A Practical Approach to the Use of SCADA Data for Optimized Wind Turbine Condition Based Maintenance

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Abstract

Condition monitoring systems typically detect a change in system health through the measurement and analysis of variables that are directly influenced by the evolution of component damage. In many cases such systems require the installation of specialized hardware, and typically large volumes of data are generated that must be subsequently managed and processed.

Readily available SCADA data contains valuable information about the performance and load history of wind turbines, and can be effectively used as a tool for condition monitoring. In some cases the link between such data and the required health indicators is not immediately apparent; however this may be solved if the system behaviour and the relevant failure mechanisms are understood and modelled in sufficient detail.

In addition to its use as a diagnostic tool, SCADA data may used for failure prognostics and the calculation of remaining life. The key to this approach is an effective application of physics of failure methodology as well as feedback from field experience as part of a probabilistic, learning system.

In order for such techniques to be applied for large numbers of wind turbines it is important that data transfer, storage and analysis tasks are automated as far as possible. An expert software system must provide clear statements concerning required actions.

Through a combination of statistical methods, fundamental physics and customized software tools, a practical solution is presented that serves as an early warning system for upcoming failures so that they can be prevented well before they impact the system performance. On this basis the required maintenance actions and spare part logistics may be tailored to achieve an optimal ratio between cost and benefit.

Keywords: condition monitoring, reliability, diagnostics, prognostics, wind turbine

1. Introduction

The modern wind turbine market is characterized by rapidly maturing technologies and individual turbines of increasing power output, complexity and cost. Experience in other more mature industries such as automotive or rotating power machinery (gas turbines, steam turbines), has shown that as technology reaches more advanced stages of development, increasing emphasis is placed on achieving high quality and reliability targets. The motivation is generally to achieve increased profitability by minimising downtime and costs of maintenance. Furthermore, an important competitive advantage can be achieved by companies able to distinguish their products through high levels of reliability.

Ambitious plans are in place for the construction of large numbers of offshore wind turbines, potentially in deep water and remote locations [1]. Indeed 3GW of offshore wind has already been installed, with the oldest machines already in operation since 1991. It has been demonstrated that the costs of operation and maintenance of such turbines is relatively high, resulting in an urgent need for optimisation and practical solutions.

Given the volume of planned financial investment and a growing global wind turbine fleet, it is clear that asset management must play a central role in achieving profitability in particular under harsh off-shore conditions. However, the subject of maintenance optimization is complex and multi-disciplinary in nature, requiring consideration of issues such as manpower, resource planning, spare parts logistics, availability of service equipment and the trade-off between down-time and service costs. Compared to other industries, the challenge for wind is complicated by the fact that units are geographically distributed. Furthermore for offshore wind, variable weather conditions introduce a significant element of uncertainty into the planning of maintenance.

2. Condition Monitoring: Current Practice

The extent of the uncertainty concerning maintenance planning may be reduced through the effective application of condition monitoring systems as part of a condition based maintenance (CBM) approach. In recent years such systems have proven effective in the detection of a variety of wind turbine failures, in particular relating to the drivetrain. For example, damage to bearings, shafts or gears can be detected relatively early in the damage evolution through vibration measurement or monitoring of wear debris in oil. Such advanced warning allows the operator to plan inspection and potentially part replacement prior to complete system failure, hence providing valuable inputs to a maintenance optimisation regime.

However, in practice such condition monitoring systems are subject to limitations. The cost of purchasing and installing customized hardware such as sensors, cabling, data processing units, data storage etc, is relatively high, typically in the range 1-2% of total turbine cost. Even where a comprehensive monitoring system is installed, only a proportion of potential failure modes may be detected. Field experience has shown that failure modes are numerous and distributed across a wide range of systems and components (e.g. pitch, yaw, control system, power electronics, blades, hydraulics, cooling) [2]. In particular for offshore wind turbines, also minor failures may lead to several weeks of lost revenue, should weather conditions prevent timely access and repair.

The large variety of possible failure modes requires a correspondingly comprehensive monitoring approach rather than the current strategy, which concentrates on relatively few failure mechanisms. Ideally it should be possible to monitor all major systems of a wind turbine and to detect the relevant failure modes for each. This goal should be achieved without the addition of a large number of additional sensors which are not only costly but also represent potential sources of failure. The volume of data resulting from the monitoring system should not be so large that transfer and storage is problematical and the process of data validation, aggregation and analysis should be automated as far as possible.

3. Use of SCADA for Condition Monitoring

All modern wind turbines are instrumented with a variety of sensors used predominantly for wind turbine control and for the safety systems. This forms the basis of the SCADA (Supervisory Control And Data Acquisition) system. Measured data are communicated to the wind turbine controller at relatively high frequency (>1Hz). Although such high frequency data is rarely archived, it has become standard to generate and store 10-minute values, typically consisting of a mean value calculated during the interval, and often including also maximum, minimum and standard deviation values.

SCADA logs are therefore readily available, require no additional instrumentation and include a wealth of information concerning the system behaviour. Therefore, such data may be effectively used for performance and condition monitoring. The practice of applying automatic monitoring algorithms to standard performance data has already been proven for several decades in more mature technologies such as steam and gas turbines used for stationary power or aircraft engines [3]. Therefore, it is useful to look at such industries and at the potential benefits of technology transfer. Published methods are varying in nature, but typically consist of a combination of data validation, signal processing, feature extraction, modelling and statistical techniques in order to identify unexpected system behaviour and to deliver fault diagnosis. A specific example for the application of such techniques to wind turbine monitoring is presented below.

SCADA logs have also been shown to provide a source of information for physics of failure based prognostics and remaining life calculation [2], [4]. The approach is based on a thorough definition of root cause failure modes that contribute to system down-time and the modelling of such failure modes using the physics of failure approach in order to quantify the relationship between loading and damage accumulation [5]. Finally statistical methods are applied in order to deliver statements concerning failure probability. As we shall see, the physics of failure approach may be effectively combined with the aforementioned fault detection techniques to deliver a complete diagnostic and prognostic solution.

There are some limitations associated with the use of SCADA logs. According to the Nyquist theorem a signal must be measured with at least twice the resolution of the highest frequency of interest in the observed system in order for full information capture to be achieved. Due to the fluctuating nature of wind speed, turbulence and direction many of the SCADA channels are of dynamic nature with relatively high frequencies. Pitch activation events typically last several seconds, wind speed and resulting variations in active power, current flows through the generator and small changes in rotor speed may all occur with periods of between a few seconds and several minutes. In all such cases, 10-minute average logs reduce the information content of the data and some critical signal features will be missing.

Referring to the physics of failure approach, care must be taken in the modelling of failure modes where the damage kinetics are non-linear functions of the load. Examples include high cycle fatigue, thermal aging and thermal mechanical fatigue. In such cases, missing events in the 10-minute logs such as shock loads (for example resulting from emergency stop events) will not be considered according to their actual damage contribution, leading to inaccuracy in the calculation of failure probability / remaining life.

4. Overview of a Practical Solution

In the following sections a method is presented for combining traditional diagnostics and prognostics techniques as part of a complete solution for turbine monitoring. The emphasis is on describing the process in its entirety. Figure 1 shows an illustration of this process.

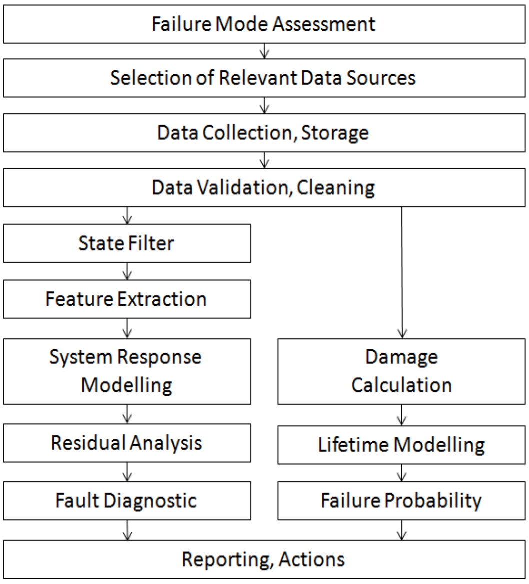

Figure 1: Overall workflow, diagnostics & prognostics with SCADA logs.

Initially a Failure Mode Assessment is performed in order to identify significant root cause failures and their relationship with the available load data. The latter is gathered and stored in a central server, typically requiring scheduling and integration services in order to automate the process of collection from geographically distributed windpark servers consisting of varying technologies.

Typically data is collected from a variety of turbine types, potentially of largely differing age and with differing specifications from various manufacturers. Therefore a common challenge is data normalisation in order to achieve a uniform format. Data is initially stored in separate databases in a so-called “Staging Area” and then through a process of Data Transformation, variables are mapped to a common naming convention [6] and basic plausibility checks are performed to pass the data quality gate.

A detailed data validation process is performed including automatic error correction, or “cleaning” in order to ensure adequate quality prior to use for analysis purposes. Having achieved a homogenous and high quality reference data set, a variety of analysis techniques, including diagnostic and prognostic procedures, may be applied. Figure 2 shows an illustration of a typical database architecture used to support this activity.

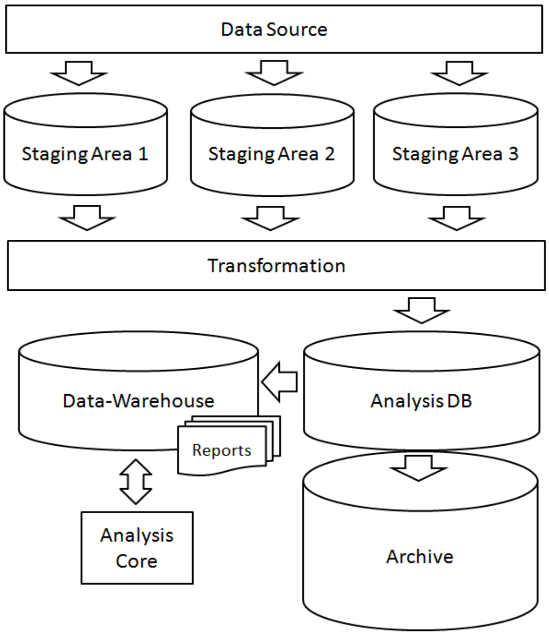

Figure 2: SCADA Database architecture as platform for wind turbine performance and condition monitoring.

The fault diagnostic process usually begins by modelling of the expected system behaviour. Specific features within the measured data are extracted (e.g. variable values within a certain frequency range or specific events) to be used as input to system response models. Such models are used to define the expected behaviour of key performance parameters in response to measured load and environmental conditions.

The difference between the predicted and the actually measured values is called a residual term. This term is further analysed using probability distribution models in order to automatically identify significant deviations from the system health state, i.e. trends or changes in system behaviour.

In parallel to this diagnostic activity, the normalised and validated data set may also be used for failure prognostics. Damage calculations based on a physics of failure approach are applied to calculate remaining life and failure probability of specific components and failure modes. In combination with the aforementioned diagnostic techniques, the wind turbine operator is provided with automatic indicators of impending or existing problems (performance deficit, incipient failures) as well as statements concerning the amount of time remaining before maintenance action must be taken. Such a system, including both diagnostic and prognostic capabilities, offers interesting possibilities such as the triggering of on-site investigation for turbines and systems classified as being high risk failure candidates. Furthermore, prognostic methods may be applied to predict the expected remaining time to failure for faults identified by the diagnostic algorithms.

It must be emphasized that the practical application of the above described methods requires a systematic and structured data management, based on well designed, scalable and secure software architecture. Although during methods development it is sufficient to perform data analysis manually, a wind-park or even corporate scale system requires automation to the utmost extent, with built-in intelligence and clearly structured reporting capable of highlighting the recommended operator response. Therefore, the realisation of a practical solution relies on the effective combination of several key disciplines, namely

- signal processing for exploitation of the information content in the measured data,
- physics for the modelling of the system behaviour,
- statistics for model training, optimisation, trend detection and prediction of error propagation as well as
- IT to provide a robust functional solution.

The main modules within the analytical process are now described in further detail.

5. Failure Mode Assessment

An effective monitoring system is capable of identifying not only that a problem exists but also the nature of the problem, possible root causes and ideally the required response (either in terms of service actions or modification to the control strategy). Furthermore, in order to define the appropriate and available techniques for modelling of specific subsystems and failure modes, a link must be made between technology, failure modes and data.

A structured Failure Mode Assessment has been developed to generate the required input. During the analysis process the wind turbine is divided into subsystems and for each of these an expert assessment is performed in order to identify potential field failures. The focus is on the identification of root causes, the mechanisms driving the failure and the critical operating and environmental conditions.

During such an assessment wherever possible, links are made between load and damage, i.e. between measured data and a failure mode. The aim is generally to identify the extent to which system modelling and fault detection is possible given existing inputs, as well as highlighting areas where additional measurement may be required. Figure 3 shows an illustration of this concept.

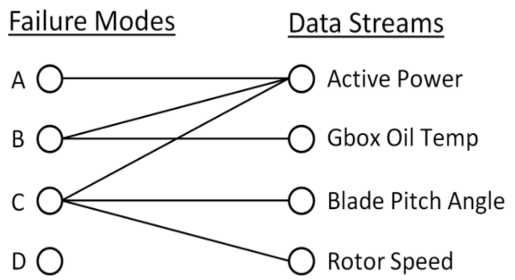

Figure 3: Correlation between failure modes and available data streams.

In this example, the parameter “Active Power” may be used as input for modelling of three of the identified failure models (A, B, C). Failure mode D is not associated with any available data streams and may therefore require custom instrumentation for detection, if deemed a priority item.

An example taken from part of a Failure Mode Assessment for a wind turbine generator is shown in Figure 4. The outcome of such an assessment provides a reference for all following activities. The basic physical and chemical failure mechanisms are identified and the available model inputs are specified. Furthermore, such an analysis provides a basis for automatic fault diagnosis as part of an expert system.

Failure Mode Assessment					*Generator*			SCADA Observables				
Subsystem	Component	Failure mode	Failure location	Cause of failure	Damaging operating conditions	Boundaries	Consequences	Wind speed	Active Power	T_env	Rotor speed	etc...
Cooling system												
	Filter	deposition		particle stream in coolant air	air flow - prop. generator speed (direct rotor air flow concept); 2nd circle cooling: acc. to el. power of generator ?	desert, agricult. area in spring ?	insufficient cooling --> overheating of windings --> aging, etc.		+		+	
	Pump motor	contact corrosion of switch	switch contact face	frequent on-off	cyclic power	low ambient temperature	insufficient cooling --> overheating of windings --> aging, etc.		+	+		
	Radiator	fouling	inner surfaces	aging of coolant	rated power if it leads to max. coolant temperature --> aging		reduction of cooler efficiency -> rising of temp. level		+	+		
	Hose/Fitting	corrosion	welding connections	salt content of environment air		off-shore, condensation, T-ambient air	coolant leakage	+		+		
Stator												
	Winding	thermal aging	insulation	temperature	rated power ?				+	+		
		TMF	insulation	shear forces in insulation layers due to difference in thermal expansion and thermal gradient between Cu and insulation	cyclic power		ground fault		+	+		
Etc...	Etc...	Etc...										

Figure 4: Failure Mode Assessment to document potential root cause failures and provide a link to SCADA data

6. Data Validation

In the field of condition monitoring, the issue of uncertainty, error propagation and finally the accuracy of error detection is of central importance. In order to ensure that false alarms (generally false positives) are avoided it is important to ensure that the quality of the data used as the basis of the analysis is high.

The data validation process typically consists of initial parameter mapping according to a specific naming convention. Data quality checks are performed, problematical channels and time intervals are identified and corrected where possible. Data quality issues commonly affecting SCADA 10-minute logs include for example:

- Missing values / NULL entries / zeros
- Plausibility limits exceeded
- Statistical outliers
- Large blocks of identical values consecutively
- Incorrect data format (e.g. non-float)
- Variable measurement frequency

There are a variety of potential responses to such problems, the choice of which must be defined according to the nature of the subsequent analysis to follow and the required level of accuracy. Strategies include for example:

- Correct using linear or exponential interpolation
- Set extreme values to limit value
- Remove time section of data (all channels)
- Remove complete channel
- Simulate missing channels based on physics-based stochastic models (depending on available information)

It is essential that this process is performed automatically; therefore detection and correction must be handled using intelligent algorithms and a summary report of performed actions made available to the system user.

7. Fault Diagnostics

A wide range of statistical and signal processing techniques are available for fault diagnostics and decision making based on operational time series data. These include neural networks, genetic algorithms, Bayesian inference, fuzzy logic and many others. [7], [8]. A pragmatic approach is the use of system response modelling (also referred to as process modelling), which is based on understanding of the system behaviour and physical principles [9]. This approach has the advantage that if the system can generally be well understood, the extent to which various parameters influence the system can be observed and the results can clearly be interpreted.

In order to illustrate this approach, an example of gearbox oil temperature modelling and monitoring is presented. The oil temperature in a dynamically loaded wind turbine typically varies significantly with time. Increased power leads to higher loads within the drivetrain and the resulting frictional forces (at contacts such as bearings, gear teeth) generate heat energy, a part of which is dissipated into the oil (indeed the function of the lubricant is partly the removal of heat from highly loaded areas). Therefore it is expected that oil temperature will correlate strongly with the measured active power. Furthermore, the rate at which heat is dissipated from the system depends on the temperature gradient between the system and its surroundings, therefore ambient temperature must be included in the model. Finally it must be considered that due to thermal inertia effects, a time constant needs to be applied to correctly describe the rate at which oil temperature responds to changes in heat input. Having understood these fundamental influencing factors, an analytical solution can be developed for the evaluation of the expected oil temperature under a given set of load conditions.

Figure 5 shows an example of comparison between a time series of measured oil temperature values in a gearbox where an incipient failure was successfully detected. The expected temperature value was

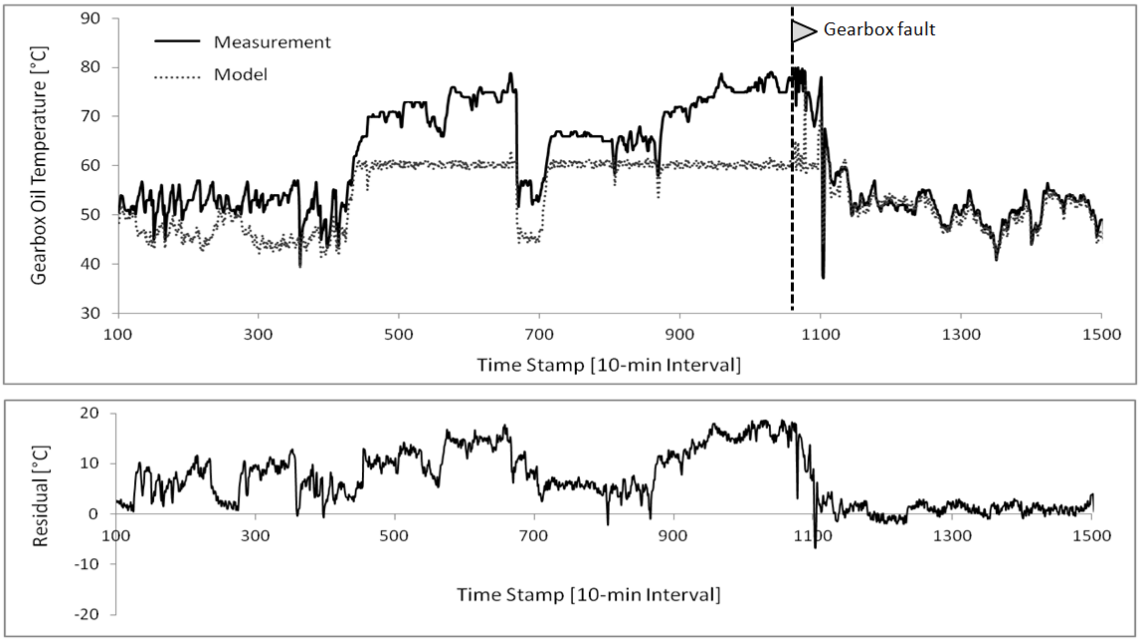

Figure 5: System response modelling of gearbox oil temperature, residual value deviation as fault indicator

evaluated using the system response model and compared to the measured value. The difference between the two - the residual – is monitored in order to detect deviations with a high degree of accuracy.

In the illustrated example, a gearbox fault occurred at a reference Time Stamp of around 1100, when corrective action was taken. During the time preceding this event, the model was able to successfully identify a temperature excess, based on the consistently high residual value. Following the repair, the system response once again followed very closely the behaviour (temperature) predicted by the model. A significant benefit of this approach is that the deviating system response can be detected even under part load operating conditions. As a consequence, incipient failure is detected long before the oil temperature is high enough to trigger an automatic alarm from the wind turbine controller.

Similar modelling techniques may be applied to a range of parameters delivered by SCADA systems for the majority of modern wind turbines, including gearbox bearing temperatures, generator winding and bearing temperatures, generator voltage and current flows, pitch angle and rotor speed, slip ring temperature and so on. Clearly this is of great benefit to the wind turbine operator due to the opportunity for early intervention to avoid a complete system failure and a reduction in costs associated with downtime and repair.

If the system response model is of sufficient accuracy, this indicates that all physical effects have been considered (i.e. de-trending is complete). The remaining residual is symmetrically distributed around zero, and conforms to a Gaussian probability distribution. Indeed it is of great importance to perform model quality checks by using these criteria prior to the implementation of a model in a monitoring system. Figure 6 shows a normal probability plot for the residual resulting from a model of generator voltage.

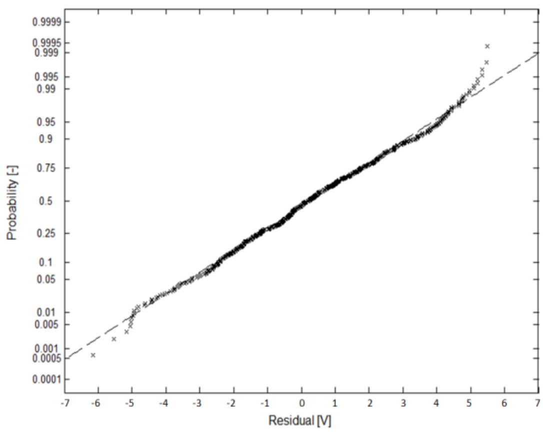

Figure 6: response model quality testing using a normal probability plot.

This is a transformation of the Gaussian cumulative distribution into a linear function. In the example shown, the linear trend as well as the minimal deviation between the plotted values (measurements) and the dashed line (ideal Gaussian distribution) confirms that high model quality has been achieved.

A model of insufficient quality either leads to an unacceptable level of false alarms or non-detection of failure indicators. Improvements may be achieved either by transformation of the analytical definition or by further investigation into the suitability of the selected input parameters. Once a high model quality has been achieved, the identification of a trend in the residual value may be detected by checking for deviations from the Gaussian probability distribution. This procedure lends itself readily to automation using software algorithms and may be effectively integrated into the condition monitoring system architecture. Note that in principal also alternatives to the Gaussian distribution are possible (e.g., Gamma distributions). However due to its excellent probabilistic properties and suitability to describe random deviations from a defined process state, the Gaussian distribution is preferred.

It is important to note that in practice the behaviour of individual turbines can vary strongly according to the turbine specification. Furthermore, even when comparing turbines of similar specification, small differences can be expected due, for example, to changes in control system parameterisation or manufacturing tolerances. Therefore, system response models must be calibrated to suit each individual turbine. In practice this can be achieved through parameterisation of the models themselves. Coefficients are specified and defined during a training phase for each turbine. A data set is selected that includes a sufficiently long time period to cover also low frequency influences (e.g. seasonal temperature effects) and assigned to a training routine. This routine then fixes the aforementioned coefficients using statistical regression methods. Through this process, models of suitable accuracy can be achieved in a time efficient manner.

8. Failure Prognostics

As discussed in Section 4, the diagnostic approach is complemented by prognostic modelling techniques. For many failure modes, SCADA 10-minute logs include sufficient detail and resolution for the definition of the turbine load history and calculation of accumulated damage.

Damage models are defined based on an understanding of physics of failure mechanisms. Such models are used to convert load inputs (available as time series vectors) to a history of damage increments, relative to a specific component and failure mode. These increments are then summed over the complete operational life of the component and used to derive statements

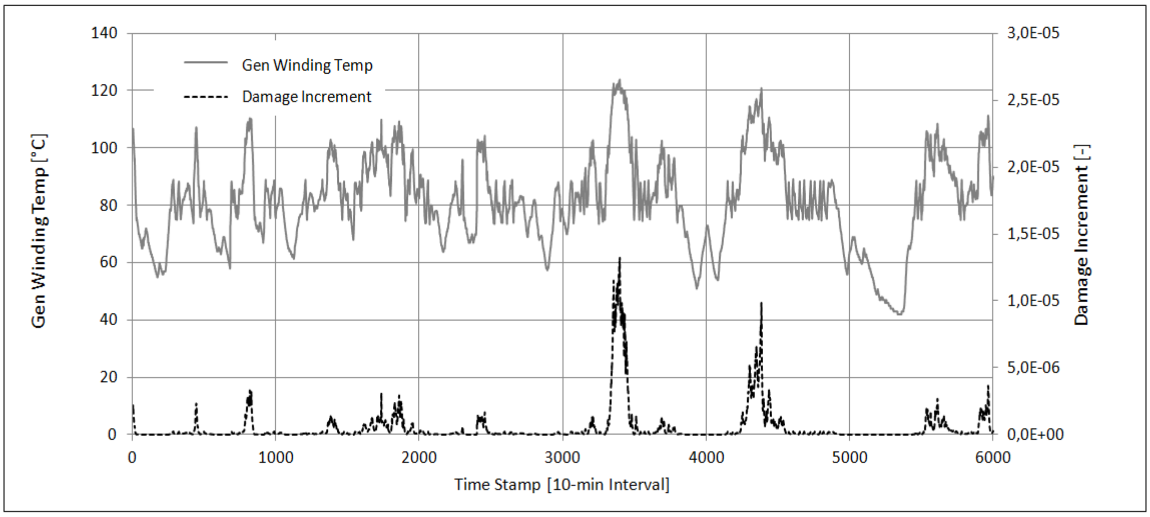

Figure 7: Damage calculation: thermal aging of generator winding insulation

concerning failure probability. Note that a linear damage summation presumes that the Miner rule applies in general. Although reasonably accurate for a range of failure modes, this must be recognised as a potential source of error.

An example of such a damage calculation is provided in Figure 7. In this case the considered system is the generator, and the failure mode under investigation is thermal aging of the winding insulation material (as identified in the Failure Mode Assessment of Figure 4). A full description of the damage kinetics is beyond the scope of this paper, however it is known that the physical mechanism is linked to thermally activated diffusion processes, well modelled using an exponential relationship with temperature [10]. An analytical solution for this process is used to calculate the damage resulting from the measured generator winding temperature. Note that due to the strongly non-linear relationship between temperature and diffusion rate, just a few high temperature events (occurring at Time Stamp ~3400 and ~4300) contribute the majority of the damage during the time period shown.

A similar treatment has been applied to many of the failure modes identified in various Failure Mode Assessments. Such an approach is effective in systematically identifying individual turbines that have been subject to severe loading during their operational lifetime, and offers interesting possibilities in terms of risk identification and ranking, allowing for optimisation of maintenance activities.

In order to further convert the calculated damage values into statements concerning remaining life and / or failure probability, the load capacity of the component in question must be defined. This is challenging, given potential variations in turbine build status and the typical lack of information concerning actual material properties or endurance. However, this may at least in part be overcome by applying statistical lifetime modelling and including input / feedback from documented field failures as part of a learning system [2].

9. O&M Strategy Integration

In order to convert the statements derived from such techniques into profitability gains it is necessary to integrate such a condition monitoring system into the operation and maintenance strategy. This is a challenging task, complicated by the fact that different organisations typically operate with differing business processes, therefore customization is generally required.

There are however certain aspects that are generic in nature. For such a system to be effective, it is necessary to document and monitor the build status of all turbines, including the specification of the components. This is typically managed using a database solution directly coupled with the monitoring system.

Alarms and fault diagnostic information delivered by the monitoring system have to be delivered to the operator via a clear and automated reporting system, as far as possible, including precise statements concerning the probable causes of observed system anomalies (diagnostics) or the description and time to failure for failure modes identified as critical (prognostics). These recommendations must be fed into the maintenance planning, triggering actions such as detailed inspection of specific systems, spare parts and equipment orders, selection of tools and parts to be taken to site, optimised order of scheduled repair activities and so on. By turning such recommendations into actions, the proposed data driven, risk focused approach to maintenance optimisation has the potential to result in significant improvements in availability and hence enhanced profitability.

10. Conclusions / Outlook

The benefits of SCADA 10-minute logs as a tool for wind turbine condition monitoring and maintenance optimisation have been discussed. A complete system has been described including workflows, requirements in terms of software and database architecture and diagnostic and prognostic modelling techniques. The capacity for early identification of a wide range of failure modes combined with techniques to identify failure probability, risk ranking and remaining life offers great potential for significant cost reductions through improved field reliability.

The success of the approach relies on effective integration of the disciplines of physics, statistics and software engineering in order to provide a cost effective and scalable solution. Practical issues such as varying turbine type and build status, the need to efficiently monitor large numbers of units and to detect and predict a multitude of failure modes demands the maximum feasible level of automation.

Ongoing development of the described techniques will focus on expanding the portfolio of available system response and damage models. Increasing levels of built-in intelligence are to be developed in order to improve the capacity of the system to deliver probabilistic statements concerning failure diagnosis and time to failure. Further integration of all available data sources, potentially including high frequency vibration measurements, online oil analysis and live SCADA data logs is expected to reveal new insights into system behaviour and allow an even greater level of detail in condition monitoring.

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