuously check and record the condition of the component. There are various techniques to access the component condition. These techniques include vibration analyses, acoustics, oil analyses, strain measurement, and thermography. In case of wind turbine these techniques are used to monitor the major components such as blades, gear box, tower, bearings etc. A condition monitoring may be ONLINE or OFFLINE. A ONLINE monitoring provide instantaneous feedback of condition while OFFLINE provide data collected at regular intervals. For a fast fault detection while the component is in operation require good data acquisition system and appropriate signal processing. Maintenance tasks may be planned and scheduled with great efficiency which increase the reliability, safety and maintainability of the system and reduce the downtime and operational costs [15]. Therefore CM techniques are widely adopted by the industry [16,17] and its most benefits are used in offshore wind farms [18]. The economic exploitation of wind energy is largely dependent upon the high reliability of wind turbines and their components. Wind turbines operate in harsh environments which generate large loads on wind turbine blades, which can lead to faults and failures in wind turbine components. In addition, with wind farms increasingly being located offshore, the costs of performing both scheduled and unscheduled maintenance are even greater. Studies have suggested that maintenance costs can consume up to 20 to 25% of the total income generated, and that a considerable percentage of these costs are due to unexpected equipment failure, which require corrective maintenance [19]. As a result, wind farm operators are keen to exploit condition-based maintenance in an effort to reduce overall maintenance costs.

4. Diagnostics, Prognostics Methods and Techniques

4.1. Fault Diagnostics

The speed-up gearbox is one of key components in the large-sized wind turbine. During the operation, some faults often cause long maintenance downtime and higher cost. In this investigation, the gearbox faults were diagnosed by Bayesian Networks method. Based on the analysis of fault factors, the different signal features of fault diagnosis were confirmed. According to Bayesian Networks theory, the fault model of speed-up gearbox was established. The probability of sub-node was obtained by the conditional probability relationship of different nodes. Using the conditional independence of each node, and simplifying the probability distribution, the fault probability was counted out. Finally, the availability of Bayesian Networks method is proved by a calculation case on the test-platform. The study shows that the method can improve the fault diagnosis and operation level of the large-sized wind turbine when be used to judge the fault position in the gearbox.. Indeed, as described by Vachtenvanos *et al.* [13] "the diversity of application domains in fault diagnostics is matched only by plurality of enabling technologies that have surfaced over the years, in attempts to diagnose detrimental events". For the interested reader, a series of review publications by Venkatasubramanian *et al.* [20-22] and Jardine *et al.* [23] provide an excellent introduction and reference source to the different approaches and techniques used in fault diagnostics, and the different applications to which such techniques have been applied. In addition to the development of fault diagnostic capabilities for specific application domains, a number of fault diagnostic related issues are also often considered in the development of PHM solutions. Two such issues are failure modes and effects criticality analysis (FMECA) studies and feature extraction techniques.

4.1.1 FMECA Studies

A FMECA study considers each mode of failure for every component of a system, and determines their effects on system operation. Failure modes are classified in relation to likelihood of the failure occurring and severity of failure effects. Likelihood in combination with severity will generate a criticality rating for each failure mode, which is based upon a predetermined risk matrix. The key benefit of performing a FMECA is to detect risks to system performance. The cost of mitigating such risks is a lot cheaper if they are detected early, hence undertaking a FMECA in the early stages in design is desirable. If FMECA is part of a design development, the appropriate design option can be chosen for optimised reliability, maintainability and availability. This will help in achieving performance targets and improve project cost efficiency. The objective of FMECA studies is to relate failure events to root causes [13]. As part of this objective, FMECA studies investigate all relevant issues regarding potential failure modes of monitored systems including: the severity of different failure modes, their frequency of occurrence, their testability, the fault symptoms which are suggestive of a systems behaviour under different fault conditions, and the sensors and monitoring equipment required to monitor and track fault symptomatic behaviour.

4.1.2. Feature Extraction

Feature extraction means preprocessing of equipment sensor data. The feature extraction stage is specially designed for generation of a vector to infer the current fault status of monitored system. The type of vector generation depends upon type of application.

4.2. Fault Prognostics

To enable the benefits of a truly condition-based maintenance philosophy, real predictive prognostic capabilities are required. Such capabilities are designed to provide maintenance staff with prior notice of pending equipment failure and ideally provide sufficient lead-time so that the necessary personnel, equipment and spare parts can be organized and deployed, thus minimizing both equipment downtime and maintenance costs.

Real predictive prognostics is understood to be the generation of long-term predictions, describing the evolution of a signal of interest, or fault indicator, for the purpose of estimating the remaining useful life (RUL) of a failing system or component [26].

4.2.1. The Remaining Useful Life PDF

One of the key concepts within the prognostics framework is the RUL PDF. The RUL PDF is the output generated by a prognostic algorithm, describing the distribution in time of likely equipment failure times.

Consider Figure 4.2, which illustrates the key concepts of a RUL PDF. At time t_P , a prediction is made and an estimate of the RUL PDF is generated. Once the RUL PDF has been generated, the next question is to decide when to carry out corrective maintenance actions. Ideally, the time chosen for maintenance action will both avoid equipment failure and maximise the useful-life of the equipment. However, these are conflicting requirements and, as a consequence, selecting when to perform maintenance is typically an exercise in risk management.

In the development of a requirements specification for a prognostic algorithm, a key consideration will be the maximum allowable *probability of failure* (PoF). This value defines the maximum acceptable level of risk of equipment failure, beyond which equipment can no longer be operated as the risk of equipment failure is deemed excessive. Using the defined maximum allowable PoF and the estimated RUL PDF, an important value known as the just-in-time-point (JITP) can be identified. The JITP defines the latest point in time before which corrective maintenance actions must be carried out to avoid operating equipment beyond the maximum allowable PoF. In a real-life application, selecting the maximum allowable PoF would usually consider a number of factors.

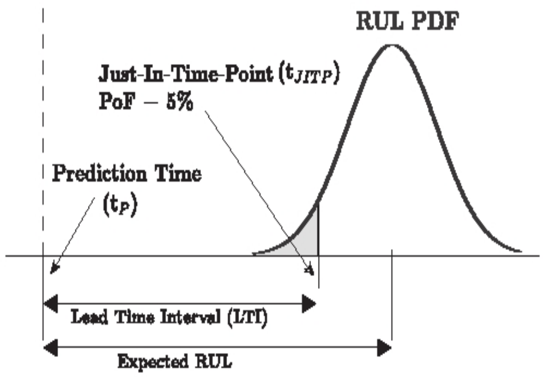

Figure 4.2. *The remaining useful life PDF*

In Figure 4.2, a maximum allowable PoF value of 5% is assumed for illustrative purposes. Once the JITP has been identified, another key measure can be computed, the lead-time interval (LTI). The LTI is defined as the time interval between the time the prediction is generated t_P , and the JITP $t_{JIT\ P}$, so that

$$t_{LTI}=t_{JITP}-t_P \tag{4.1}$$

The LTI provides a real-time estimate of the remaining time before a system operates above the maximum allowable PoF. Maintenance actions must be performed before this time elapses, to avoid operating equipment beyond the maximum allowable PoF. The RUL PDF and the LTI value represent key information that should be presented to maintenance staff as part of the human-machine interface (HMI). This information allows for maintenance staff to make informed operational decisions, regarding when to perform maintenance and avoid instances of equipment failure.

4.2.2. Prognostic Techniques

Generally there are two types of prognostics approaches used for predicting the RUL of monitored system. These approaches can be categorized as model based and data driven based.

4.2.2.1. Model-Based Prognostic Approaches

Model-based prognostics attempts to incorporate physical understanding (physical models) of the system into the estimation of remaining useful life (RUL). Modeling physics can be accomplished at different levels, for example, micro and macro levels. At the micro level (also called material level), physical models are embodied by series of dynamic equations that define relationships, at a given time or load cycle, between damage (or degradation) of a system/component and environmental and operational conditions under which the system/component are operated. The micro-level models are often referred as damage propagation model. For example, Yu and Harris's fatigue life model for ball bearings, which relates the fatigue life of a bearing to the induced stress, Paris and Erdogan's crack growth model, and stochastic defect-propagation model are other examples of micro-level models. Since measurements of critical damage properties (such as stress or strain of a mechanical component) are rarely available, sensed system parameters have to be used to infer the stress/strain values. Micro-level models need to account in the uncertainty management the assumptions and simplifications, which may pose significant limitations of that approach. Macro-level models are the mathematical model at system level, which defines the relationship among system input variables, system state variables, and system measures variables/outputs where the model is often a somewhat simplified representation of the system, for example a lumped parameter model. The trade-off is increased coverage with possibly reducing accuracy of a particular degradation mode. Where this trade-off is permissible, faster prototyping may be the result. However, where systems are complex (e.g., a gas turbine engine), even a macro-level model may be a rather time-consuming and labor intensive process. As a result, macro-level models may not be available in detail for all subsystems. The resulting simplifications need to be accounted for by the uncertainty management.

The most capable prognostic approaches use *physics-of-failure* models of the system under observation, derived from first principles. The main application domain of such approaches, to date, have involved the use of fatigue models for modelling the initiation and propagation of cracks in structural components [27].

4.3. Data-Based Prognostic Approaches

Data-driven prognostics usually use pattern recognition and machine learning techniques to detect changes in system states. The classical data-driven methods for nonlinear system prediction include the use of stochastic models such as the autoregressive (AR) model, the threshold AR model, the bilinear model, the projection pursuit, the multivariate adaptive regression splines, and the Volterra series expansion. Since the last decade, more interests in data-driven system state forecasting have been focused on the use of flexible models such as various types of neural networks (NNs) and neural fuzzy (NF) systems. Data-driven approaches are appropriate when the understanding of first principles of system operation is not comprehensive or when the system is sufficiently complex such that developing an accurate model is prohibitively expensive. Therefore, the principal advantages to data driven approaches is that they can often be deployed quicker and cheaper compared to other approaches, and that they can provide system-wide coverage (cf. physics-based models, which can be quite narrow in scope). The main disadvantage is that data driven approaches may have wider confidence intervals than other approaches and that they require a substantial amount of data for training. Data-driven approaches can be further subcategorized into fleet-based statistics and sensor-based conditioning. In addition, data-driven techniques also subsume cycle-counting techniques that may include domain knowledge. The two basic data-driven strategies involve (1) modelling cumulative damage (or, equivalently, health) and then extrapolating out to a damage (or health) threshold, or (2) learning directly from data the remaining useful life. As mentioned, a principal bottleneck is the difficulty in obtaining run-to-failure data, in particular for new systems, since running systems to failure can be a lengthy and rather costly process. When future usage is not the same as in the past (as with most non-stationary systems), collecting data that includes all possible future usages (both load and environmental conditions) becomes often nearly impossible. Even where data exist, the efficacy of data-driven approaches is not only dependent on the quantity but also on the quality of system operational data. These data sources may include temperature, pressure, oil debris, currents, voltages, power, vibration and acoustic signal, spectrometric data as well as calibration and calorimetric data. Features must be extracted from (more often than not) noisy, high-dimensional data.

4.4. Time Series Approaches

The simplest data driven approach to prognostics based on projection method is time series approach to access the level of degradation in future. There are variety of time series approaches such as Autoregressive models and exponential smoothing techniques. The latest time series approach used these days is Autoregressive integrated moving average model (ARIMA) which is driven from Autoregressive moving average (ARMA) model. ARMA consist of two parts Autoregressive (AR) and Moving Average (MA) part. The advantage of ARIMA on ARMA is that ARIMA can also be employed for non stationary time series signals.

4.5. Artificial Neural Networks

Artificial Neural Networks are relatively crude electronic models based on the neural structure of the brain. The brain basically learns from experience. It is natural proof that some problems that are beyond the scope of current computers are indeed solvable by small energy efficient packages. This brain modeling also promises a less technical way to develop machine solutions. This new approach to computing also provides a more graceful degradation during system overload than its more traditional counterparts. Perhaps the most common data-driven technique applied to prognostic problems are artificial neural networks (ANNs). ANNs model relationships between input and output variables with a model structure inspired by the neural structure of the brain. For ANN based approach we employ here the strategy where we learn the damage state as an intermediate step. To that end data were first transformed into log space, where damage propagation was observed to be linear. Then the rate of change for operational setting could be learned such that the states for which there were no supporting experimental data were covered by a smooth curve, employing a network with a low complexity to avoid overfitting.

5. Turbine Condition Monitoring Algorithm

This section introduces a proposed algorithm for main bearing condition monitoring and remaining useful life (RUL) prediction. A model-based approach is proposed. Figure 5.1 presents a flow chart illustrating the different stages in the proposed condition monitoring and prognostic algorithm. The basic principle of the model-based approach is to develop a model for each turbine which describes the fault-free behaviour of the main bearing temperature. The estimated main bearing temperature generated by the fault-free model is then compared with the actual main bearing temperature at each iteration of the algorithm. The difference between the estimated and actual main bearing temperature, known as the residual, is then evaluated. Assuming the turbine remains fault-free, the residual signal should generate a Gaussian distributed signal with a mean of zero and a small variance. Once a fault develops, the residual signal may change and no longer be zero-mean. Analysis of the residual signal is performed by the residual processing and decision logic stages. Assuming no fault condition is detected, the algorithm continues to iterate at 10-minute intervals as data is recorded by the SCADA system.

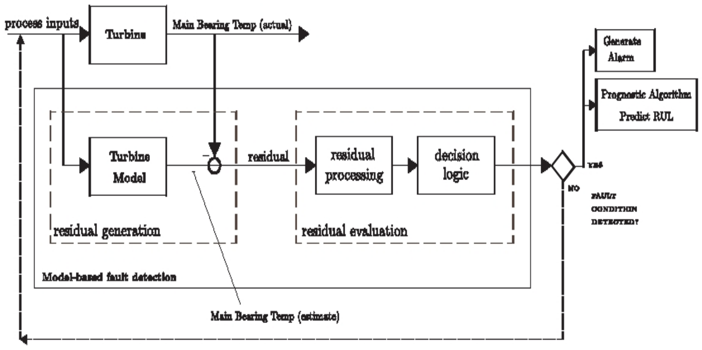

Figure 5.1. *Main bearing model-based condition monitoring algorithm*

Assuming a fault condition is detected, this generates an alarm and initializes the prognostic stage, which estimates the RUL of the main bearing. The algorithm then continues to iterate and the RUL predictions are recursively updated using the latest filtered value of the residual signal to detect fault conditions in the main bearing by analyzing the residual signal. Section 7.6 then describes the decision logic stage which is used to determine whether a fault condition is present and also describes the proposed RUL prediction approach and the

5.1. Modeling Main Bearing Temperature

In this section, the detailed steps in developing a model to describe the fault-free behaviour of the main bearing temperature are presented. Firstly, in Section 5.1.1, a description of the data set available for this study is presented. Section 5.1.2 then introduces the proposed modelling approach, including the inputs and model structure to be used to model the behaviour of the fault-free main bearing temperature. The motivation for using sparse Bayesian learning for regression to model the behaviour of the main bearing temperature is also discussed. Section 5.1.3 then discusses data detrending, to address the variability in sensor values caused by changes in the ambient temperature, as the seasons change. Finally, in Section 5.1.4, the proposed model is trained and tested on historical turbine data to demonstrate the performance of the trained model on fault-free turbine data.

5.1.1 Data Collection

For starting any study on onboard SCADA system it require a large amount of data for input hence data is collected from a medium wind farm with the help of sensors information which are installed at various positions of each turbine. A 6 month data is collected. The SCADA system records the average value of sensor information for every 10 minutes.

5.1.2 Input Variables

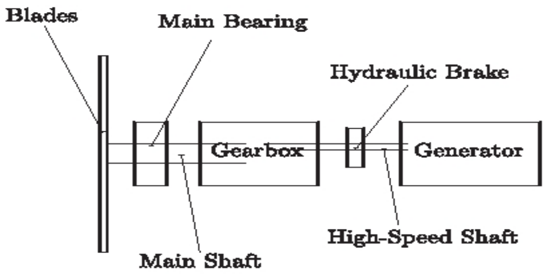

Figure 5.2. *Turbine components layout*

Modelling the behaviour of the fault-free main bearing temperature required selection of appropriate input variables, which can be used to estimate the fault-free main bearing temperature under varying load conditions. A range of different variables were investigated to identify their usefulness in estimating the main bearing temperature. The final set of input variables, selected for inclusion in the feature vector for estimating the main bearing temperature are described below. Figure 5.2 illustrates the location of the different components whose sensor values are described below.

Main Shaft RPM The heat generated in the main bearing will be a function of the load on the bearing. The main shaft RPM describes the load exerted on the main bearing under varying wind conditions.

Hydraulic Brake Temperature The turbine brake is located on the high-speed shaft, which connects the gearbox to the generator, and analysis has demonstrated that, under fault-free conditions, the brake temperature is closely correlated with the main bearing temperature.

Hydraulic Brake Pressure The average hydraulic brake pressure over a ten-minute interval provides a measure of the brake friction applied to the high-speed shaft, which in turn generates friction within the main bearing, resulting in a response in the main bearing temperature

Blade Pitch Position All modern turbines employ pitch control to pitch the blades under high-wind conditions. While the main shaft RPM may remain constant, the load imparted on the main bearing will vary with the blade pitch position.

The model used to describe the behaviour of the fault-free main bearing temperature signal is of the form

$$\hat{q}(s) = f(q(s-1), w_1(s), w_1(s-1), w_2(s), w_3(s), w_4(s)) \tag{5.1}$$

where $\hat{q}(s)$ is the estimated main bearing temperature at time s, $q(s-1)$ is the actual main bearing temperature at time $s-1$, and $w_i(s)$, $i = 1, ..., 4$, is the value of input i, at time s. The input variables, u_i, represent the following turbine variables, which are described above

- w_1: Main Shaft RPM
- w_2: Hydraulic Brake Temperature
- w_3: Hydraulic Brake Pressure
- w_4: Blade Pitch Position

To model the relationship between the main bearing temperature and the input variables, described by Equation (5.1), sparse Bayesian learning for regression [44, 45] was used. In previous similar studies [46, 47],

5.1.3Ambient Temperature Compensation

In modelling wind turbine behaviour, a major consideration is the effect of ambient temperature. Turbine sensor variables, and particularly temperature sensor variables, are a function of both the current operating conditions and the ambient temperature. This presents some issues when trying to model fault-free turbine behaviour. For a model to be sufficiently descriptive of turbine behaviour, across all seasons and weather conditions, significant volumes of historical data would be required to capture the turbine responses under varying conditions. Alternatively, some approach to detrending the data, to remove the ambient temperature relationship, must be considered. In this study, an approach to detrending turbine temperature variables, suggested by Wiggelinkhuizen *et. al* [49, 50], was employed. To detrend the turbine temperature values, and remove the ambient temperature contribution, each relevant turbine signal was linearly corrected for ambient temperature, using data collected when the turbine was operating under a small rotational speed. Figure 5.3 shows a scatter plot of ambient temperature and main bearing temperature, over an 11-month period from January to November. The samples shown were recorded when the turbine was operating under a small rotational speed, between 0.1 and 1 RPM. Figure 5.3 illustrates the linear relationship between main bearing temperature and ambient temperature under low rotational speed.

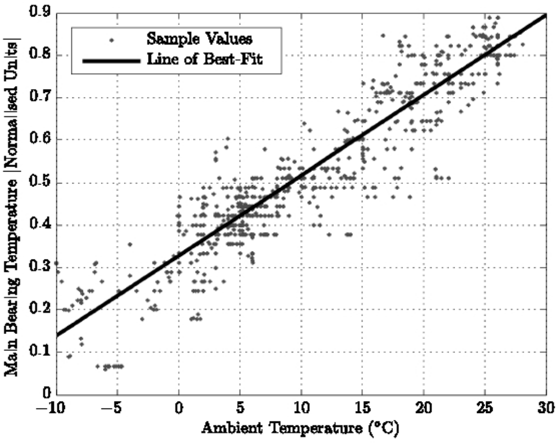

Figure 5.3. *Relationship between main bearing temperature and ambient temperature, under low-load conditions*

5.1.4 Model training and validation

For carry out this study 12 month historical data is collected. Foe each turbine there were approximately 12000 samples at an sampling interval of 10 min. From this collected data set 2 turbines were selected randomly for validation of proposed modeling approach. Each fault free turbine had 4000 samples which represents a 3 month data. A 3 month data was selected foe training and developing model for describing the fault free behaviour of turbine. Once each of the models, describing normal fault-free main bearing temperature behaviour, were trained, they were each tested on the remaining previously unseen samples for each turbine. Figure 5.5 shows the performance of the first fault-free turbine model over a 20-day period of previously unseen data. Figure 5.5 (a) shows the model estimate and the actual main bearing temperature, and Figure 5.5 (b) shows the residual term, which is the difference between the estimated and actual main bearing temperature.

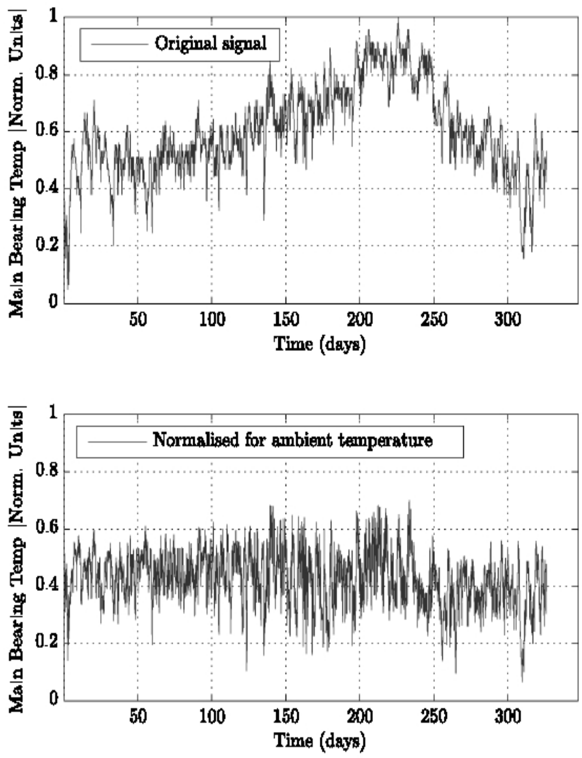

Figure 5.4. *Main bearing temperature: original signal ((a) upper plot)and normalized for ambient temperature signal ((b) lower plot)*

The second turbine data collected for 5 months is used as historical data for confirmation of error signal to be zero mean and Gaussian distributed.Figure 5.6. As can be seen in Figure 5.6, the error-term is zero-mean and Gaussian distributed.

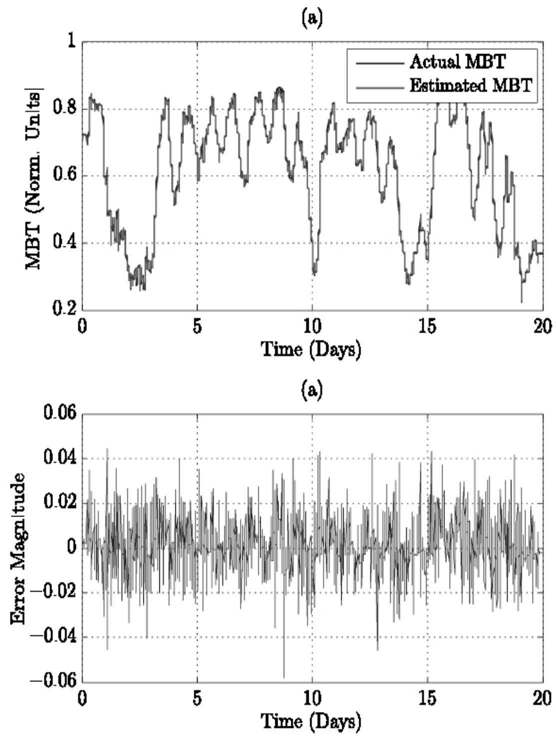

Figure 5.5. *Main bearing temperature estimation (a) and generated residual signal (b) indicating error magnitude at each sample time (fault-free turbine)*

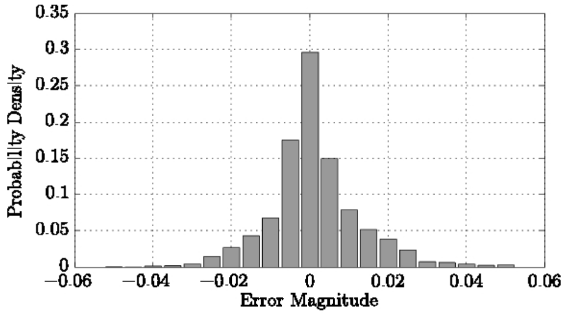

Figure 5.6. *Distribution of residual signal between estimated and actual main bearing temperature (fault-free turbine)*

5.2. Fault Detection of Main Bearing

Now it was the time to investigate if the proposed model is capable of identifying and tracking the position of fault developed in the main bearing. There may be various faults in main bearing such as corrosion, pitting or fretting which may generate excessive heat in the main bearing and this heat is beyond the limit of fault free bearing. In available data set we find two turbines suffered with main bearing during general visual inspection and bearing is replaced by removing the turbine from service.

But in turbine 2 the main bearing temperature exceeded the fault free main bearing temperature limit and automatically shut down the turbine. Turbine remains far out of service for a number of weeks while the main bearing was replaced. Figure 5.7 (a) illustrates the main bearing temperature in the final 105 days of operation of Turbine A, which was removed from service following a visual inspection of the main bearing. Figure 5.7 (b) shows the residual term generated between the estimated and actual main bearing temperature. Visual analysis appears to show some changes in the characteristics of the residual signal after approximately 150 days. Before Turbine A was removed from service, the mean of the residual signal is clearly above 0. Using the residual signal in Figure 5.7 (b), in its raw form, the ability to make informed maintenance decisions, regarding when to perform maintenance, is clearly difficult. Guo *et al.* [51] suggest using a moving average (MA) filter to detect statistically significant changes in the mean and variance of the residual signal. Figure 5.8 (b) illustrates a moving-average filter applied to the residual signal from Figure 5.7 (b). A two-day window, comprising 288 samples, was used to generate the signal shown.

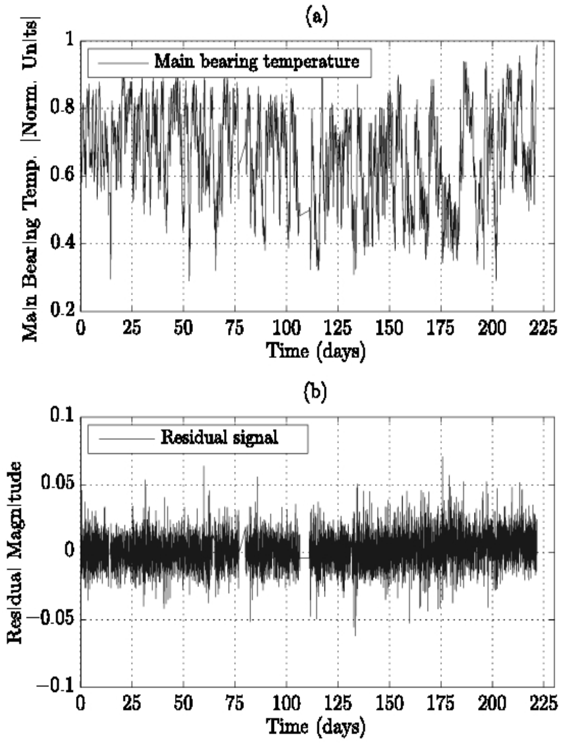

Figure 5.7. *Main bearing temperature and residual signal (Turbine A)*

5.2.1 How to detect Fault by turbine operating mode

Still the discussion was limited up to identification and tracking of turbine incipient faults by using simple moving average filter which does not account for different turbine operating modes. In previous sections the turbine fault free modeling was limited up to, when residual signal was free of turbine operating modes. But in actual practice the residual signal may vary with different turbines operating modes. In such conditions the residual signal is not only the function of component degradation but to evaluate moving average signal also need to account different changing operating of turbines. Now objective is to achieve improved error tracking when turbine is operating within a specific region. The turbine operating modes can be classify on the basis of power output. Because power output is a function of generator RPM which in turn depends upon shaft RPM. The turbine operating modes can also be identify by generator and gear box bearing and also by gear box oil temperature. At high wind speed the gearbox and generator bearing temperature increases very rapidly as compared to no wind speed and low load operations. The main focus is to identify turbine operating modes to increase the efficiency of this system to track main bearing fault degradation.

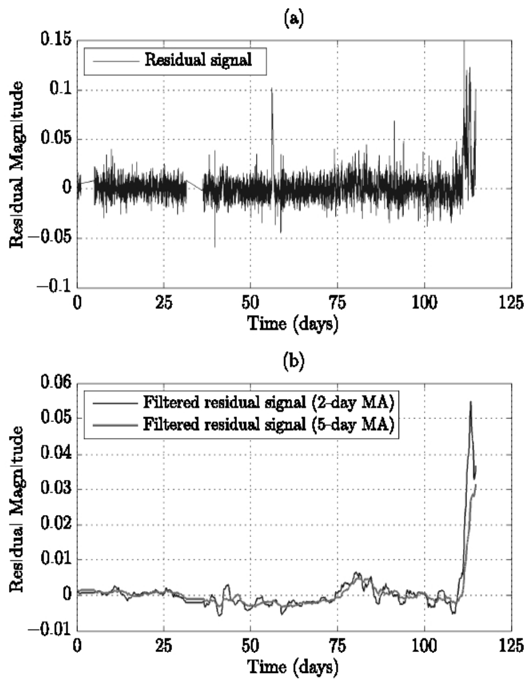

Figure 5.10. *Main bearing temperature residual and filtered residual signal (Turbine B)*

5.3. Fault prognostics for wind turbine

In this section application potential of the multiple filtering for wind turbine prognostics are identified. There was only one historical example hence work presented here is a simply a proof of concept and a number of assumptions are made. However general concept and applied approach shows the potential for development of prognostic capabilities for wind turbine.

5.3.1 Incipient fault detection

For developing prognostic capabilities for main bearing it require first to identify the presense of incipient fault condition. A residual signal independent of any turbine operating mode can be evaluated without any filter but it require a exponential average filter (EWMA) to measure the statistical characteristics of residual signal, during low load operations. The occurance of any fault can be identified by deviation in value of residual signal. First it need to set a threshold value for confirmation of presense of incipient fault condition. Three fault free turbines are used for model development and testing. Using the model developed for each turbine each model was tested on previously test data. The residual signal is is filtered using EWMA filter and distribution of the three EWMA filtered residual signals was then analyzed. Figure 5.13 illustrates the distribution of the three filtered residual signals, during Low-Load operations, for each of the three fault-free cases. The distribution of the EWMA filtered fault-free residual signal, during Low-Load operations, can be approximated by a Gaussian distribution, as illustrated in

Figure 5.13. The distribution is approximately zero-mean, as might be expected during fault-free

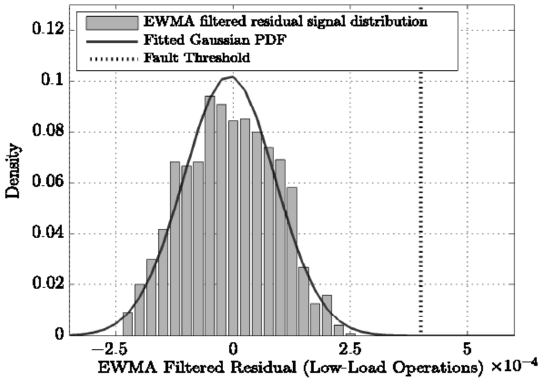

Figure 5.13. *Distribution of EWMA filtered residual signal during Low-Load operations for 3 fault-free turbines*

operation, with a standard deviation (σ) of approximately 0.0097. For a Gaussian distribution, the 99% confidence limits are defined by approximately 3σ. Therefore, to provide a sufficient separation between the expected limits of "normal" fault-free operation, a value of 0.004 ($> 4\sigma$) was chosen to define the threshold at which a fault condition is confirmed. The location of the fault threshold is illustrated in Figure 5.13.

Having selected an appropriate fault threshold for the EWMA filtered residual signal, during Low-Load operations, Figure 5.14 illustrates the point at which the fault condition is first identified in the available historical main bearing failure example, i.e. Turbine B. Using the selected fault threshold value, a fault is first detected approximately 32 days prior to failure. Predicting the evolution of the filtered residual signal, which henceforth is described as the *fault indicator*, defines the realm of prognostics.

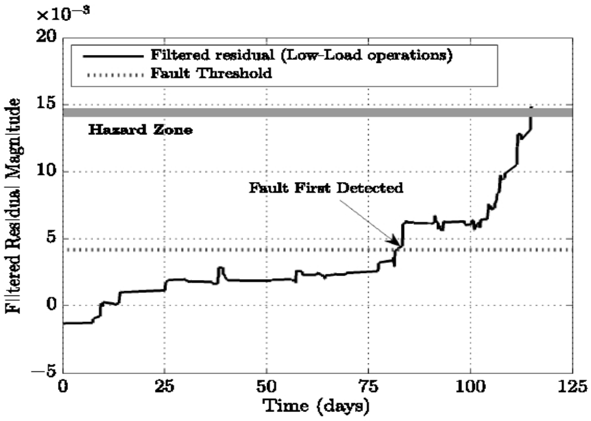

Figure 5.14. *Evolution of EWMA filtered residual signal during Low-Load operations for faulty main bearing (Turbine B)*

5.3.2 *Multiple particle filtering for wind turbine prognostics*

The application of particle filtering for prognostics involves two distinct stages 1.) *state estimation* and 2.) *long-term predictions*. In the first stage, predictions generated by the state-transition model are combined with fault indicator measurements (i.e. EWMA filtered residual signal values), to generate a *posterior* estimate of the current degradation state. This process is repeatedly recursively as new fault indicator measurements are generated. Once the current degradation state is estimated, the second stage can be carried out; long-term predictions. Using the state transition model, the set of particles defining the current degradation state estimate can be propagated into the future, until the value of the degradation state exceeds a predefined threshold. The predefined threshold is defined by the hazard zone specified for the current application. Figure 5.14 illustrates the hazard zone chosen for the current application.

The performance of a particle filtering approach relies upon the ability to accurately model the degradation process. However, without a physics-of-failure model, developing an accurate model with sufficient fidelity to describe the likely behaviour of all future failure examples is difficult. In addition, uncertainty regarding the future load profile, which in the case of wind turbines depends upon future weather conditions, introduces a significant level of uncertainty regarding the future behaviour of the degradation process. To address this challenge, a multiple model particle filtering approach is considered. By generating a large set of candidate models, designed to approximate the possible behaviour of future failure examples, the predictions of each of the models can be combined and, as the fault evolves, the plausibility that each model is descriptive of the observed behaviour can be computed. The mathematics involved in updating the candidate model weights and generating RUL estimates which are a weighted combination of RUL estimates generated by each model.

Modeling turbine main bearing degradation

In applying the particle filtering framework for main bearing prognostics, the first task is to identify a suitable model to describe the evolution of the main bearing degradation process, as described by the fault indicator signal. With only a single failure example available, some significant assumptions regarding the degradation behaviour of future main bearing failures, must be made. The form of the model used to describe the evolution of the main bearing fault indicator is given by

$$Z_s = z_{(s-1)} + \beta_1 \exp[-\beta_2 / u_s) / u^2_s] + \beta_3 \exp[\beta_4 u_s] + \omega_s \quad (5.3)$$

where z_S represents the degradation state at time u_S, the β_i values represent model parameters which can be tuned to fit the model to describe specific behaviour, and ω_k is a zero-mean Gaussian distribution representing the process noise term. The structure of the model described by Equation (5.3) provides great flexibility in tuning the model to describe observed behaviour.

With only a single historical failure example available, generating a set of candidate models, which are designed to describe the potential behaviour of future examples, is difficult. To address this task, the model parameters in Equation (5.3) were first tuned to fit the available historical example. Using the identified value of each β_i parameter, a distribution of values for each β_i parameter was generated, using the identified β_i parameter value as the mean of the distribution. By setting a range of values for each β_i parameter and sampling randomly from each distribution, a large set of candidate models was generated to describe the behaviour of future failure examples. By appropriate tuning of the distribution from which each β_i value is sampled, a set of candidate models which were deemed sufficient to describe future failure examples, given the lack of current understanding, were generated.

6. Conclusions

This paper has investigated the development of algorithms for condition monitoring and prognostics main bearing of wind turbine. Finally, a condition monitoring solution for the main bearing on utility scale wind turbines was presented. The approach developed exploits data collected by SCADA systems, which are installed as standard on most modern wind turbines. The benefit of using such data in developing condition monitoring solutions is that no additional hardware, in terms of sensors, data collection, storage, and processing capabilities are required, thus enabling wind farm operators to better exploit already installed data collection and monitoring systems.

This paper has focused on the development of condition monitoring and prognostic algorithms for wind turbines. While the developed algorithms are specific to the individual problems addressed, a number of more general issues can be concluded. The first issue, which is common across all of the investigated application domains, is the importance of investigating equipment response to degradation under different operating modes. The primary contribution of the paper is the development and demonstration of a multiple model particle filtering algorithm for prognostics. The developed algorithm has a number of desirable properties, which enable it to be adapted and applied across different application domains.

7. Future work

From a wind turbine perspective, the presented work has demonstrated the potential for the development of prognostic capabilities for wind turbines. As the number of historical failure examples grows, the demonstrated capabilities can continue to be improved. As the size of wind turbines continue to expand, and with wind farms increasingly being located offshore, the potential benefits of prognostic capabilities will also continue to grow. In addition, the developed approach to modeling the fault-free behaviour of the main bearing can also be replicated for other turbine components, such as the gearbox and generator, enabling wind farm operators to better exploit already available information. Furthermore, the spare Bayesian learning scheme for regression has clear potential in the wind turbine domain, as it has been identified that it is necessary to model the fault-free behaviour of each individual turbine. The fast marginal likelihood maximization scheme developed by Tipping enables the fast training of such models, which is of particular use across a wind farm with potentially hundreds of turbines.

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