UNIVERSITY OF STRATHCLYDE

INCREASING THE RELIABILITY OF WIND TURBINE CONDITION MONITORING SYSTEMS

A thesis presented in fulfilment of the requirements
for the degree of Doctor of Philosophy

DAVID FERGUSON

Centre for Doctoral Training in Wind Energy Systems
Department of Electronic and Electrical Engineering
University of Strathclyde

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Signed:

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Abstract

Wind turbines are leading the way in helping to reduce the dependency on fossil fuel energy sources. However to compete with other energy sources there is a need to reduce the cost of energy from wind turbines. It has been shown in the literature that as wind turbines increase in size their reliability decreases. As wind turbines move further offshore and into deeper water this becomes more of an issue as carrying out maintenance becomes more challenging and costly. One way of improving the reliability of wind turbines is through the use of condition monitoring systems (CMS) which can continually monitor the health of the machine and allow more optimised maintenance and repair scheduling.

Although the benefits of using a CMS may seem evident, operators have been slow in the uptake of such systems. One reason for this is due to issues with the reliability of CMS themselves. As stated in the literature, CMS must accurately detect 60-80% of faults to be economically justifiable. Not detecting faults or the occurrence of false alarms is detrimental to the effectiveness of CMS. The work presented in this thesis aims to address the issue of CMS reliability.

Through the installation of two CMS in operational wind turbines the author of this thesis has gained valuable insight into the design, build and installation of CMS which has facilitated the novel contributions from this work.

The first contribution comes from the formulation of an engineering design process which incorporates five categories of robustness which were identified by the author through Failure-Mode Effects Analysis on a wind turbine CMS that was installed in an operational wind turbine. The engineering design process incorporating the robustness categories will allow wind turbine CMS to be designed which are capable of operating reliably in the harsh environment they are subjected to.

The second contribution comes from the development of three techniques which will increase CMS reliability by reducing false alarms and introducing the ability to detect erroneous data.

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Contents

Index of Figures

Index of Tables

Associated Publications

Ferguson, D., V.M. Catterson, C. Booth, A. Cruden, *Designing Wind Turbine Condition Monitoring Systems Suitable for Harsh Environments,* in IET Renewable Power Generation. 2013, IET: Beijing

Ferguson, D. and V.M. Catterson, *Big Data Techniques for Wind Turbine Condition Monitoring*, in European Wind Energy Association. 2014: Barcelona.

Ferguson, D. and V.M. Catterson, *Designing for Reliability in Wind Turbine Condition Monitoring Systems,* in European Wind Energy Association. 2015: Paris.

1 Introduction

1.1 The cost of Wind Energy

Almost every publication in recent years that relates to wind energy will open with a statement describing the desire to reduce the dependency on fossil fuels as an energy source and move towards a cleaner, more sustainable alternative. Wind energy, being the most mature renewable energy technology [1], is so far leading the way in providing this alternative. Until very recently however, the advancement of the wind energy sector has been very much aided by Government support mechanisms, namely, feed-in tariffs and renewable obligation certificates (ROCs) which ensure investors of a reasonable return on their investment in the technology. With these feed-in tariffs now being phased out [2], it is more imperative than ever to reduce the cost of energy from wind turbines.

Wind turbines are continually increasing in size which is beneficial for lowering the cost per MW; however this is countered in offshore wind turbines by the increase in installation and connection costs. Until 2003 there was a trend of reducing capital costs for offshore wind farms [3]; however more recent trends have shown capital costs of offshore wind farms doubling from £1.5-3m/MW in 2009 [4]. This increase in capital costs is the result of moving further offshore and into deeper waters which not only increases capital costs but the costs associated with the operation and maintenance (O&M) of the wind farms. This is where the advantage of condition-based maintenance over the more traditional time-interval-based maintenance becomes more apparent and emphasises the need for wind turbine condition monitoring systems (CMS).

1.2 The Cost and Justification of Condition Monitoring

According to a survey into the technical and commercial challenges of wind turbine condition monitoring (CM) [5], the price of the majority of wind turbine CMS is over £10k. For a traditional fossil-fired or nuclear power plant the justification of this expenditure is fairly obvious; however for wind farms it may not be so apparent. To equip an entire wind farm with CMS the wind farm developer would have to invest millions of pounds. As noted by [6] wind farm operators are wary of blindly adopting CMS without a reasonable economic justification.

McMillan and Ault [7] attempt to quantify the economic benefits of implementing CMS on offshore 5 MW wind turbines through the use of probabilistic models. The authors begin by modelling a base case with an optimistic figure for the O&M costs for offshore wind turbines as three times that of onshore wind turbines and a CMS which is 100% effective. The results showed that the benefits of implementing a CMS were quite clear given this optimistic scenario. The effect of varying the O&M costs were then investigated which showed that the benefit of implementing a CMS reduced as the O&M costs for the wind turbine increased. This investigation however did not account for the effectiveness of the CMS itself. The authors concluded by exploring the capability of the CMS to perform its function in order to evaluate its impact on the cost effectiveness of implementing a CMS on offshore wind turbines. The results from this study indicated that for a CMS to be economically beneficial it must accurately diagnose 60-80% of cases, depending on the maintenance actions taken.

Crabtree [8] provides a brief cost justification for the use of a CMS on a wind turbine based on the price of a commercial SKF Windcon CMS. The author makes the comparison between monitoring the condition of a 500 MW nuclear or fossil fuel turbo generator and a 3 MW wind turbine. The initial comparison is based on downtime of the equipment as the result of a failure. Downtime of a 500 MW turbo generator may cost the operator £360k per day in lost energy revenue. Where the value of implementing a CMS may be around £14k, the cost of implementing such a system is easily justifiable. The downtime of a 3 MW wind turbine however may only cost the operator £4.32k per day in lost energy revenue which makes the cost of implementing a CMS at £14k seem unjustifiable.

Crabtree however, provides a scenario of two gearbox failures, one on a wind turbine that had a CMS installed and one that did not. It was assumed that the wind turbine with the CMS installed was able to detect deterioration at an early stage and therefore only a bearing had to be replaced. The system without the CMS required a complete gearbox replacement which cost the operator approximately £170k without taking into consideration the cost of labour, access equipment and more importantly downtime. Therefore it could be said that the overall savings as a result of implementing a CMS in this case were over £170k which would cover the cost of installing CMS at £14k on 12 wind turbines.

The author concludes by stating that although downtime alone may not be justification for implementing a CMS the potential savings through avoiding major component failures are. A similar statement is made in McMillan et al. [9] which states that the value of implementing a CMS on a wind turbine may be more than just informing maintenance but may also provide information on how wind turbines react to specific operating conditions. The question of when to monitor is put simply by Tavner et al. [10]: “One should monitor when it is cost-effective to do so, or when there are over-riding safety considerations to be observed”.

1.3 Increasing the Reliability of Wind Turbine Condition Monitoring Systems

According to Yang et al. [11] commercial wind turbine CMS have not performed as well as anticipated; mainly due to false alarms and not demonstrating satisfactory performance in detecting incipient faults. The occurrence of false alarms can lead to significant cost implications due to unnecessary downtime and labour hours occurring through the necessity for investigatory actions by a technician. Furthermore, not detecting an incipient fault could result in any level of damage or failure to the wind turbine. As already stated, McMillan and Ault [7] found that wind turbine CMS must accurately diagnose 60-80% of impending faults to be economically beneficial. The failure of a wind turbine CMS to the extent that it is not operational not only results in a wind turbine being left unprotected but also means that a significant capital asset is ineffective. The issues associated with wind turbine CMS failures become even more apparent for offshore wind turbines where access is limited by the location and impact of harsh weather conditions.

1.4 Thesis Contributions

The key novelty of this thesis comes from providing methods of increasing the reliability and robustness of CMS for wind turbines. Through the installation of two CMS in operational wind turbines the author of this thesis has gained valuable insight into the design, build and installation of CMS. These insights have firstly allowed the author to provide guidance on the design, build and installation of wind turbine CMS and secondly to develop techniques for reducing false alarms from wind turbine CMS. Increasing the reliability of wind turbine CMS is crucial in lowering the cost of energy from wind turbines and this is the main focus of the research presented in this thesis.

1.4.1 An Engineering Design Process Incorporating Five Categories of Robustness

Through performing Failure Mode Effects Analysis (FMEA) on the first system installed, five categories of robustness have been identified by the author and incorporated into an engineering design process which will increase the reliability of wind turbine CMS through better design. The categories of robustness identify areas in which a CMS will be vulnerable if not designed correctly.

The five types of robustness defined by the author are:

- Weather robustness
- Operational robustness
- Personnel handling robustness
- Electrical signal robustness
- System software robustness

To further aid researchers who may wish to install a system in an operational wind turbine, advice is given based on lessons learnt by the author which will prepare them for the challenges likely to be faced during the installation process.

1.4.2 Techniques for Reducing False Alarms from Wind Turbine CMS

In working with the data captured by the installed CMS the author has developed three techniques which can further increase the robustness of CMS. The purpose of these techniques is to allow a CMS to detect the presence of erroneous data, which may be the result of a faulty sensor, and allow the data to be discarded or repaired so that it may still be used for fault detection. The detection of erroneous data is essential in the prevention of false alarms. In the case of a faulty sensor it may not always be possible to access the wind turbine to repair the sensor so being able to correct any erroneous data may be crucial in determining the health status of a wind turbine.

Through increasing the reliability of CMS it is hoped that there would be a greater uptake in use of these systems which would ultimately lead to better reliability of wind turbines themselves. Not only can a CMS prevent catastrophic failures but it will allow the wind farm operator to carry out maintenance far more efficiently through enhanced scheduling regimes.

1.5 Research Questions

The work in this thesis aims to address the following research questions:

1. Having identified from literature that wind turbine CMS need to be more reliable, can a design process be constructed that would facilitate this through better design with an awareness for the environment in which the system must operate?
2. Given that false alarms from CMS are hindering their uptake, how could the occurrence of false alarms be reduced in order to give the operator greater confidence in the information provided by a CMS?
3. Given the occurrence of erroneous data, how could this data be removed or corrected to allow the remaining non-erroneous data to be used for determining the health status of the wind turbine?

1.6 Thesis Overview

The key aim of the work presented in this thesis is to increase the reliability and robustness of wind turbine CMS; firstly through better design of the systems, and secondly through the introduction of data handling techniques.

This introduction, Chapter 1, has introduced the overall desire of reducing the cost of energy from wind energy and indicated how the implementation of WTCMS can help achieve this. It has also illustrated that in order for WTCMS to do the job for which they are intended their reliability must be increased.

Chapter 2 begins by discussing the main components and principles of operation of the typical wind turbine. It then discusses wind turbine reliability and again shows the need for condition-based maintenance over the traditional maintenance strategies. It discusses the different types of condition monitoring leading on to introduce the instrumentation used by WTCMS and the common signal processing techniques used to analyse their data. It then gives the findings of a review of the literature into wind turbine condition monitoring systems, finishing with what the foreseeable future may be for WTCMS.

Chapter 3 introduces five categories of robustness and their incorporation into an engineering design process to aid in the design and build of WTCMS. Through the use of a case study where two WTCMS are compared: one which is designed using the five categories and the other which is not; it is shown how the use of the five categories can improve the reliability and robustness of a WTCMS.

Chapter 4 introduces the first data analysis technique which is used to detect the presence of erroneous data within a dataset and remove this erroneous data through the use of a model which is based on the principles of operation of a WT.

Chapter 5 discusses Pearson's correlation analysis and shows through a case study how it can be used to give an indication of a change of state of health of a wind turbine or to indicate a faulty sensor.

Chapter 6 introduces a technique for repairing signals from sensors which have been clipped. The technique in this case is applied to a voltage signal which has been clipped due to an issue with the voltage transducer.

Chapter 7 summarises the research in this thesis, and presents potential areas of future work.

2 Wind Turbine Monitoring

2.1 The modern wind turbine

The modern wind turbine is a complex system encompassing electrical, electronic, mechanical, hydraulic, aerodynamic, and civil engineering disciplines. Bringing each of these disciplines together has allowed a system to be created which is capable of extracting kinetic energy from the wind and converting it into useful electrical energy. Each of the engineering disciplines stated have their own complexities involved in combining with the others to create a system which can generate electrical energy efficiently. As the work in this PhD has focussed primarily on the wind turbine drive train the main disciplines involved are electrical and mechanical engineering and this section will introduce each relevant piece of equipment.

2.1.1 Rotor

The modern wind turbine market predominantly consists of three bladed horizontal axis upwind rotors which are most commonly known as the Danish concept [12]. Arguably the most crucial part of the wind turbine, the rotor captures the kinetic energy of the wind by its three blades which are optimised to capture the wind by careful design of aerofoil sections and twist rate. The hub of the rotor, which is where the three blades come together to attach to the main shaft, is positioned upwind of the nacelle in the Danish concept. This has the benefit of avoiding turbulent and irregular air flow which would be caused by the tower if it were located downwind.

The rotor is kept facing directly into the prevailing wind by the wind turbine's yaw system [13]. Yaw motors, located on the yaw ring underneath the nacelle, will receive a signal from the wind turbine controller telling them what position to rotate the nacelle to. This position is determined by the controller based on a signal from a wind vane located on the nacelle roof.

The optimal rotational speed of a wind turbine is determined by the wind speeds on a given site usually described by the Weibull distribution [14]. The blades are designed to operate most efficiently at the most common wind speed at the given site. Most wind turbines begin generating power at 4 or 5 meters per second; generate maximum 'rated' power somewhere between 12 and 17 meters per second; and shut down at 25 meters per second to prevent storm damage [15]. In high wind speeds, wind turbines must reduce the aerodynamic efficiency of their blades in order to reduce the amount of energy captured so that structural damage is prevented. This can be done in one of two ways [16]: the first is through stall regulation, which involves designing the blades so that their aerodynamic efficiency is reduced at excessive wind speeds causing the rotor to go into stall. The second is through active pitch control, which involves changing the pitch angle of the blades, which in turn reduces the aerodynamic efficiency of them resulting in less energy from the wind being captured. As well as using pitch control to avoid structural damage at excessive wind speeds it is also used to increase the wind turbine efficiency by allowing it to track the optimum rotational speed more closely.

2.1.2 Gearbox

The function of the gearbox is to step up the rotational speed of the rotor to the required range for the generator. The advantage of using gearboxes is that it allows smaller more robust induction generators to be used which are lighter and relatively cheaper [17]. Typically a gearbox can be required to have a step up ratio anywhere between 1:31 and 1:88 determined by the generator being used. These ratios are usually achieved by three stages each with ratios between 1:3 and 1:5 [14].

The first stage of a wind turbine gearbox, known as the low speed stage, will consist of a planetary configuration with either spur or helical gears. The low speed stage is then followed by the intermediate stage which is has an intermediate shaft driven by the sun pinion which drives the high speed stage. Helical gears are used to drive both the intermediate and high speed stages [18].

There are also wind turbines on the market that avoid the use of a gearbox, known as direct-drive machines [19], through the use of much larger permanent magnet synchronous generators. The reason for avoiding the use of a gearbox is due to the potential economic savings by the reduction of gearbox failures.

2.1.3 Bearings

Bearings play a crucial role throughout the drivetrain and are located in the main bearing, which supports the shaft of the rotor as it enters the nacelle, the gearbox, and in the generator. The role of bearings is to allow rotational movement with minimal friction. A typical bearing is made up of an inner race, an outer race and a number of rolling elements in between that allow the inner and outer races to rotate in relation on one another. The main bearings used in wind turbines are roller bearings, where double-row swivel-joint roller bearings are the most frequently used rotor bearing [20].

As crucial as bearings are within a wind turbine they are also known for being problematic and have been identified by [18] as the source of the majority of gearbox failures. This is an issue that the industry is well aware of [21] and which work such as that by Fuentes et al. [22], which focusses on detecting damage of bearings, aims to address.

2.1.4 Generator

The efficiency of a wind turbine is very much dependant on how well the generator can convert the kinetic energy delivered from the main shaft into electrical energy. The induction (or asynchronous) generator is generally the generator of choice for wind turbine applications due to a number of advantages including robustness and its relatively low cost [23]. The basic principle of operation of an induction generator is that an electric field is induced by a relative movement between the rotor and the rotating stator field which produces a voltage across the rotor windings. A connection to the rotor is usually made by slip rings which allow the electrical characteristics of the rotor to be influenced from the outside. By altering the resistance of the rotor windings the slip can also be altered which gives some control of the rotor speed which is important when directly coupling to the fixed-frequency power grid [24].

There are several different electrical configurations that are used in modern wind turbines however the doubly-fed induction generator (DFIG) as illustrated by Figure 1, is widely used due to a number of benefits [25]. In this variable speed configuration the stator of the generator is connected directly to the grid and so the output of the stator must therefore be at grid frequency. The rotor is also connected to the grid however this time indirectly via a pulse width modulation (PWM) converter. The PWM converter monitors the rotational speed of the rotor and generates a frequency which is superimposed on the rotating field of the rotor, so that the resulting superimposed frequency remains constant, regardless of the rotor speed. This ensures that a constant (grid) frequency is fed into the grid. An added benefit of the DFIG is that the rating of the converters can be reduced since only approximately 1/3 of the rated power of the machine is passing through them thus reducing costs associated with the electronics.

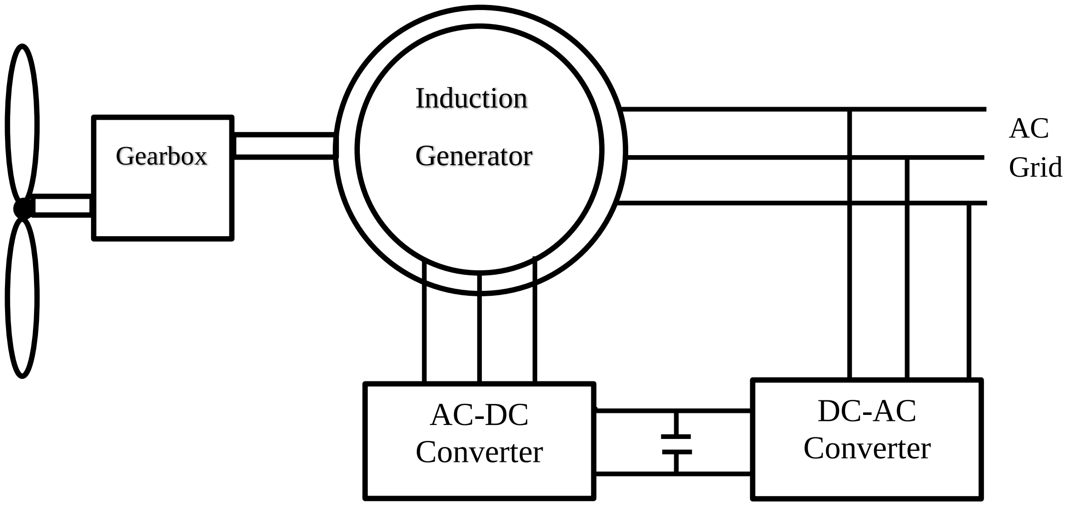

Figure 1: Doubly fed induction generator

2.2 Wind Turbine Reliability

Since O&M costs can account for 10-20% of the total cost of energy for wind projects [26], reliability levels of a wind turbine can have a significant impact on a wind farm's profits, especially when competing with conventional energy generation sources. Numerous studies [27, 28] have been carried out to try and quantify the reliability of wind turbines and their sub components with most results giving output similar to that of Figure 2.

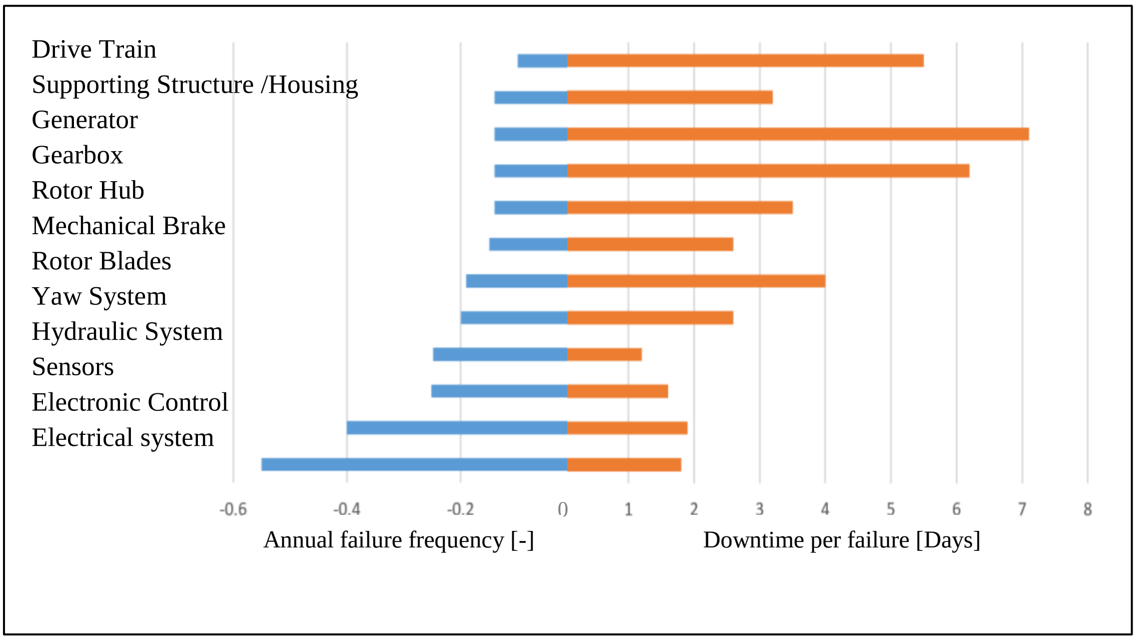

Figure 2: Failure Frequency and Downtime of Components (reproduced from [28])

Without doubt gearbox and generator failures account for the highest level downtime which will result in significant financial loss to the wind turbine owner. This is because failures of gearboxes or generators will generally require a full replacement of that component which requires heavy lifting equipment as well as suitable weather conditions for carrying out such operations. Failures of the electrical system on the other hand, although frequent, result in relatively little down time due to the ease with which these faults can be corrected. Crucially the failures which occur most often tend to have the lowest associated downtime.

The reliability of wind turbines and their sub-assemblies will differ for on and offshore locations but for offshore wind turbines the need for greater reliability is even more crucial. A study by Tavner et al. [29] found that a failure rate of 1-3 failures per wind turbine per year onshore is common yet for offshore the failure rate per turbine per year is necessary to be 0.5, since planned maintenance visits need to be kept at or below 1 per year, in order for them to be economical. Unscheduled maintenance can have a significant impact on the financial return of a wind turbine due to the high costs associated with deploying technicians offshore.

Reliability of assets is generally assumed to follow a bathtub curve, as shown in Figure 3, and describes the failure intensity over the lifetime of a plant. As can be seen, failure rates are highest at the beginning and end of the lifespan. Failures at the beginning of the life cycle are likely due to manufacturing defects whereas failures at the end of the life cycle are due to deterioration. The failure intensity function, $\lambda(t)$, describes the failure rate of the wind turbine where β is a parameter that describes the shape of the intensity function [30]. In the deterioration stage, where failure intensity is increasing due to the age of the machine, a decision will have to be made on when the wind turbine should be decommissioned due to the maintenance costs being greater than the revenue received.

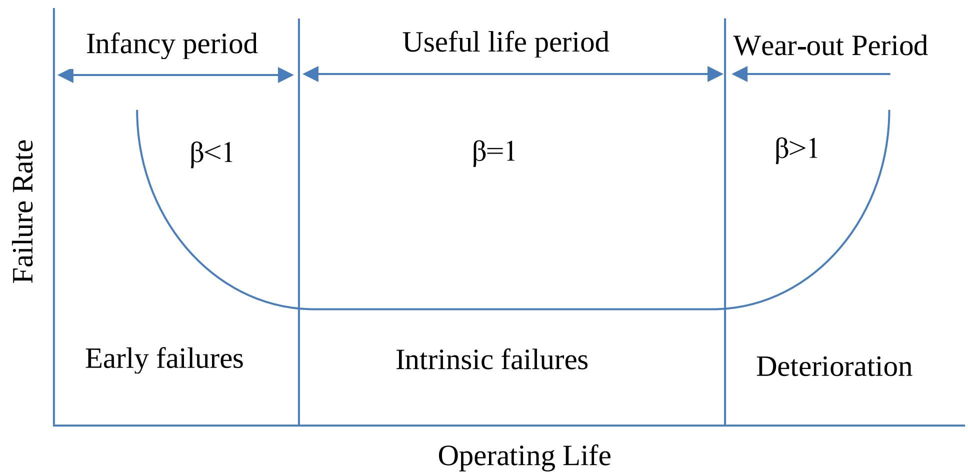

Figure 3: Bathtub curve illustrating the reliability of wind turbines

Not only do failure rates vary between on and offshore wind turbines, and between different stages of a wind turbine's operating life as seen in Figure 3, but they also vary for different sizes of wind turbines. Tavner et al. [31] in their attempt to quantify the reliability of different wind turbine concepts find that as wind turbines increase in size so too does the failure rate. In Figure 4 it can be seen that the failure rate more than doubles when the size of the wind turbine increases from 250 kW to 1000kW. This increase in failure rate is not purely a result of the increase in size but is due to the change in the electrical configuration of the generator and power electronics being used in modern wind turbines. With wind turbines rated at 8MW generating power at present and wind turbines rated at 10MW likely to be deployed commercially in the coming years this trend is concerning. Not only is the reliability of these wind turbines reducing as their size increases but they are also being located further and further offshore making maintenance and repair more difficult. Improving reliability rates of these wind turbines will be crucial to sustaining their economic viability.

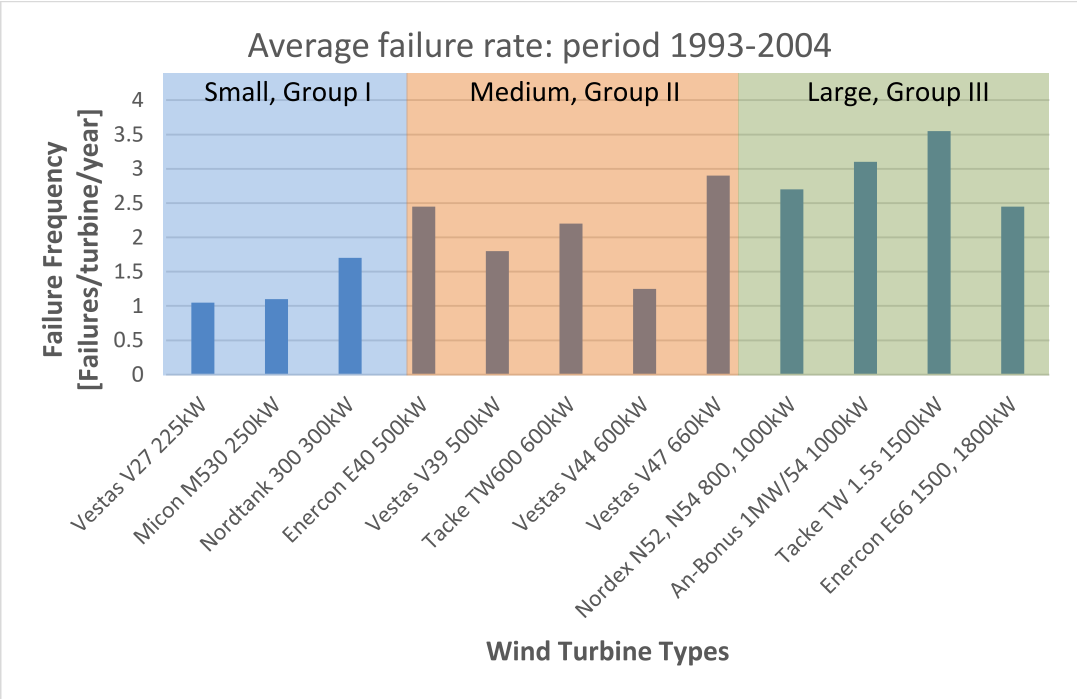

Figure 4: Distribution of failure frequencies between different turbine models, sorted by turbine size (reproduced from [31])

The literature indicates that failure rates of offshore wind turbines have a critical impact on the operation and maintenance costs and ultimately the economic efficiency of wind energy as a viable option for increasing electricity generation from renewable sources. In order to ensure failure rates and resulting downtime are minimised, an effective strategy is required which will optimise the available resources for carrying out maintenance and repair works.

2.3 Maintenance Strategies

There are three maintenance strategies that are used in asset management in general to determine when maintenance should be carried out, each having its advantages and disadvantages [32]. Figure 5 below shows the three strategies and the principles of their use. The choice of which strategy to use is very much dependent on the implications of a failure to that system, such as the resulting cost of a failure. The objective of performing maintenance can be described in three ways:

- Ensure equipment performs its intended function in a satisfactory manner;
- Reduce long term costs by servicing equipment before deterioration causes avoidable damage;
- Avoid unexpected outages by detecting failures in advance.

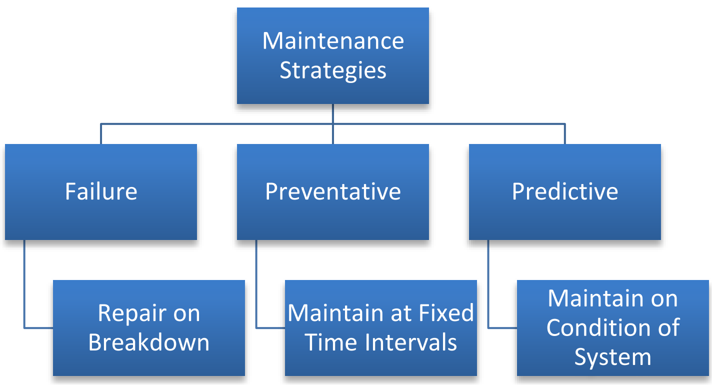

Figure 5: Maintenance strategies

2.3.1 Repair Maintenance

The most simplistic form of system maintenance is the repair on breakdown strategy described by the well-known saying "if it isn't broken, then don't fix it". This maintenance strategy is still widely used in a number of industrial sectors for a number of reasons. Failure based maintenance has low costs associated with it, requires a lower number of staff, allows equipment to run until failure thus utilising its maximum life, and is a very simple method if the consequences of failure are minimal. There are of course a number of drawbacks associated with failure based maintenance mainly as a result of the unpredictable nature of activities. Drawbacks of this maintenance strategy also include increased labour costs with overtime working hours being likely, inefficient use of maintenance staff, inventory problems due to the difficulty of planning requirements, consequential damage such as engine seizure due to oil pump failure, and also safety issues that may result from a failure.

2.3.2 Time-Interval-Based Maintenance

The majority of maintenance carried out in differing industrial sectors is on a time-interval basis [33] meaning that routine maintenance is carried out at set time intervals based upon the manufacturer's guidelines. This type of maintenance can be very effective when the system condition is very closely related to the time and/or duty and is easily justifiable when the impact of failure is high. An advantage of this type of maintenance is that no condition monitoring equipment is required to be bought, installed or monitored making the implementation of this strategy simple. The disadvantage however is that a large amount of time and money is spent inspecting wind turbines and carrying out maintenance that is not immediately necessary. It also does not allow manifesting major faults to be identified at an early stage which could potentially result in prolonged downtime. There is also a belief that inappropriate maintenance actions may cause increased failure rates similar to that shown in Figure 6. This may be the result of damage to adjacent equipment during a maintenance task; installing material that is defective or could essentially be the result of introducing infant mortality by installing new parts or materials.

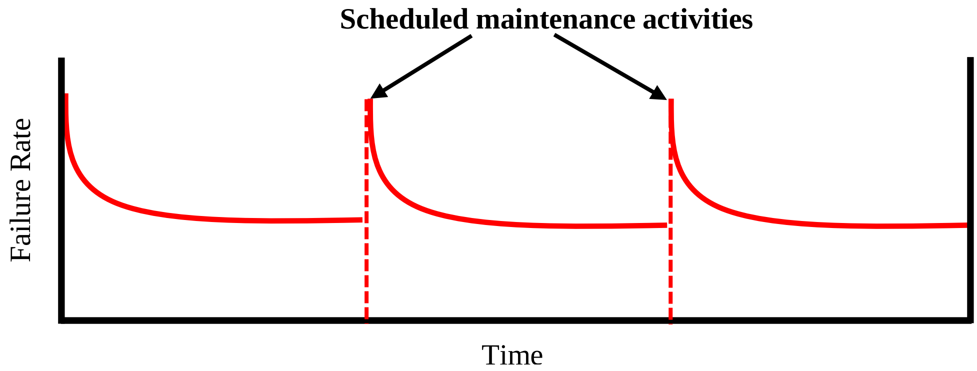

Figure 6: Possible impact of scheduled maintenance

2.3.3 Condition Based Maintenance

Condition-based maintenance on the other hand means that maintenance is only performed when indicators of machine condition highlight that it is actually required, thus optimising the operation and maintenance process [32] of a wind farm. The monitoring of the machine condition can be done either by visual inspection or through the installation of sensors throughout the machine. These sensors, as part of a condition monitoring system, would provide on-line data which can be analysed to determine the condition of the machine. Having this information allows wind farm operators to plan maintenance in an efficient and cost effective manner based on resources available and the associated costs. Carrying out maintenance in this way will increase efficiency by avoiding wind turbines being taken offline for maintenance that is not necessarily needed at that moment in time and freeing up time for wind turbines that require maintenance and repair work.

Although the benefits of condition-based maintenance are evident the justification for implementing such a system may not be so straight forward. Issues which hinder the uptake of condition monitoring include the lack of knowledge required to interpret the data obtained. The operator must know what to look for in the data and what the characteristics of a fault look like. A more significant issue with implementing such a system is the occurrence of false alarms which may in turn lead to unnecessary shutdowns thus neutralising the benefits of the system.

2.4 Review of Wind Turbine Condition Monitoring

Following the consideration of the economics behind condition monitoring, this section considers the technical aspects associated with condition monitoring systems for wind turbines.

The monitoring of a wind turbine can typically be broken down into four classes of system [34], as shown in Figure 7, each having different data rates that are sent to the wind turbine operator or monitoring engineer.

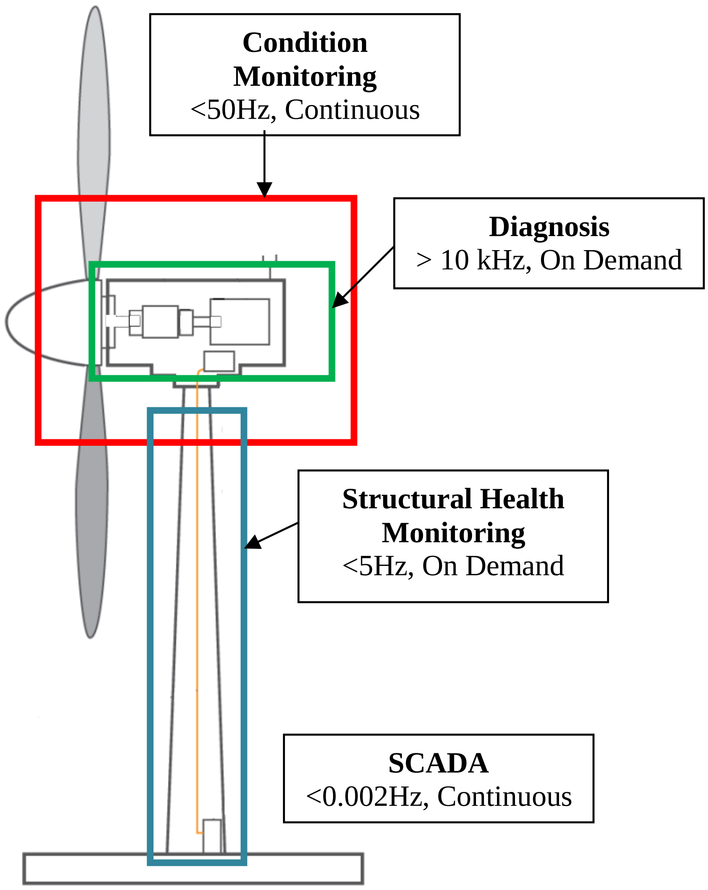

Figure 7: Structural health and condition monitoring of wind turbines (reproduced from [34])

2.4.1 SCADA

The first class of system and that which is used presently in all modern wind turbines [8] is the Supervisory Control and Data Acquisition (SCADA) system. This system is required in order to confirm the satisfactory operation of a wind turbine by recording the energy generated and additional parameters indicating the operational condition of the wind turbine. SCADA systems typically sample at high frequencies however only transmit a 10-minute average of the sampled data. SCADA systems are capable of raising alarms when thresholds are exceeded such as component temperatures. According to Zaher et al. [6] the parameters below are commonly monitored by commercial wind turbine SCADA systems.

- Active power output (10 min average and standard deviation (SD) over 10 min interval)
- Anemometer-measured wind speed (10 min average and SD over 10 min interval)
- Nacelle temperature (1 h average)
- Gearbox bearing temperature (10 min average)
- Gearbox lubricant oil temperature (10 min average)
- Generator winding (10 min average)
- Power factor (10 min average)
- Reactive power (10 min average)
- Phase currents (10 min averages)

Whilst the standard SCADA systems can alert operators when faults or failures occur they may not always be able to identify the root cause of a failure. The data provided by SCADA needs further interpretation to extract detailed information about the health of a wind turbine such as when a component may need replaced.

2.4.2 Structural Health Monitoring

Structural health monitoring (SHM) is a very important aspect during the operation of a wind turbine due to the catastrophic events that may result from a weakening or failure of the structure. Causes of structural damage on a wind turbine may include moisture absorption, fatigue, wind gusts [35], thermal stress, corrosion, fire and even lightning strikes [36]. By implementing a SHM system the structural health of the wind turbine can be continually monitored allowing any structural weaknesses to be revealed before catastrophic damage. According to Ciang et al. [37] an ideal SHM system typically consists of two major components: a built-in network of sensors for collecting response measurement, and a data analysis algorithm/software for interpretation of the measurements in terms of the physical conditions of the structure.

When discussing the structure of a wind turbine the main assemblies to be monitored consist of the foundations, the tower and the blades. Various techniques are used to monitor the condition of these assemblies including visual inspection, C-scan, acoustic emissions, and shearography [35]. These techniques however can be labour intensive, inaccurate and difficult to use and research is therefore looking into new methods for structural health monitoring [35].

One potential new method for damage detection on the blades in particular is vibration measurement which can allow damage to be identified without having to scan over the entire blade with a sensor [35]. Other benefits of implementing a SHM system in general include: avoidance of premature breakdown, reduced maintenance costs, supervision of remote sites and remote diagnosis, and improvement of capacity factor [37].

2.4.3 Condition Monitoring and Diagnosis

The third and fourth classes of system are the condition monitoring and diagnosis systems which can be grouped together due to their dependence on one another. Condition monitoring and diagnosis systems essentially have the same transducer inputs however have different internal functions and outputs as will be discussed.

A condition monitoring system differs from a conventional protection system in that it is designed to pre-empt failure whereas a protection system is essentially retroactive [10]. A condition monitoring system should also provide essential information regarding the operational health of a wind turbine. The success of a condition monitoring system may be based on its ability to reliably identify the presence of a fault and indicate the location and severity of that fault. Based on the severity of the fault the monitoring engineer will make the decision whether or not a more thorough investigation is required.

Condition monitoring systems may be capable of providing data of high sampling rates however these large quantities of data are generally not of key importance to a wind farm operator. An operator is essentially concerned with the reliability of any alarms that indicate a fault so that a definite decision can be made regarding the actions to be taken when a fault is present i.e. reduce power capture or shut down the wind turbine. A condition monitoring engineer on the other hand may use the detailed data to gain an understanding of the wind turbine’s operational health allowing maintenance to be scheduled prioritising those wind turbines in greater need. The high frequency data may also allow the condition monitoring engineer to monitor the progression of a fault further enabling the efficient scheduling of maintenance with the wind farm operator. As wind farms increase in size reliable alarms triggered by data from condition monitoring systems will be crucial to allow efficient scheduling of maintenance in order to keep the operational and maintenance costs to a minimum.

In order to reduce the level of data transmitted and since operators are generally only interested in alarm signals, not all condition monitoring data has to be collected on a high frequency basis. High frequency data may only be recorded intermittently when a fault is present to allow detailed investigation thus reducing the requirement for greater transmission bandwidth and storage capabilities.

Following the initial alarm from the condition monitoring system a diagnosis system could be activated to begin capturing the high frequency data. This would initially give an indication of the location and severity of the fault, and then allow the condition monitoring engineer to carry out a detailed analysis into the root cause and precise location of the fault. An effective condition monitoring system should provide the correct amount of data to be able to identify the fault without overloading the CM engineer with copious amounts of data.

Based on reliability data from Crabtree et al. [38], there are three sections of a wind turbine that may require monitoring. These consist of:

- Electrical system monitoring
- Conventional rotating machine monitoring
- Blade and pitch monitoring

Although stated as separate entities each of these sections will merge into the one condition monitoring system to provide a holistic view of the wind turbine health.

2.5 Condition Monitoring Instrumentation

Tavner et al. [10] state that there are four essential tasks in a condition monitoring system:

1. The measurement or transduction task (sensing of primary variables).
2. The data acquisition task (conversion of sensed variables into digital data in condition monitoring system).
3. The data processing task (identifying of information buried in data).
4. The diagnostic task (acting on processed data).

This section will focus mainly on the first of these tasks which is carried out during the normal operation of a wind turbine. The condition monitoring approach taken on wind turbines is non-obtrusive meaning that no signals are injected and all monitoring is done using transducers which have no effect on the normal operation of the wind turbine.

2.5.1 Temperature Measurement

Temperature sensing is one of the most widely monitored parameters in any type of system due to the low cost and good reliability of the sensors [39]. According to [10], when temperature measurement is combined with information about the loading and ambient conditions of the machine, it provides valuable monitoring information. A rise in temperature above the normal operating temperature, can indicate excessive grinding and wear between metal components which is likely the result of a fault or general wear. To measure temperature within a system there are three principle methods:

- Resistance temperature detectors (RTDs)
- Thermistors
- Thermocouples

According to Zaher [40], the commonly measured temperatures within a turbine include the gearbox oil, gearbox bearing, generator winding and ambient nacelle temperature. Feng et al. describe in [41] how gearbox failure can be predicted by monitoring transmission efficiency and rotational speed, and relating them to the rise in temperature of the gearbox. It should be noted that due to the variable nature of a wind turbine the operating conditions for the moment in time being analysed must always be taken into consideration.

The two CMS discussed in this thesis use PT100 sensors, also known as RTDs, to measure temperature across the drive-drain and on the nacelle roof for measuring ambient temperature. There are different materials used for the sensing element of RTD however platinum is deemed to be the best metal for a stable, linear and repeatable sensor [42]. As the temperature of the sensing metal changes the resistance of it will change when there is an excitation current (less than 1mA) applied to it and this change in resistance allows the temperature to be measured. Figure 8 below shows the PT100 patch sensor being used to measure the temperature of the main bearing.

Figure 8: PT100 sensor (red patch) and accelerometer mounted on the main bearing

One example of the use of temperature monitoring is presented by Guo et al. [43] who use it for the detection of generator faults. To begin with a normal operating model for the wind turbine generator temperature is developed through the use of the nonlinear state estimate technique (NSET). This normal behaviour model is then used at each time step to predict the generator temperature. Using the estimated and real temperature values a time series of residuals can be found. In the presence of a fault the evolution and distribution of these temperature residuals will differ from that during normal operation. To reduce the sensitivity of this method to isolated model errors a moving average window is used to smooth the time series of the residuals.

A method that is being used more often in the field of wind turbine condition monitoring is thermography. It is a technique which, at the moment, is only applied offline but is used for detecting hot spots particularly in electronic and electrical components [44]. At present it is not widely used due to the high cost of the thermographic camera and difficulties in practical application on an operational wind turbine [39]; however according to [45] cameras and diagnostic software that are suitable for online monitoring are beginning to become available. Ciang et al. [37] touch on the use of thermography for structural health monitoring stating that acquiring reliable data for detecting impending failure or damage of certain components requires optimally placing sensors in the appropriate places i.e. hot spots.

2.5.2 Vibration & Acoustic Measurement

Vibration monitoring is the most commonly used technique [46] for the condition monitoring of rotating machinery such as gearboxes, shaft couplings, bearings and rotor unbalance. It can also be used to detect broken rotor bars [47] due to the axial force generated through the interaction of the interbar current and stator flux. Used with spectral analysis vibration monitoring is the typical choice particularly for gearbox monitoring and diagnostics within a wind turbine [48].

Acoustic measurement is a technique which is closely related to vibration monitoring and has recently been used for monitoring wind turbine bearings [22]. Acoustic emission monitoring takes place when vibration monitoring is not effective enough due to the relatively slow speed of the wind turbine which results in vibrations being less obvious. Vibration sensors work by registering local motion on the component whereas acoustic sensors "listen" for high frequency vibration and can therefore give an indication of defects in their developing stages [40].

According to Tavner et al. [10] vibration monitoring revolves around the measurement of three quantities that are related by numerical integration or differentiation: displacement, velocity and acceleration. Which quantity to measure depends on the plant size to be measured and the frequency range of interest. Tavner et al. provide the following approximate ranges for using each quantity:

- Displacement - ~0 to ~7000Hz
- Velocity - ~8 to ~7000Hz
- Acceleration - ~20 to ~100,000+Hz

The wind turbine drive-train is a complex electromechanical system giving rise to a range of frequencies of vibration. For vibration monitoring it is essential to identify these frequencies so that any abnormal frequencies can be detected. Most incipient faults within a wind turbine produce some level of vibration therefore making vibration monitoring an effective tool for the detection of faults. The faults that are commonly detected by vibration monitoring include gearbox bearing and gear wheel damage, the main bearing associated with the main shaft of the turbine, torsion and oscillation of the main tower and in some cases acoustic vibration on the blades through the use of spectral emitted energy sensors which measure at very high frequencies [40].

Figure 9 shows the type of accelerometer used in the system designed by the author for measuring vibration on the main bearing of the wind turbine. The accelerometer is attached to a mounting stud which is secured to the casing of the bearing using an epoxy resin. This type of sensor has a frequency response of 2 Hz to 10 kHz which will allow all frequencies of interest within the bearing to be detected.

Figure 9: Accelerometer mounted on main bearing

2.5.3 Force and Pressure Measurement

Force and pressure are another common form of monitoring technique for condition monitoring in general asset management [40]. Force is measured through the application of strain gauges which consist of a length of resistance wire formed into a zigzag shape and securely bonded to a surface that will change shape when a force is applied [10]. As the resistance wire changes shape its cross-sectional area and length change therefore altering its resistance. As the change in resistance is related to the force applied the force on a particular component can be measured. One application for the use of strain gauges on a wind turbine is to measure the strain on the blades [49]. This however would be an expensive measurement method to implement on a wind turbine due to large area of the blades which is one reason that this type of measurement on blades is not common place in this specific area. Research such as that in [50-52] illustrates how strain gauges can be used to monitor the loads on blades and further research like this will likely lead to the wider application of blade monitoring.

Within one of the CMS discussed in this thesis two load pins are used to measure the torque in each of the gearbox mounting arms. Used with an amplifier these load cells can measure a force of up to 30 tonnes which can be measured as a 4-20mA or ±10V signal.

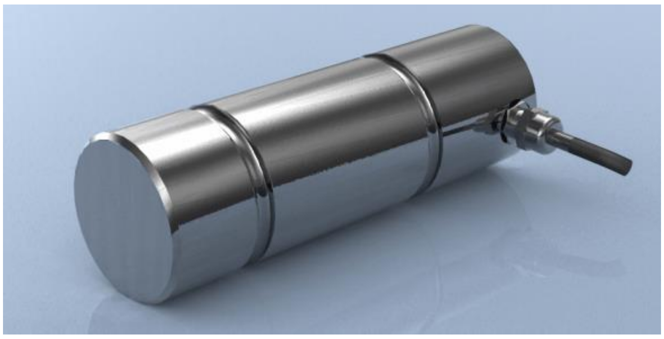

Figure 10: Load pin used in CMS for monitoring gearbox reaction torque [53]

Oil Pressure is a parameter commonly measured within the hydraulic system of the wind turbine [6]. The pitch control system within a wind turbine uses hydraulics to alter the pitch of the blades so it is therefore desirable to monitor the oil pressure when performing actuations of the pitch system. A fault within the pitch control system may result in increased mechanical force on the structure of the wind turbine leading to reduced energy capture or in a worst case scenario structural damage. The pressure of the oil in the gearbox is also measured since low oil pressure could result in catastrophic failure [41].

The pressure sensor shown in Figure 11 was used in one of the CMS discussed in this thesis to measure the oil pressure that is applied to actuate the emergency brake on the wind turbine. Being able to see when the emergency brake had been applied was seen as a useful parameter for understanding the health of the wind turbine since emergency stops have a significant detrimental effect on the health of a wind turbine [54].

Figure 11: Pressure sensor used to measure the oil pressure applied to the emergency brake [55]

2.5.4 Wear and Debris Measurement

In many electromechanical machines information about the condition can be assessed through the monitoring of the lubricant or coolant. As wear on a component increases or a fault occurs it is likely that increased debris or contamination will be seen in the lubricant or coolant. In the case of wind turbine, oil is the main lubricant and coolant of the gearbox and is also used within the hydraulics of the pitch control system making it an important parameter to monitor. The oil within a wind turbine is commonly monitored for moisture [46] and other particles in order to obtain an indication of the health and rate of deterioration. According to Hameed et al. [46], oil monitoring has two main purposes: safeguarding the oil quality and safeguarding the components involved. Since the price of the sensors to monitor oil quality has come down it is now at a point that makes it justifiable [40] to implement them for online monitoring.

The most common way of monitoring the oil within the gearbox is through the use of a debris sensitive sensor [10]. The oil will pass through the device which is suited to that particular oil and will usually use either an electrical transducer to measure changes in inductance capacitance, or conductivity, or optically by measuring changes in the turbidity of the lubricant [10]. A detailed review of oil analysis techniques was carried out by Hamilton et al. [56] and a recommendation given that a combination of different types of oil monitoring sensor be used to give a better picture of the condition of the oil. Following this review the same authors go on to present a novel wear detection system in [57]. The system which incorporates a webcam has the aim of being able to capture the size and shape of contaminants in the oil; characteristics deemed crucial for indicating the type of wear occurring within a gearbox.

Online monitoring of the oil within the gearbox can give an indication of gear tooth damage and any other contamination within the oil [40]. Contamination within the gearbox oil can significantly reduce the lifetime of the gearbox. Also, water in the oil can have the effect of reducing the effectiveness of the lubrication properties of the oil [40]. The ability to detect this contamination at an earlier stage may prolong the operational life of the system by ensuring it is well lubricated.

2.5.5 Voltage and Current Measurement

Voltage and current monitoring are not techniques that are commonly discussed when WT CMS are reviewed; possibly because of the lack of experience of analysing these signals in the WT industry [39]. They are however commonly monitored in the field of rotating electrical machines [10, 58]. Within a wind turbine voltage and current will typically be measured by the SCADA system [6] so that the performance of the wind turbine can be assessed through analysing the power curve which describes the power output in relation to the wind speed.

Measuring a voltage is carried out by measuring the electrical potential at one point with reference to another point. On a wind turbine generator this other point is either neutral or one of the other phases. Measuring the voltage in the two CMS discussed in this thesis was carried out using probes that attached over the nuts on the generator terminals, as can be seen in Figure 12. The output from these probes are then fed into a voltage transducer board which uses a current transformer to step the voltage to a lower range that can be safely inputted to the digital to analogue converter. Further details of the transducer boards are given in Section 6.1.

Measuring the current within a conductor can be fundamentally described as measuring the movement of charge carriers [59] and done by counting the number of charges per unit of time. Rogowski coils, as seen in Figure 12 and used in the CMS discussed later, are one method of measuring current and have the advantage over current transducers of not requiring a physical connection. A Rogowski coil consists of a wire wound on a non-magnetic core which is placed around the conductor whose current is to be measured [60]. The output voltage from the coil can then be defined if the core of the coil has a constant cross-section and the wire is wound perpendicular on the core centre line with constant density [60].

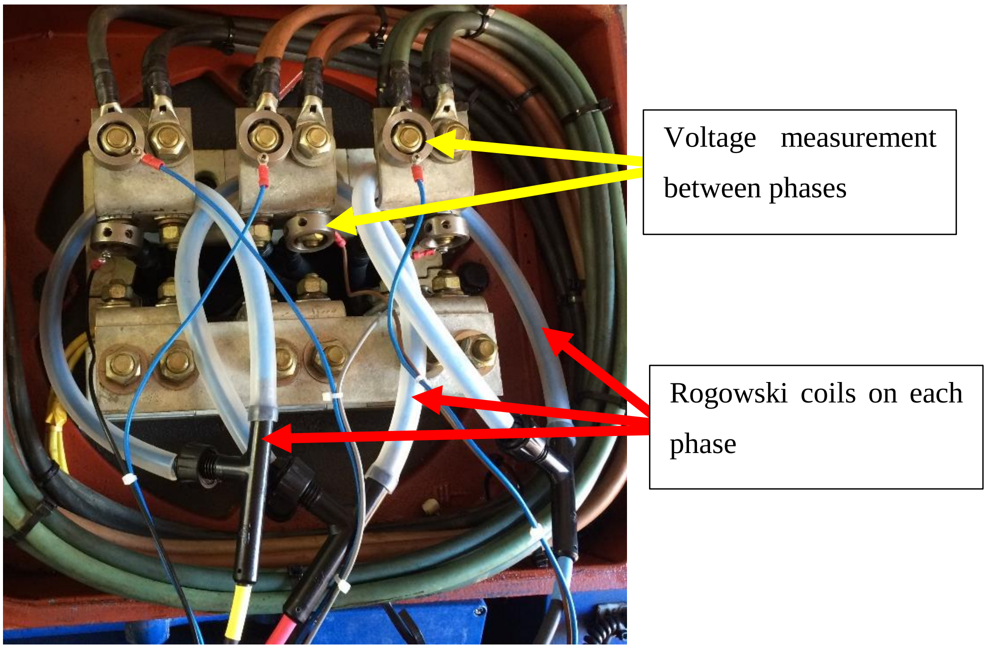

Figure 12: Voltage and current being measured on the generator terminals using voltage probes and Rogowski coils

One condition monitoring technique that relies on a current signal and which is seeing greater use [61, 62] in the field of wind turbine monitoring is motor current signature analysis (MCSA). MCSA is a technique where the spectrum of the current signal is analysed to detect faults which may become apparent by the occurrence of harmonics in the frequency domain when a fault is present. MCSA can be used for detecting faults in generators such as broken rotor bars, shorted turns in low voltage stator windings, and airgap eccentricity [63].

2.6 Common Signal Processing Techniques

Wind turbine condition monitoring, compared to conventional condition monitoring, is a complex task due to the stochastic and aerodynamic effects of the wind [64]. To effectively monitor the condition of the wind turbine a clear understanding of the effects of variable speed and variable load conditions is crucial. Therefore the condition monitoring engineer must develop processing techniques and algorithms with non-stationary and erratic, stochastic signals in mind.

This section will discuss the common techniques used in condition monitoring for analysing signals with the aim of extracting useful information about the health of a machine. The principles and applications of each technique will be provided along with the advantages and disadvantages of their implementation.

2.6.1 Spectral Analysis

Spectral analysis refers to the analysis of signals in the frequency domain which have been transformed from the time domain. The spectral representation of a time series signal is made up of a number of components in the frequency domain each having a specific frequency, amplitude and phase angle. A well-known technique for transforming signals from the time domain to frequency domain representation is the Fourier transform [10]. Fourier analysis is based on the rule that any periodic and sinusoidal function can be broken down into its harmonic components. Separating a function into its harmonic components allows each frequency component present in the function to be identified. It should also be noted that as the number of harmonic components increases so too does the accuracy of the transformation [10]. The Fourier transform for a continuous signal, x(t), can be given by:

Equation 1

$$\mathcal{F}\{X(t)\} = X(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}\,dt$$

The calculation consists of evaluating the signal, x(t), against sine and cosine functions of positive and negative frequencies over the entire function length, from negative to positive infinity.

This form of Fourier transform is not suitable for many engineering applications. Since the signals have been sampled in time at a specific sampling rate they are no longer strictly continuous in time and therefore the discrete Fourier transform (DFT) must be used.

To carry out discrete analysis the continuous signal x(t) is replaced by a discrete signal, x(nt), which has a sampling period T. This gives the transform [65]:

Equation 2

$$X(f) = \sum_{n=-\infty}^{\infty} x(nt)e^{-j2\pi fnT}$$

It is now implied by the discrete time domain nature of the signal that the signal is now discrete in the frequency domain also. The DFT of the discrete signal is therefore given as [65]:

Equation 3

$$X(f_k) = \frac{1}{N}\sum_{n=0}^{N-1} x(t_n)e^{-j2\pi kn/N}$$

where f_k defines the frequency components being analysed. In practice the DFT is implemented using the fast Fourier transform technique which is a very efficient way of achieving the DFT [10].

One problem however concerning the use of DFT for wind turbine condition monitoring is that it relies on stationary signals. During this transform the total sampling length must be taken into consideration and therefore any small, time-localised signatures will likely be insignificant compared to the overall signal length. Therefore, by using the FFT, the time location of characteristic frequency components or impulsive responses cannot be examined [48].

It is favourable in many situations to know the time information when analysing the frequency content of a signal, however this is something the DFT cannot provide. For this reason the short-time Fourier transform (STFT) was developed to allow time-frequency analysis of non-stationary, time varying signals [8].

The STFT calculates the spectral content for a short time sample of a particular signal. This is done iteratively in the time domain until the entire signal has been processed in these short samples. The resulting spectra are then plotted in time to produce a 3D (time, frequency, amplitude) representation of the signal's spectral content [8]. However since the STFT is essentially an iterative DFT process, there are certain limitations on the frequency resolution applied, such that a longer time window allows for a greater frequency resolution. For the STFT, however, the frequency resolution is not the only factor to consider and a certain degree of compromise is required. A higher resolution may be obtained through a longer time window, and therefore an accurate representation of frequency content, however this will result in reduced resolution in the time domain. Time accuracy of analysis may be improved through the use of a smaller window such that the signal is effectively stationary during analysis [8]. Based on the signal under analysis it is up to the user to select a suitable time window or frequency resolution for their analysis.

2.6.2 Wavelet Analysis

The STFT has many advantages over the DFT however still has the limitation of providing a constant resolution for all frequencies since it uses the same window for the entire signal and therefore is only suitable for quasi stationary signals. Wavelet analysis overcomes this issue and can be used for multi-scale analysis of a signal through dilation and translation, so it can extract time-frequency features of a signal effectively [66]. Therefore, in the case of wind turbine condition monitoring, where there are non-stationary signals, wavelet analysis is more suitable.

Over the past decade wavelet analysis has become a popular mathematical and signal processing tool due to its many distinct merits. The first wavelet concept was put forward by Morlet in 1984 [66] before it was formalised as the continuous wavelet transform (CWT) with the help of Grossman. The CWT is given in [66] as

Equation 4

$$W_x(a,b;\psi) = a^{-1/2} \int x(t)\psi^* \left(\frac{t-b}{a}\right) dt,$$

Where *a* is the scale parameter, b is the time parameter, $\psi(t)$ is an analysing wavelet, and $\psi^*(\bullet)$ is the complex conjugate of $\psi(\bullet)$. As parameter *a* is changed, signatures at different frequencies in the signal are revealed. As parameter b is varied the *x(t)* is scanned through in terms of time [10].

The CWT expands the concept of Fourier analysis by considering that a time domain signal, not necessarily periodic, can be reconstructed using a series of small waveforms that can be transitioned in time and scaled in amplitude [10]. These waveforms are called wavelets and do not require periodicity like sine waves. By correlating between the signal and analysing wavelet at each stage the wavelet content of the signal can be identified.

The basic wavelet, known as the mother wavelet, is usually chosen as an oscillatory waveform that decays in both directions from the centre of the wavelet [10]. It is also stated by [67] that the mother wavelet should have no DC component, be a band-pass filter, decay rapidly towards zero with time and be invertible. A commonly used wavelet is the Morlet wavelet. In many mechanical dynamical signals, impulses are always the symptoms of faults and the Morlet wavelet is very similar to an impulse component [68]. Figure 13 illustrates the shape of a Morlet waveform, which appears as an impulse.

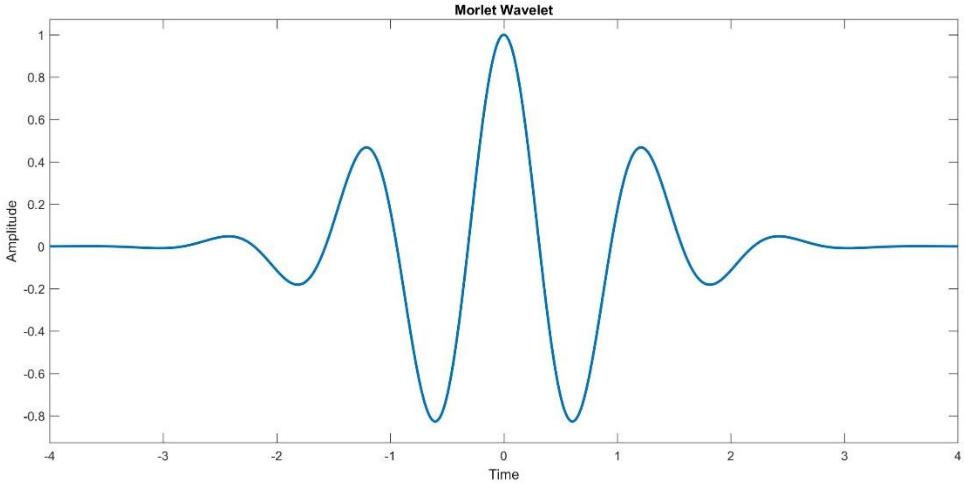

Figure 13: Morlet waveform

The Morlet wavelet has a mother wavelet defined as:

Equation 5

$$\Psi(t) = e^{-j\omega_0 t} e^{-t^2/2}$$

And has the Fourier transform:

Equation 6

$$H(\omega) = \sqrt{2\pi} e^{-(\omega-\omega_0)^2/2}$$

The mother wavelet is scaled to give a family of mother and baby wavelets so that each baby wavelet is given by:

Equation 7

$$\frac{1}{\sqrt{c}} \Psi \left\{ \frac{t-\tau}{c} \right\}$$

where c is a variable scaling constant and τ is a constant of translation. The scaling parameter, c, is approximately inversely related to its frequency such that high values of c correspond to low frequencies and vice versa.

By increasing c the wavelet is dilated in time and therefore contains lower frequencies. By increasing the value of τ the wavelet is moved in time along the x-axis such that the CWT is given as:

Equation 8

$$CWT(c,\tau) = \left(\frac{1}{\sqrt{c}}\right)\int s(t)\Psi\left\{\frac{t-\tau}{c}\right\}dt$$

Amirat et.al [69] review a number of different applications of the CWT. These include the detection of stator turn faults in a DFIG, the detection of damage on a blade, and also to remove noise and intervening neighbouring features in an induction motor to detect rotating shaft frequencies. It can therefore be seen that wavelet analysis is a valuable tool for the analysis of non-stationary signals where there is a requirement of the time-frequency information.

2.6.3 Correlation Analysis

Correlation analysis is a time domain technique and is mathematically very similar to convolution [10]. The auto-correlation function can be used to measure the similarity between a waveform and a time shifted version of itself, whereas the cross correlation function refers to two different time functions. The auto-correlation function of a time signal f(t) is given by [10]:

Equation 9

$$R_{ff}(\tau) = \int_{-\infty}^{\infty} f(t-\tau)f(t)dt$$

The function f(t – τ) is a time-shifted version of f(t), by a time τ. The process may be thought of as one signal searching through another to find similarities. The correlogram of the auto-correlation function will show when τ is around the time it takes the signal to show some repetition, given that there is repetition in the signal. Auto-correlation is therefore a very useful tool for identifying any repeating features that can be hidden in a signal mixed with noise and disturbances.

The cross-correlation function of two different signals f(t) and h(t) is given by [10]:

Equation 10

$$R_{fh}(\tau) = \int_{-\infty}^{\infty} f(t-\tau)h(t)dt$$

The cross-correlation function, as with the auto-correlation function, can be used to recover both the amplitude and phase of signals lost in a noisy background [10]. Therefore in wind turbine condition monitoring correlation functions may be used to reveal the similarity in signals that may be inherently related but are phase shifted due to transmission delay. In particular, correlation functions are suited to the monitoring of faults such as bearing degradation and can provide a means of relating the condition monitoring signatures to the causes of faults.

Correlation analysis will be further discussed in Chapter 5 with a greater focus on the application of correlation for fault detection for both that of the wind turbine and the CMS itself.

2.6.4 Time Synchronous Averaging

Time Synchronous Averaging (TSA) is an algorithmic tool for the analysis of signals captured from rotating equipment. Used particularly with vibration signals, TSA involves averaging the time domain signal in synchronisation with the running speed of the machinery being monitored [70]. The main advantage of using TSA is that it allows periodic signals to be separated from background noise [71], particularly useful for gearbox monitoring. This is done by averaging together a series of segments each corresponding to one period of a synchronising signal [71]. The synchronising signal is generally provided by a tachometer which provides an *n* per revolution signal. It is however also possible to perform TSA without this signal by using a time domain feature, such as a gear mesh as is described in [72]. That being said, having a once per revolution signal is by far the preferred option as is pointed out in [73] where almost every partner of a collaborative project stated that their vibration analysis of a gearbox was significantly challenged due to the absence of this signal.

An application of TSA for monitoring planetary gearboxes is presented by Ha et al. [74]. Due to the complexity in monitoring planetary gearboxes, caused by multiple contacts and axis rotation of planet gears [75], Ha et al. propose the pre-processing technique of autocorrelation-based TSA (ATSA). Autocorrelation analysis is used on the vibration signal in order to identify the instances when a similar pattern of vibration occurred. By using a window with an optimised size and shape the performance of the TSA is greatly improved. This was illustrated by the successful identification of a fault signature in the tooth domain for a simulated dataset.

2.7 Review of Research into Wind Turbine Condition Monitoring

Condition monitoring of wind turbines is a continually developing field with a number of researchers attempting to define technology and methods suited to this complex application. There are a number of different areas of wind turbine condition monitoring which can be developed in isolation particularly the different areas of the wind turbine requiring monitoring, i.e. blades, gearbox, generator and tower structure etc. This section will discuss the findings from a review of the literature regarding the research that has been and is currently being undertaken for the development of wind turbine condition monitoring systems.

This PhD project is the continuation of work carried out by two previous PhD students who produced two papers on the subject. The first of these two papers was written by Swiszcz et al. [76]. This paper begins by discussing the requirements of the CMS with regards to safety, leading on to the selection of the measurands. The measurands were selected partly based on the capabilities of the chosen data acquisition (DAQ) cards. The DAQ cards do not allow sampling rates to be set for individual channels and therefore the parameters to be measured were divided into two groups - low speed and high speed. The low speed parameters would be sampled at a rate of 50 Hz whereas the high speed parameters would be sampled at a rate of 20 kHz. The low speed parameters include temperature sensors, rotational speeds, wind speed and direction, and tower movement. The high speed parameters include the generator voltage and current output, and 7 vibration sensors. The authors then describe different techniques for storing large volumes of data, highlighting the reasons for the choice of using the MySQL database, namely due to its two types of tables available that allowed 2TB of data to be stored and easily read. The authors go on to provide an overview of the data acquisition platform and the associated user interface which was developed using National Instruments Labview software.

The second paper relating to the project was written by Zaher et al. [77]. This paper places more focus on the design and layout of the system hardware. The system is divided between two computers, one at the base of the tower and the other in the nacelle of the turbine. The computer at the base of the tower acts as the data storage device, transferring all the data recorded onto a 2TB external hard drive. The computer in the nacelle acts as the main data acquisition unit with both the low speed and high speed DAQs directly connected to it. The two computers are then connected via a fibre-optic cable which allows high speed data transfer of 1 GB/s between them. The authors discuss the data acquisition software architecture which is crucial to the efficient capturing of the data.

It is the combination of work by the two previously discussed authors that led to the development of the first condition monitoring system built within the university. The work carried out on the system in relation to this PhD project will be discussed in Chapter 3.

The advantages of the implementation of the system discussed is that it would provide continuous high frequency data from a live wind turbine; therefore one which has been subjected to all the naturally occurring processes caused by the stochastic nature of the weather. Based on a review of the literature it is common practice to develop condition monitoring systems through the use of test rigs. Test rigs have been used in a number of research projects in an attempt to verify findings from research studies.

One such test rig is described by Crabtree and Tavner [78]. This paper describes a test rig for the development of condition monitoring techniques for wind turbines. The test rig has features of a wind turbine such as variable speed and torque, a gearbox, induction generator and a grid connection. Although the test rig cannot provide a true representation of data from a live wind turbine it can provide very realistic conditions. It does this through the use of a Labview control environment which allows conditions obtained from a 2MW wind turbine model to drive the test rig. To illustrate the capability of the test rig the authors provide an example where asymmetry with differing severity is applied periodically whilst the test rig is run with varying wind conditions. Twice the slip frequency ($2sf_{se}$) of the generator was tracked as it is a known fault frequency. Through the use of an energy tracking method based on the wavelet transform it was shown that asymmetry could be detected in the electrical power signal.

A similar test rig is discussed by Wilkinson et al. [79] which was established to act as a model for a wind turbine and to allow the investigation of failure modes found in previous work to develop an appropriate CMS. The test rig consists of a DC motor rated around 50 kW, a two stage gearbox, and the prototype Slim generator. The authors state that although the generator is of unusual topology, it is harmonic rich and has a number of clearly identifiable modes, determined through modal analysis. Similarly to the previous test rig discussed, this test rig can also simulate the torque input that is seen as a result of transient and gusting wind conditions. This can be applied using either real or simulated wind speed data using the computer-controlled DC drive system. Therefore, again this test rig can give a good approximation of real wind conditions; however, as stated by Swiszcz et al. [76], the data may not necessarily reflect processes happening in the real turbine application.

In an attempt to assess the added value of various techniques of health monitoring to optimise the maintenance procedures of offshore wind farms an investigation was carried out as part of the EU funded Condition Monitoring for Offshore Wind Farms (CONMOW) project [80]. This was a collaborative project carried out by a number of large and well established institutes working in the area of wind turbine condition monitoring. The project involved the implementation of CMS along with the “traditional” measurement systems for measuring mechanical loads and power performance, on five wind turbines on a small wind farm. The authors stated that at the time of drafting the state of the art CM techniques report, no successful applications of wind turbine CM examples were found in the literature. Therefore unlike the previous test rigs discussed this would be the first project to implement CMS on live wind turbines with the aim of obtaining data that would allow the added value of CM techniques to be determined along with the development of new techniques for wind turbine applications. In particular the project was aimed at developing data analysis algorithms which would aid operation and maintenance, and at the same time lower the cost of CMS. Unfortunately, however, the project was hampered by mainly non-technical issues, such as the lack of time, which resulted in less data being captured than had been hoped.

There have been several reviews in the literature which attempt to summarise the state-of-the-art advancements in condition monitoring and fault diagnosis of wind turbines. One of these reviews was carried out by Lu et al. [48] which gives a thorough review of recent advances at the time of writing. The authors split the wind turbine into five of the major subsystems in order to summarise the monitoring and diagnostic methods applicable to each of them. The authors draw a number of conclusions from the review stating that wavelet transforms are a necessary tool for time-frequency analysis and that acoustic emission is considered a more robust approach for monitoring low-speed operation compared to classic vibration based methods. The authors conclude by advising that grey-box modelling and a multi-agent system approach deserve more study for analysing such a system.

Similar reviews are provided by [46, 58], and a continual effort is required to summarise the state-of-the-art technology due to the continual development in a relatively immature area of the condition monitoring sector. Amirat et al. [81], again, review well established techniques for the condition monitoring and fault diagnosis of wind turbines; however, with increased emphasis on the monitoring of the generator terminals. In particular, the authors measure the output from a doubly-fed induction generator (DFIG) and uses the well-established techniques developed for induction motors to show that drive train faults can be detected in this manner. It is also stated that imbalances and defects in small wind turbine blades can be detected through measuring the power spectral density at the generator output. Finally the authors state, as do many others, that wind turbine operations are predominantly transient and the use of non-stationary techniques is necessary for fault detection.

A paper by Popa et al. [82] also discusses the application of monitoring a DFIG in order to detect different types of fault. The authors use a test rig in order to apply three different faults: a stator phase unbalance using a variable resistance and inductance in series on one phase, a rotor phase unbalance using a resistance of the same value as the rotor phase resistance inserted in series on one rotor phase, and finally a turn-to-turn fault using an inductance in parallel on one stator phase. Machine current signature analysis (MCSA) was chosen as the fault detection technique due to its powerful merits in fault detection and diagnosis [82]. The authors confirmed that the experimental results clearly demonstrated the ability to diagnose turn-to-turn faults as well as inductive and resistance unbalance in one stator and rotor phase through the use of MCSA. Monitoring of DFIGs is a commonly occurring theme throughout the literature; however more work is related to the signal analysis and data interpretation which will be discussed in the following section.

A substantial review of techniques and methods of condition monitoring of wind turbines was carried out by Márquez et al. [45]. The authors begin by discussing the different maintenance strategies: corrective (repair), scheduled (time-interval-based) and condition based maintenance, discussing the main differences between them and the reasons for their use. It is then highlighted how that the implementation of a CMS can minimise costs of maintenance, improve operational safety, and reduce the quantity and severity of in-service system failures. A review of the technology for condition monitoring is given, discussing the different techniques and methods, and providing an indication of their level of deployment. The authors also state that vibration analysis continues to be the most popular technology employed in WT CM, especially for rotating equipment, which is backed up by [40]. Another similar method described is the measurement of acoustic emission which measures elastic waves that are given off when the structure of metal is altered. It is stated that these sensors have been used successfully not only in the monitoring of bearings and gearboxes but also for damage detection in WT blades.

Ultrasonic testing (UT) is another technique discussed in [45] which can be used for the structural evaluation of WT towers and blades. UT is generally used for the detection and qualitative assessment of surface and subsurface structural defects. Using signal-processing algorithms, including time-frequency techniques and wavelet transforms, more information can be extracted from the measured signal.

As mentioned earlier a technique for the monitoring of WT blades is strain measurement which involves the installation of strain gauges on the blades. Assessment of the strain gauge signal can allow lifetime forecasting and protection against very high stress levels. Márquez et al. [45] state that although optical fibre sensors are very expensive, new cost-effective systems are being designed based on fibre optics. Another technique that is described for the monitoring of the blades, and also the tower, is radiographic inspection however this technique is rarely used as it is not easy to implement [45].

Márquez et al. [45] conclude by defining the main obstacles facing the designers of CMS which include:

i. Selection of the number and type of sensors;
ii. Selection of effective signal processing methods associated with the selected sensors;
iii. Design of an effective fusion model (i.e., the combination of sensors and signal processing methods which give an improved performance).

The technical and commercial challenges of condition monitoring in the wind energy sector are also discussed by Yang et al. [5]. The paper was written with the aim of providing industry with a detailed analysis of the current practical challenges with existing wind turbine condition monitoring technology. As well as providing industry with an analysis of the current challenges it also identifies the areas in which further research is required in order to develop CMS to a state that makes its implementation economically justifiable for wind farm operators. Yang et al. discuss the practicality and deployment status of a number of monitoring methods including techniques that are in the early stages of development, namely: ultrasonic testing, for tower and blades; torsional vibration, for the main shaft and gearbox; and shaft torque measurement for the blades, main shaft and main bearing. From the techniques identified, vibration analysis is still the most advantageous due to its low cost, its capability for online monitoring and fault diagnosis, and the large number of WT components it can be used to monitor.

The authors also identify a number of techniques for signal processing and those which are presently being researched. With regards to the future work required for the development of WT CM, the authors break it down into three subsections: CM techniques for other key assemblies, WT prognosis, and WT CMS reliability. It is stated that more work is required into the techniques for monitoring the electrical and power electronic systems as well as the yaw and pitch systems due to the long downtime caused by failures in these areas. One of the major areas identified as requiring work is the processing of the data from CMS, in particular, non-linear CM signals. This includes analysis of time-domain and frequency domain signal changes under incipient fault conditions as faults progress from detection to failure, thereby providing information necessary to validate CM techniques. Crabtree [34] also believes this to be a key area for future work stating that major innovation will occur in terms of developing signal processing techniques following his survey of commercially available condition monitoring systems for wind turbines.

The literature so far has identified that vibration monitoring remains the standard method of monitoring the health of wind turbine drive-trains. More sophisticated processing techniques are required however, to understand the data being captured due to the stochastic nature of wind turbine operation. Test rigs are often used to develop CM techniques, due to the lack of data from operational wind turbines, and have the benefit of allowing faults to be artificially generated. These generated faults however may not necessarily represent a true fault as would be seen in a wind turbine and it is still therefore essential that data is obtained from a monitoring system installed in a live wind turbine.

2.8 Review of Wind Turbine Condition Monitoring Data Analysis and Interpretation

As identified in the previous section, an increasing amount of research is being focused on the data analysis and interpretation for condition monitoring systems. This section will cover the research found in the literature that is related to the data analysis and interpretation of wind turbine CM, particularly the techniques used to identify faults or abnormalities in the acquired signals from the gearbox and generator.

Table 1: Summary of reviewed literature

Author/s	Test rig or field	Components/Faults addressed	Techniques applied
Yang et al. [83]	No Data Required	Whole turbine	Platform using SCADA systems
Yang et al. [11]	SCADA Data	Blades & drivetrain	Correlation based analysis
Feng et al. [84]	SCADA & CMS	Gearbox	Algorithm using vibration & oil debris
Guo et al. [43]	SCADA Data	Generator	Normal model and comparison of residuals
Wilkinson et al. [85]	SCADA Data	Drivetrain	Signal trending, self-organising maps, physical model
Zaher et al. [6]	SCADA Data	Gearbox & Generator	Normal behaviour models using Neural Networks
Djurovic et al. [86]	Test rig	DFIG Unbalance	FFT, spectrum analysis
Crabtree et al. [87]	Test rig	WRIG	FFT, spectrum analysis
Yang et al. [64, 88]	Test rig	Generators	Wavelet transforms
Al-Ahmar et al. [89]	Test rig	DFIG, elec/mech faults	Wavelet transforms
Watson et al. [90]	Test rig & field	Generator eccentricity	Wavelet transforms
Yang et al. [91]	Test rig	Power quality & drivetrain	Fast Individual Harmonic Extraction (FIHE)
Crabtree & Tavner [92]	Test rig	Generator imbalance	Frequency tracking, Fourier analysis, IDFT
Wang et al. [93]	Not specified	Gearbox	Vibration, time-frequency, order, envelope analysis
Round Robin Project [73]	Test rig	Gearbox	Numerous vibration-based techniques

There is a large amount of literature available relating to techniques for diagnosing faults within a wind turbine however this section aims to provide a brief overview of techniques used for detecting faults within the drivetrain. Table 1 provides a summary of the literature reviewed in this section and shows that analysis and interpretation techniques are typically developed using either SCADA data or data obtained from test rigs.

2.8.1 SCADA Data Based Techniques

One particular trend in the research into the monitoring of WTs is to make use of the data from SCADA systems which are already installed in the majority of WTs. Using data from an already installed SCADA system removes the requirement to install a potentially expensive CMS. Yang et al. [83] describe, at a high level, how wind farm SCADA systems can contribute to a Reliability Centred Maintenance strategy. The authors state that SCADA data is useful for the detection of an occurrence of a fault but may not be able to accurately diagnose a fault.

Leading on from this work, the authors in [11] present a method of using SCADA data for condition monitoring. The method begins by pre-processing the data in order to extract the true information within the SCADA data that may be hidden or smeared as a result of operating conditions of the wind turbine. The technique for identifying a fault is derived based on the correlation between SCADA data parameters and defined as the condition monitoring criterion, c. The key to this technique however is that analysis is only performed on data captured at wind speeds lower than the WT's rated wind speed where it will begin to pitch its blades and thus introducing nonlinearities. If these nonlinearities were able to influence the data used, the correlation between parameters would be greatly affected.

To test the technique it was applied to fault data generated from two failure scenarios created using a test rig. The first was a winding fault on the rotor of a generator. Through adjusting the phase resistances in load bank electrical imbalance was created. The results of the test showed that the presence of the fault caused a reduction in the efficiency of the generator and the application of the technique allowed this reduction to be clearly visible when plotting power output against generator speed: two parameters which are directly correlated. The second test involved detecting the presence of a gear tooth fault in a gearbox. This was again tested using the test rig to generate data where the damage on a gear tooth was progressively increased. To detect this fault, correlations between both generator torque and DC motor speed, and generator power and DC motor speed were used. The results of this test showed that the model could clearly detect an increase in damage. This could be seen from the position of the model curves and the resulting CM criterion value.

The idea of using both SCADA data and CMS data is applied in a paper by Feng et al. [84] for failure detection and diagnosis of a wind turbine gearbox. SCADA and CMS measurement methods for the gearbox are identified, with the main measurements from the CMS being vibration and oil debris, and with temperature and oil pressure being the main measurements taken by the SCADA system. The author introduces a new algorithm based on SCADA oil and bearing temperature, and the relationship between temperature, efficiency, and power output or rotational speed. The authors were able to show that the temperature rise of one of the gears is proportional to the power output provided the efficiency of the gear has not changed; since when a fault occurs the efficiency decreases. The authors' findings show that observable trends are available six months before the failure of the gearbox planetary gear. Based on the results of the case study carried out the author states that analysis of SCADA signals using simple algorithms can give early warning of failures in gearboxes and that analysis of CMS signals can locate and diagnose failures with detailed information.

Another example of the use of SCADA data for the fault detection of a generator bearing is presented by Guo et al. [43] as was already discussed in Section 2.5.1. Adding to that in Section 2.5.1, NSET is a non-parameter model construction method which was first proposed by Gross et al. [94] for use in nuclear plant signals. In order to construct the NSET model, the variables in the observation vector must be chosen carefully. Since it is the generator bearing temperature that is of interest anything that has a relationship with this should be taken into account. Therefore, the five variables that were selected to construct the observation vector were: power, wind speed, ambient temperature, the generator temperature, and the generator bearing temperature. The paper used 10-minute average SCADA data, of which there were 3,952 effective 10-minute average records. Faults using this method are detected by looking at the difference between the observation vector of NSET and the normal working space; as the fault worsens the residual will increase. This method has the advantage of not requiring a time-consuming training procedure and allows direct physical interpretation. The author shows that this method can identify incipient WT generator bearing failure well ahead of serious damage occurring.

As stated already, the benefit of using SCADA systems for condition monitoring is that they are already installed making it an economical way of monitoring the health of a wind turbine. There are different methods of using SCADA data, three of which are reviewed by Wilkinson et al. [85], namely: signal trending, self-organising maps and physical model. The signal trending approach involves comparing one turbine against another or one time period against another. Although simple to implement it was found that it was not accurate or reliable enough to account for intermittent changes in temperature that resulted from varying operational modes or environmental conditions. The self-organising map method is a type of artificial neural network used to group similar phenomena within a dataset; in this case between SCADA parameters. In the comparison the self-organising map was found to be more sensitive to faults than the other approaches. The drawback of this method however was its inability to identify the nature of abnormal operation, making it difficult to identify impending failures. The physical model method predicts a signal, such as temperature, based on all the properties which may influenced that parameter. Contrary to the signal trending approach, this method was more difficult to implement however once established it was found to have the most success in identifying abnormal conditions.

As identified by Zaher et al. [6], most techniques using SCADA data are specific to a component, i.e. gearbox or generator. In order that all these techniques can be brought together as one system, Zaher et al. present a platform for wind farms which brings together a number of independent analysis techniques, processes data from multiple sources and focuses on a wider range of components or problems than systems do presently; thus providing a single decision support environment for the operator. In addition to presenting anomaly-detection techniques, the authors bring together normal behaviour models, in this case for the gearbox and generator, which are captured through the use of neural networks (NN). These techniques are then integrated through a framework known as a multi-agent system (MAS) which provides a flexible and extensible structure for designing such systems, allowing different tasks to be encapsulated into separate modules (agents) with independent objectives. The author states that the system will provide a 'yellow-pages' like facility known as the directory facility which allows each agent to register with it the services it provides along with the information or services it is interested in. This allows other agents to also learn about a newly introduced agent's existence and the services it can provide that may be of use to them. In this way a system is developed which can make fault detection and diagnosis based on a view of the entire wind turbine's condition. Results from the paper show that the system can be used to automatically interpret large volumes of SCADA data presented to an operator and highlight only the important aspects that would be of interest to them; therefore increasing the efficiency of the operation and maintenance of a wind farm.

2.8.2 Test Rig Based Techniques

One trend throughout the literature is the analysis of signals in the frequency domain to extract meaningful information. As discussed in Section 2.6, a well-known technique for transforming time domain signals into the frequency domain is the Fourier transform. As will be discussed in this section, although well-used, basic Fourier analysis has its limitations in wind turbine applications due to the nature of the signals captured.

An example of the use of the standard Fast Fourier Transform (FFT) is given by Djurovic et al. [86] who present the results of a comparison of the use of DFIG steady state stator line current and instantaneous power as a means of generator condition monitoring, based on an examination of their frequency spectrums. In order to carry out the work the authors developed an analytical model which makes it possible to simulate DFIG operation under a range of supply and winding balanced/unbalanced operating conditions. A DFIG test rig was also built to allow results of the model to be verified experimentally. The authors compare current and power spectra for a DFIG operating with a stator open-circuit fault using simulation data from the time-stepped model. The authors found from the study that harmonic components are present in both the current and power spectrums which are directly related to the presence of the type of winding unbalance that would arise in the case of a winding fault. It was also found that by comparison the power spectrum contained more potential fault-specific information than that of the line current spectrum. As stated by the authors however, measurement of the power spectrum requires greater attention to the reduction of noise. The authors of this paper also contributed to a paper by Crabtree et al. [87] which also proposes a method for using the standard FFT to analyse the electrical signals from a wind turbine DFIG.

Crabtree et al. [87] use analytical expressions previously derived by Manchester University [95] to find the frequency content of the line current and instantaneous power for healthy and faulty wound rotor induction generators. These expressions, which show all possible frequencies, were evaluated against experimental data using two test rigs; one from the University of Durham and the other from the University of Manchester. The Manchester test rig consisted of a 4-pole, three phase 30kW wound-rotor induction generator (WRIG) mechanically coupled to a 40kWDC motor by a common shaft. The DC motor speed is controlled by an industrial variable speed drive allowing a range of operating points to be achieved. Similarly the Durham test rig consisted of a 4-pole, 30kW WRIG of identical manufacture and altered winding arrangements but driven through a 5:1 two stage gearbox by a 54kWDC motor. A variable speed drive allowed the rig to achieve similar steady state operating points as those used at Manchester. In each case two phase voltages and line currents were sampled by the same set of voltage and current probes and a precision oscilloscope. Using the test rigs, data was recorded for 10 seconds at 2 kHz and analysed offline using the proprietary FFT function in MATLAB. The results showed that healthy and faulty wound rotor induction machines have clearly defined and calculable frequencies in current and power signals which can be predicted using the analytical expressions that were described. The authors also found that rotor electrical unbalance faults can be detected during variable speed operation, representative of that experienced on a wind turbine, using frequency tracking based on the same analytical expressions.

In attempt to overcome the limitations associated with standard Fourier analysis Yang et al. [64, 88] introduce a technique based on wavelet analysis as was discussed in Section 2.6.2. Yang et al. discuss the application of wavelet transforms for use in the monitoring of synchronous generators and synchronous generator drive trains. Investigations into the use of wavelet transforms are carried out using a test rig at the University of Durham [88]. The results showed that wavelet transforms allowed the issues associated with use of spectral analysis and the stochastic nature of wind turbines to be overcome. The authors find that the use of a discrete wavelet transform (DWT) is useful for noise reduction in the highly variable torque and speed signals; whereas the continuous wavelet transform (CWT) is effective for the extraction of time-frequency features from the highly variable signals.

Al-Ahmar et al. [89] also use the DWT in their work; in this case for the electrical and mechanical fault diagnosis in a DFIG based wind turbine. They propose a transient technique which is a combination of the DWT, statistics and energy. Experiments are carried out using a 1.1kW induction generator based test rig. The results showed that a technique based on the variance and energy analysis of wavelet decomposition stator current signals is very useful for condition monitoring and failure diagnosis in wind turbine generators.

Watson et al. [90] continue the work in use of wavelets for monitoring the power output of wind turbine generators. In this case it is shown how measuring the power at relatively low frequencies (~30Hz) and by applying a CWT to the resulting data, the magnitude of the component at twice slip frequency divided by pole pairs ($2sf_1/p$) may be tracked as an indicator of rotor eccentricity in a DFIG. As stated by the authors, rotor eccentricity is often the result of increased bearing wear and an indication of potential failure. The main advantage of using a wavelet is that it can be used to track the $2sf_1/p$ frequency component under varying rotor frequency, which is more problematic when using the more traditional frequency Fourier transform. Therefore the method described by the author could be applied to any variable speed wind turbine using an induction generator and would not require a great deal of instrumentation over the already used SCADA systems, since power will already be monitored by the wind turbine control system [90].

One drawback of wavelet based analysis however, as identified by Yang et al. [91], is the computational demands imposed on a system. Yang et al. [91] present a technique named Fast Individual Harmonic Extraction (FIHE) with the aim of efficiently detecting faults and also monitoring power quality, something which is not commonly addressed by condition monitoring systems. The authors believe that the use of power signal monitoring will reduce the need for monitoring using vibration-based techniques which produce large amounts of data that are difficult to transmit, analyse and store. The authors state that any defects existing in the system should be evident in the power flow; therefore justifying the proposal of a more efficient condition monitoring method – FIHE. Through the monitoring and analysing of the line current signals from the wind turbine generator, an improvement on the FIHE has been made in order to meet a more generic purpose. The authors lead on to describe how FIHE can be used for detecting the shift of grid frequency and the harmonics contained in WT electrical signals. The FIHE method in comparison to the traditional method, which calculates the spectrum of the electrical signal first and then measures the frequency shift from the spectral diagram, has two main advantages. Firstly the FIHE method does not have any special requirements on the sampling rate whereas the traditional method requires a minimum sampling rate of 20 kHz. And secondly, whilst the traditional method only takes into account a limited number of higher order harmonics the FIHE based method considers all harmonics without increasing any additional calculation. Both of these advantages enhance the online analysis capability of the proposed technique. For the purpose of WT CM using the FIHE method a new concept called Instantaneous Variance (IV) is introduced. Through calculating the IV it was shown that mechanical fault indicating harmonics could be extracted from the power signals. Therefore it can be said that the IV is an effective tool for detecting the effects of harmonics in FIHE results.

Similarly to [91], Crabtree and Tavner [92] also identify the necessity to process data more efficiently, particularly as the volume of data captured by wind turbines increases. The authors present an algorithm for frequency tracking which is based on Fourier principles. The algorithm is successfully applied to detect changes in fault level in electrical and mechanical monitoring signals on a variable speed laboratory test rig, as was used in previous papers. By only analysing the instantaneous frequency of interest and a narrow frequency band around it, the processing requirements are significantly reduced, compared to the STFT and CWT techniques. The algorithm proposed by the authors is an improvement on a previously proposed method in [96], and attempts to overcome some of these issues faced. The new algorithm differs from the previous through the use of Fourier-based frequency tracking instead of CWT-based frequency tracking. As for any Fourier transform analysis the signals must be sinusoidal, which according to the author, WT drive-trains are. The signals must also be analysed in short time samples of data for the Fourier-based method as signals must be stationary. Due to the iterative and frequency localised nature, the final algorithm is referred to by the author as the iterative localised discrete Fourier transform ($IDFT_{local}$). In order to verify the algorithm, non-stationary experimental data was required which contained known fault information. To obtain this the test rig described in [78], was driven at a variable speed using data derived from a 2MW variable speed WT model. The experiments found that the $IDFT_{local}$ compared favourably with the CWT_{local} due to the fact that the CWT_{local} failed to produce acceptable results for electrical asymmetry when data at the original sampling rate of 5 kHz was analysed. The authors found that the analysis of high speed shaft mass unbalance data was successful and suggest that this algorithm is ideally suited to WT CM.

So far, the literature reviewed has mainly focussed on the detection of faults through analysing the electrical signals captured at the generator terminals i.e. voltage, current and power. Although it is has been mentioned that faults outwith the generator can be detected from these signals, the majority of gearbox monitoring is carried out using vibration based analysis.

Wang et al. [93] discuss the development of a gearbox data analysis and fault diagnosis system. The majority of the monitoring on the system is carried out using vibration sensors; the data of which is analysed using a combination of methods. The system itself is made up of a number of modules including the signal pre-processing module, the signal analysis module and the fault diagnosis module. Firstly the pre-processing module works to remove the noise from the signal since vibration signals are inherently noisy. The de-noising method is selected based on singular value decomposition — which is a factorisation of a real or complex matrix. Following the de-noising, three functions are used within the signal analysis module: time-frequency analysis, order analysis and the envelope spectrum analysis. The time-frequency analysis is carried out using the Hilbert-Huang transformation in order to obtain time-frequency spectrum. Order analysis is then carried out on the signal either with or without a speed signal. According to the author the order analysis based on instantaneous frequency estimation is used without a speed signal. Envelope demodulation is then carried out on the signal using the envelope spectrum. The aim of the paper is to develop a system capable of predicting faults earlier and therefore assisting in the operation and maintenance of wind farms.

One substantial piece work which focussed on the vibration monitoring for gearboxes was presented by the Round-Robin Study [73]. Started by the National Renewable Energy Laboratory of the U.S Department of Energy, collaborative work by a number of authors [97-104] was carried out in an effort to evaluate different vibration analysis algorithms and whether typical practices are effective for gearbox condition monitoring. Through the testing of two identical wind turbine gearboxes, one of which experienced significant damage to bearings and gears as a result of two oil loss events, data was collected which would provide an insight into the health condition of the gearboxes. One factor which was highlighted as having significant impact on the output of the analysis, as was mentioned in Section 2.6.4 was the absence of a once per revolution signal and an accurate speed signal. These are crucial to be able to carry out time-synchronous averaging: a technique which is useful for gear health condition diagnostics. This issue illustrates how the technique discussed in Chapter 4 is useful in allowing the signal from an RPM sensor to be used for analysis even when it contains erroneous readings.

Another key point made in the study, regarding diagnosing gearbox faults, is that due to the complexity in gearbox design and the dynamic operating conditions, an integrated approach must be taken whereby diagnostic information from all components (gears, bearings and shafts) of the system is used. A final point made is that fusing vibration results with those from other sensors, such as oil debris, oil temperature and casing temperature, would improve diagnostic coverage and provide additional evidence of impending failures.

In relation to the Round Robin project discussed above Zhang et al. [105], who were involved in the project, also produced a paper which further discusses data mining algorithms and statistical methods for the analysis of vibration data. Data obtained from the NREL test rig was used to carry out fault identification analysis in both the time and frequency domains. The vibration data used was captured at a very high sampling rate of 40 kHz which is higher than the sampling rates used for the CMS discussed in this thesis.

Three test cases with differing rotational speed and electrical powers for different torque levels, were analysed. Jerk data which describes the rate of acceleration change and is often used to indicate the excitement of vibration is used for the tests. Since the sampling period of 40 kHz is very high, the vibration jerk data of 40 kHz is converted into much lower frequency data (1/15 Hz) by computing the mean of jerk at 15 second intervals. The standard deviation and maximum value of the jerk data in each 15 second interval are also calculated.

For the time domain analysis the authors use the correlation coefficient and clustering analysis to investigate the failed components of the gearbox. The correlation coefficient analysis analyses the linear dependence between parameters and according to the authors is widely used in research. The cluster analysis, used to further analyse the jerk patterns, is an unsupervised method of data analysis. Clustering algorithms work on the basis of grouping observations into clusters by evaluating similarities among the observed data.

Root cause analysis which looks at both the correlation and clustering analysis indicates the failure of components in the gearbox at the intermediate and high-speed stage. The analysis finds that the possible root cause is lubrication starvation and damaged gears which is proved by the inspection report of the disassembled gearbox provided by the NREL.

The frequency domain analysis is carried out using the fast Fourier transformation with time windows to develop power spectrums based on the original vibration and acceleration data measured from two of the cases. The author describes how the frequency domain analyse is able to identify damage in the intermediate and high-speed stages of the gearbox through analysing the power spectrum of the vibration data; however it is unable to identify the details of the damage and this would require the disassembly of the gearbox.

The authors conclude the paper by describing the shortcoming of the work. Since the drive train was fixed to the floor, other factors such as force from the wind and tower that could impact the vibration excitement were not accounted for. Therefore to develop a more accurate model gearbox vibration acceleration data collected from a field operated wind turbine is needed. This furthers the justification of the need to install a CMS in an operational wind turbine for more accurate analysis; since test rigs may not truly represent the conditions in a wind turbine.

Based on this review of literature it can be stated that the majority of research being carried out into WT CM data analysis and interpretation is being done so through the use of test rig or simulation data. This is likely due to the lack of extensive historical data sets and fault records due to the relatively immaturity of the wind energy sector. It is also because test rigs have the ability to allow faults to be simulated on-demand whereas it may take a long time to obtain data for a specific fault from an operational wind turbine.

2.9 Review of Research into the Design of Wind Turbine Condition Monitoring Systems

All of the literature so far has focussed on a CMS's ability to detect and diagnose faults within the wind turbine; firstly through the selection of appropriate sensing technologies and secondly through the application of algorithms to the acquired data to extract meaningful information that can be used by a wind farm operator. However in order to perform these tasks the system itself must be designed in such a way that it can operate reliably for long periods of time with minimal human intervention and allow the wind farm operator to confidently make maintenance decisions based on the information received from the system.

In a review of the technical and commercial challenges of wind turbine condition monitoring systems (WTCMS) Yang et al. [39] make the reader aware of the harshness of the WT nacelle environment and the reliability issues this causes for not only the WT but for the CMS also. Coupled with a lack of maintenance and recalibration to the CMS itself [39], the CMS reliability may be significantly reduced over time. CMS must therefore be carefully designed taking these factors into consideration.

In an attempt to advance the uptake of CMS Hameed et al. [106] evaluate their viability along with important parameters to consider with regards to design, system architecture, testing and installation. The authors discuss the requirements of an efficient and robust CMS including factors such as: modularity, ease of configuration, generic interfaces, and being self-starting and stable. Apart from the very last word in the previous sentence, these factors only describe functionality as opposed to increasing the reliability of a CMS. According to [107], reliability can be defined as "the probability of success or the probability that the system will perform its intended function under specified design limits". Given that this definition uses functionality to describe reliability suggests that reliability and functionality are two different properties of a system. The authors fail to mention the environmental conditions imposed on the system as a result of its installation in a wind turbine nacelle. The authors go on to discuss the other aspects of implementing a CMS including system architecture with examples from commercial systems, however these aspects again relate more to functionality than increasing reliability.

Throughout the reviewed literature the trend in work relating to the design of CMS, such as [108, 109], primarily focuses on the functionality of the system, i.e. which instrumentation was required to monitor a given parameter, or which data analytical techniques should be used for the detection of faults within the wind turbine. Although these factors are crucial to the development of an effective CMS they do not aid in increasing the reliability of the CMS. It is also apparent when reviewing the literature that the authors do not have real working experience of the environment in which a wind turbine CMS must operate. The work presented in this thesis will address this gap in the knowledge in order to increase the reliability of wind turbine CMS.

2.10 The Future of Wind Turbine Condition Monitoring

Wind turbine condition monitoring differs from the condition monitoring of conventional electrical generation technologies due to the complexity introduced by the stochastic nature of the wind. It is clear that there are potential benefits for the implementation of these systems however their immaturity and lack of evidence proving their worth has hindered their deployment. Since there is not a lot of experience in the condition monitoring of variable speed and load machines, it seems common practice to install a large number of sensors in order to obtain as much data as possible. This however will significantly increase capital costs of the system without necessarily improving reliability or functionality.

Based on a number of papers there are several areas of wind turbine condition monitoring that require greater research resources invested. One of these areas is the development of condition monitoring techniques for wind turbine sub-assemblies that are not so commonly monitored. It is common for CMS to mainly focus on the gearbox, generator and main bearings; however more problems within a wind turbine are actually associated with the electrical and power electronic systems and also the yaw and pitch systems. The failure of these systems can cause prolonged downtimes, particularly offshore, emphasising the need for their monitoring. Also, greater attention should be focused on the monitoring of sub-assemblies which have higher failure rates regardless of the ease with which they can be replaced.

Another area which requires attention is the development of the ability of CMS to predict failures well in advance of them occurring. Increased prognostic ability will increase safety by reducing the risk of catastrophic failure, and improve the scheduling of maintenance in wind farms. Therefore if the progression of a fault can be predicted then a predictive condition-based maintenance strategy will be realistic.

In addition to the ability to predict faults CMS must increase their reliability by reducing the number of false alarms occurring and accurately identifying the presence of a fault. As stated in Section 1.2 it was found in [7] that CMS must provide correct diagnosis in around 60-80%

of cases, depending on the cost of maintenance actions, to be cost-effective. As the price of maintenance increases it becomes more essential for CMS to be reliable.

2.11 Chapter Summary

It is evident that there is a need to reduce the cost of wind energy in an attempt to meet the intensifying demand to increase the level of energy generated by renewable sources. One way of reducing the cost of energy from wind turbines is by reducing O&M costs through the use CMS to reduce the number of unexpected faults or outages and allow for optimised maintenance scheduling. This chapter has introduced the main components of a wind turbine and the techniques used to monitor their health.

A review of the literature has been carried out into both condition monitoring instrumentation, and the data analysis and interpretation techniques used for detecting faults within the wind turbine. There was a greater focus on literature that discussed the monitoring of WT drive trains, particularly the gearbox and generator, due to these sub-assemblies being the main components monitored by the systems discussed in this research.

The reviewed literature also identified a number of areas which researchers themselves believe require future work and investment. A key area commonly discussed as needing significant further work was the development of techniques which analyse large volumes of data in the time and frequency domain efficiently. Furthermore, it is essential that a large amount of data from operational wind turbines is available in order to validate these techniques, highlighting the need for CMS for research purposes.

It was identified from the literature that most research projects into condition monitoring techniques validate the techniques through the use of test rigs or simulation data. Test rigs provide a controllable environment in which to carry out analysis, allowing faults to be simulated and the diagnostic techniques to be tested; however these simulated conditions may not necessarily precisely replicate that of an operational wind turbine. It was also apparent from the literature that there is a lack of research being carried out which is using data from operational wind turbines and any field data that is used typically coming from SCADA systems. This was the reason that the initial work carried out as part of this PhD project involved the deployment of a comprehensive CMS on an operational wind turbine which was capable of capturing continuous high frequency data to allow diagnostic techniques to be accurately tested.

One significant outcome from reviewing the literature was the lack of focus towards increasing the reliability of WTCMS themselves. Clearly, the overriding objective is to increase the reliability of wind turbines which, as identified in literature, can be done through the implementation of condition-based maintenance regimes. This however relies significantly on WTCMS which must themselves become more reliable to allow this to happen and this is the area that the work in this thesis aims to address.

3 Designing Robust Wind Turbine Condition Monitoring Systems: 5 Categories of Robustness

3.1 Introduction

A system may be considered robust if it is able to function normally in adverse conditions. Wind farms by their nature are located in areas which are inevitably subject to these adverse conditions. **This chapter addresses research question one of this thesis by presenting five categories of robustness [110], which have been identified by the author, and incorporated into an engineering design process.** Each of the categories are introduced and it is shown how incorporating then into a design process can ensure a reliable system is built. This is done by way of two case studies, the first being a CMS built without using a design process, then the second being built using a design process which incorporates the categories of robustness, highlighting the improved system design.

The five categories of robustness are:

1. Weather robustness
2. Operational robustness
3. Personnel handling robustness
4. Electrical signal robustness
5. System software robustness

Each category has been identified through the process of performing failure mode effects analysis (FMEA) on the first system that was built and installed.

3.1.1 Weather Robustness

Electrical and electronic systems come in many forms and applications, and as a result the environmental conditions in which they must operate vary significantly. Understanding the environmental conditions that the system will be subjected to is crucial in order to design a system that can operate without failure. Spacecraft present an extreme case where failure to consider the environmental conditions can result in catastrophic failure not only in terms of financial loss but also loss to human life. Although phenomena such as spacecraft charging, plasma interactions and radiation interactions [111] aren’t a concern for most systems there are many factors which pose challenges to system design, particularly in the offshore environment.

Offshore systems are faced with a number of conditions such as high humidity, high salt level and extreme wind conditions, all of which make careful design more crucial. As stated by [112], “Careful selection of equipment, design and materials for equipment exposed to the elements is essential”. This may involve decisions such as keeping electrical equipment in a controlled environment, using space heaters and stainless steel hardware [112].

A publication by the American Bureau of Shipping [113], having identified the challenges of the offshore environment, provides rules for the design and installation of offshore oil platforms which will increase the reliability and safety of these systems. Looking specifically at the rules for the electrical systems the rules include guidance for choosing equipment and enclosures, equipment earthing, and for material selection to name a few. A more detailed focus on the effects of weather on connectors is given by Callen et al. [114] who look at different connector types and how they fail as a result of harsh environmental conditions.

The key, regardless of the application and resulting environment, in designing a suitable system is to understand the conditions that the system will face. Wind turbines are subject to a wide range of weather conditions all of which must be considered when designing a CMS. Temperatures on a wind farm in Scotland can easily range between -27 and 32 degrees Celsius [115]. These extreme temperatures can have a serious detrimental effect on electrical or moving equipment. The solution to this issue is the use of heaters and fans. Heaters are mainly used on external instrumentation (namely anemometers and wind vanes) and will be built into the device itself. Under normal circumstances the temperature within the nacelle will be sufficient to protect internal equipment from low temperatures.

Fans are crucial to prevent electrical equipment from overheating. According to [116] generators can reach 150°C before a high temperature alarm leads to shut down. This gives a good indication of the internal nacelle heat sources a CMS is exposed to during operation; therefore fans are required to prevent computers and other circuitry from overheating which may result in a system malfunction.

A common occurrence on wind farms is lightning strikes. A study by the National Renewable Energy Association found that up to 8 out of 100 wind turbines could expect to receive one direct lightning strike every year [117]. To mitigate the damage caused by lightning strikes all wind turbines are fitted with lightning protection which provides a low impedance path to ground. This will shunt the lightning current away from the components susceptible to lightning damage [118]. Equipment fitted on top of the nacelle, such as the anemometer or wind vane, are very vulnerable to lightning strikes due to their elevated position and therefore must be robust enough to receive and withstand a strike. The enclosure of the CMS itself should have a good connection to earth in order to reduce the impact of any current from a lightning strike.

Rainfall and precipitation are other parameters which can have a detrimental impact on electrical equipment within a CMS. If a printed circuit board (PCB) surface was to be contaminated with a conducting material in the presence of moisture and an applied voltage, the result could cause the lowering of resistance between tracks and pads which could lead to corrosion of metals [119]. Similarly any water ingress to internal electrical terminals can cause short-circuits resulting in damage of equipment through over-currents. IEC Standards known as IP ratings classify how well a product or system can protect against the intrusion of solid objects, dust and water. As illustrated by Table 2 the rating is made up by two numbers; the first describing the protection against solid objects and the second describing the protection against liquids. Due to field experience, this thesis recommends that a CMS located within the nacelle of a turbine has a minimum rating of IP54 which will sufficiently protect it from dust and will protect it against splashing water which may result from any leak within the nacelle [120].

Table 2: IP Ratings Chart – IEC Standard 60529:1989

First Number	Protection Against Solid Objects	Second Number	Protection Against Liquids
0	No protection	0	No protection
1	Protected against solid objects over 50mm	1	Protected against vertically falling drops of water
2	Protected against solid objects over 12mm	2	Protected against direct sprays up to 15 degrees from vertical
3	Protected against solid objects over 2.5mm	3	Protected against direct sprays up to 60 degrees from vertical
4	Protected against solid objects over 1mm	4	Protected against sprays from all directions – limited ingress permitted
5	Protected against dust-limited ingress	5	Protected against low pressure jets of water from all directions – limited ingress permitted
6	Totally protected against dust	6	Protected against strong jets of water – limited ingress permitted
		7	Protected against the effects of temporary immersion between 15cm and 1m. Duration of test 30 minutes
		8	Protected against long periods of immersion under pressure

Weather Robustness Criteria

In order to use this robustness category within an engineering design process the following criteria have been defined:

- The components/system can function satisfactorily for prolonged periods of time when subjected to the extreme temperature fluctuations that occur within the nacelle as a result of the ambient temperature.
- The components/system can function satisfactorily for prolonged periods of time when subjected to high levels of moisture.
- The components/system must have suitable IP ratings for the nacelle environment.
- Lightning protection is in place to avoid damage from extreme over-currents.

3.1.2 Operational Robustness

As it was with weather conditions, depending on the application, engineering systems will be subjected to different challenges specific to the environment in which they have to operate. Operational factors relate to the conditions brought about by the operation of the system itself. One sector which is well aware of the challenges posed by operational conditions is the defence sector. High vibration and noise levels from military aircraft are undesirable and a great effort has been applied in reducing these effects. One way of doing this, which was proposed by the Defence Advanced Research Projects Agency, is through the use of smart materials which can allow aerodynamic and hydrodynamic flow control [121].

Selecting and designing the correct hardware is crucial when the operational conditions created by the system are challenging. One area where this is very much the case is subsea power. In an attempt to overcome the challenges work by [122] aims to standardise subsea connectors. By standardising components which meet a specified standard, the reliability of the components will be increased - a concept which could be applied to wind turbine CMS.

The rules and guidance set out in [113] for offshore systems also address the challenges of operational conditions by providing guidance on temperature ratings and the use of temperature sensors. It also gives guidance on the use of ventilation to guard against high temperatures.

As with all systems a wind turbine CMS must be robust enough to withstand the conditions applied through normal operation of the WT. A wind turbine during operation will have significant levels of vibration and tower movement. Vibration levels in particular can have a negative impact on components such as connectors as a result of fretting. Fretting occurs when two touching surfaces move relative to one another and connectors experiencing this will have high contact resistance as a result of a build-up of debris from base metal that has worn from the connector surface [123]. A high contact resistance on sensor connectors may result in poor quality signals. To avoid fretting, connectors should be used which have contact materials which have a strong ability to resist the formation of insulating films such as oxides so that metallic contact can be maintained. Common metals chosen for this characteristic include gold, copper, tin, and tin-lead [123].

As discussed previously the temperature within the nacelle of the WT can reach significant levels. This is mainly due to the heat given off by the gearbox and generator during operation. Fans are therefore required within CMS enclosures to ensure operating temperature limits of the individual components are not exceeded. These limits can be determined from manufacturer guidelines and a thermostat can be set accordingly to control the fan.

Another operational parameter which must be taken into consideration during the design of CMS is the effect of the WT yaw motion. In the case where cables have to be run from the nacelle to the base of the tower it is crucial that cables can move freely without becoming trapped or being put under tension resulting in a breakage. WT yaw systems have limit switches to prevent them from rotating too far in one direction; however even with these limits in it is essential that there is enough slack in any cables that are running from the nacelle to the base of the WT so that they are not damaged should the WT yaw to its limit.

Operational Robustness Criteria

In order to use this robustness category within an engineering design process the following criteria have been defined:

- The components/system can function satisfactorily for prolonged periods of time when subjected to the high levels of vibration that occur within the nacelle.
- The components/system can function satisfactorily for prolonged periods of time when subjected to the extreme temperature fluctuations that occur within the nacelle as a result of the heat given off by the wind turbine components, i.e. the gearbox and generator.
- The system takes into account the yaw movement of the nacelle and the effect this may have on the system.

3.1.3 Personnel Handling Robustness

The need for robustness is increased within a system when there is going to be a high level of personnel activity in and around the system. This is particularly the case for aerospace and defence applications where electrical equipment such as switches, sensors or cabling is subjected to regular usage and impacts from personnel. Manufactures such as Honeywell provide entire ranges suited to these applications [124] where the equipment is more rugged and suited to these environments. Offshore platforms are also to an extent faced with the need for robust hardware due to the cramped conditions [112] and increased likelihood of inadvertent impact from personnel.

Within military applications, the design of connectors is very important to reduce the likelihood of failure when being used in such a harsh environment. The United States of America, to ensure connectors are suitable for the military environment, set a standard which is known as the military standard often denoted “MIL-SD”, “MIL-SPEC” or “MilSpecs” [125]. Depending on the specific application within the military there are different military standards which should be used for connectors which define characteristics such as temperature limits, mating type, locking type and the type of contacts used [126].

A wind turbine CMS, over its lifetime, will be handled many times by anyone working with or around it. This will begin at the testing stage before the system is even installed. Sensor connectors will be connected and disconnected a considerable number of times during the testing process. This makes it essential that the connectors are robust enough and secured tightly enough to cables or harnesses to ensure they do not break or become loose. Following the testing stage the sensors will then be handled during installation further highlighting the need for their robustness. During any maintenance work being carried out on the WT, it is likely that sensors may be knocked or tugged and therefore must be of sufficient build and lockable to prevent inadvertent disconnection.

It is not only connectors but the CMS enclosures also which must be robust. The enclosure will be particularly vulnerable during the installation stage. Initially the system must be transported from where it is built to the WT where it is to be installed, usually by van or 4x4 vehicle. Roads or tracks up to wind farms are typically very rough making the CMS enclosure liable to knocks and bumps. Once at the WT the CMS enclosure will have to be lifted from the ground up to the nacelle by a winch, another stage where the CMS enclosure is vulnerable to mechanical shock. The main CMS enclosure should therefore be built of a strong resilient material.

Personnel Handling Robustness Criteria

In order to use this robustness category within an engineering design process the following criteria have been defined:

- Cables and connectors are of a build which allows high levels of connection and disconnection without the integrity of the connection being weakened.
- Connectors, sensors and fixings are of a build which can withstand being inadvertently knocked or tugged.
- All connections are lockable to present inadvertent disconnection.
- The main system enclosure is of a build which protects the system during transport and within the nacelle.

3.1.4 Electrical Signal Robustness

Systems engineers are well aware of the issues associated with electrical noise and the need to meet electromagnetic interference (EMI) or electromagnetic compatibility (EMC) standards. In an attempt to provide guidance to spacecraft engineers NASA produced a technical handbook specifically looking at the grounding architecture [126]. The aim of which provides a good definition of the need for electrical signal robustness: “to aid in the minimization of electromagnetic interference (EMI) and unwanted interaction between various spacecraft electronic components and/or subsystems" [126]. The document discusses different architectures for grounding and makes the point that different architectures are more suited depending on the characteristics of the application such as spacecraft size in this case.

Referring again to the military standard, work by Crawford and Ladbury [127], look at a technique for measuring the shielding effectiveness of cables and connectors as defined by MIL-STD 1344A. Military standards not only define the requirements of the system or component itself but also provide methods and techniques for assessing the standard. Crawford and Ladbury look specifically at the mode-stirred method, discussing problems encountered when using this method for measuring the shielding effectiveness.

EMI standards are particularly important within Navy vessels. Dixon [128], having discussed the challenges faced by manufacturers and engineers to meet EMI standard for naval applications, proposes that rather than all equipment having to meet the strict military standard for EMI, equipment which is particularly susceptible to the effects EMI should be better designed to be immune from the noise effects.

For accurate measurements from a wind turbine CMS, signals must be relatively free from electrical noise, something which is hard to avoid within a wind turbine nacelle. Noise, or interference, can be defined as undesirable electrical signals which distort or interfere with the desired signal [129]. Vijayaraghavan et al. [129] categorise noise sources into internal noise, which comes from the system itself, and external noise, which comes from an outside source. Internal noise may include thermal noise due to electron movement within the electrical circiuts or may be caused by imperfections in the electrical design. External noise on the otherhand may be caused by electromagnetic interference from currents in cables, radio frequency interference from radio systems radiating signals, or crosstalk which is interference from other cables close-by. The level of noise within a signal is defined by the signal to noise ratio (SNR), a measure (usually dB) of the signal strength relative to background noise.

The main likely causes of electrical noise within a signal cable are power cables [130] within the CMS enclosure itself (an internal noise), and the WT generator [131] along with its associated cables (external noise). The difficulty in keeping signal cables away from power cables and the generator is due to the lack of space within both the CMS enclosure (see Figure 15) and the WT nacelle. To aid against noise, signal cables and power cables should be kept separate within the CMS enclosure where possible. Furthermore, if a signal cable has to cross a power cable (such as one from the generator) it should cross at a 90 degree angle in order to reduce inductive coupling [130]. Another key factor in reducing noise is the use of screened or shielded cable. There are different types of screened and shielded cable but all will generally consist of twisted pairs; a theory invented by Alexander Graham Bell in order to reduce noise on cables [132]. A fully shielded cable, described as shielded foil twisted pair (S/FTP), which has a metallic shield on the outside of the bundle of twisted pairs as well as each twisted pair having its own foil screen, is now gaining popularity over the traditionally used unshielded twisted-pair (UTP) [133] due to its ability to reduce noise in cables. As important as it is to use screened cable however; it is just as important as to where the screen is connected [134] which should be to a suitable ground [133]. Care should be taken to avoid "ground-loops", a phenomenon that can occur when there is a potential difference between the ground at the sensor and the ground at the acquisition module or amplifier.

Electrical Signal Robustness Criteria

In order to use this robustness category within an engineering design process the following criteria have been defined:

- The system can acquire usable data with an acceptable signal to noise ratio.

3.1.5 System Software Robustness

Software now plays a critical role in most engineering systems. For certain applications this is often termed critical software, where a failure by the software system would result in catastrophe. To reduce the likelihood of failure it is imperative that the validation stage of software design detects any flaws. This requirement is discussed by Pingree et al. [135] in the area of spacecraft design. The growing complexity of systems and the resulting software means that it is becoming more difficult to validate and test software efficiently. Pingree et al. aim to overcome this through the use of model checking as a validation technique for assessing mission critical software.

Work presented by Shi et al. [136], in the application area of rail transportation, similarly present a method for verifying software design. In this case a software and hardware co-design flow is presented which is able to simulate hardware faults in order to test how the software reacts to these faults.

Validating software design is crucial for any system and ongoing validation throughout the design process can increase the success of the system as stated by Fritz and Shocket [137]. In designing a major weapon system for the US Navy, they found that the software for the system was far more maintainable as a result of disciplined planning and design.

The software for the wind turbine CMS is a crucial part of the system required to facilitate a number of functions, such as, setting acquisition rates, acquiring samples from sensors, formatting the sampled data and storing the data in a database of some sort. Other tasks may also include synchronising the system with other subsystems, allowing remote access via a virtual private network (VPN), or actuating control devices. Regardless of the tasks to be performed, for a system which must operate in a wind turbine, it is crucial that the software is able to carry them out indefinitely without the need for human intervention. The software used for the two CMSs discussed in this thesis was created using National Instruments Labview, so this section may bias towards increasing software robustness for this type of programming. As opposed to programming languages such as C or Java, Labview is a graphical programming language which uses a dataflow model rather than lines of sequential text code [138].

In terms of designing a program there are three characteristics of a bad design, defined by Robert Martin [139], which should be avoided:

- Rigidity - It is hard to make changes as every change affects too many other parts of the system.
- Fragility - When you make a change, unexpected parts of the system break.
- Immobility - It is hard to reuse in another application because it cannot be disentangled from the current application.

These characteristics apply to any programming language however the use of Labview makes these characteristics easier to avoid through the use of design patterns. Design patterns are basically templates that can be used as a starting point when designing a program. According to National Instruments using a design pattern will simplify the development process but more importantly increase reliability since many of the patterns are very much tried and tested [140].

According to Blume [141] there are seven aspects to consider when designing a program:

- Ease of use – the ease in which the end user operates the software and accomplishes their objectives
- Efficiency – how well the program makes use of the processor, memory, and input/output resources
- Readability – how easily the developer can comprehend the source code
- Maintainability – how easily the author or someone else can understand and modify the source code

- **Reliability** – being free from bugs and never crashing
- Simplicity – relating to the quantity of nodes and terminals that comprise an application
- Performance – how well the application completes its intended mission

It is believed that the most important aspect for a wind turbine CMS is reliability due to the remote location of wind turbines and the difficulty in gaining access to them should a fault arise. Blume states that an application is robust if it is bug free and never crashes. One way to ensure this is through the use of fundamental constructs which promote reliable applications; namely subVIs (virtual instruments) and error handling. SubVIs, which are similar to subroutines in textual based programming languages, allow modularisation by taking a portion of code which performs a specific task and enclose it in a subVI. The use of SubVIs makes it easier to test and debug code since single tasks are contained in a single subVI. By using subVIs that have been previously designed and tested reliability can be further increased.

Error handling within Labview is facilitated through the use of an error cluster which contains any information relating to an error and allows decisions to be made of what action to take depending on whether an error is present or not. Errors may be passed to a dedicated error handling loop which evaluates, reports and logs the error. Managing errors in this way may be the difference between a program crashing or continuing to operate having notified the operator of an error.

System Software Robustness Criteria

In order to use this robustness category within an engineering design process the following criteria have been defined:

- The system can operate for prolonged periods of time without human intervention
- The software is readable to allow faults to be easily identified
- The system has built-in error-handling to allow the system to continue to operate in the presence of an error

3.2 Vestas V47 Condition Monitoring System

3.2.1 System Overview

The first condition monitoring system designed and built by the University of Strathclyde was installed in a Vestas V47 wind turbine in collaboration with the Supergen Wind Consortium [76]. The wind turbine for the installation was located at Hare Hill Wind Farm in Ayrshire which was selected due to the harsh weather conditions it was exposed to.

It should be noted that this system was designed as a research tool as opposed to a commercial system that would be produced in high numbers. It was therefore known that although certain components were suitable for this application they would not be suitable for a commercial product.

The system which is also described in [77] was the first wind turbine condition monitoring system that had been built by the university. The objective of the system was to continuously acquire high frequency measurements taken from an array of sensors located on and around the wind turbine drivetrain. Since it was not known yet what fault signatures or degradation patterns were likely to be seen or what data was required to investigate these parameters it was deemed best practice to capture as much data as technically and logistically possible. It was decided that two acquisition rates would be used for capturing the data: a higher rate of 20 kHz and a lower rate of 50Hz. The sensors and corresponding acquisition rates are given in Table 3.

Table 3: Sensors and acquisition rates

Sensors sampled at 20kHz	**Sensors sampled at 50Hz**
Accelerometer – Main bearing X	PT100 Temperature – Main bearing
Accelerometer – Main bearing Y	PT100 Temperature – Gearbox
Accelerometer – Gearbox X	PT100 Temperature – Generator
Accelerometer – Gearbox Y	PT100 Temperature – Nacelle ambient
Accelerometer – Generator X	PT100 Temperature – CMS internal
Accelerometer – Generator Y	PT100 Temperature – Nacelle external ambient
Accelerometer – Nacelle base plate	Dual axis accelerometer – Tower XY movement
Voltage – Generator Phase 1	Wind Vane
Voltage – Generator Phase 2	Accelerometer
Voltage – Generator Phase 3	Humidity
Current – Generator Phase 1	Atmospheric Pressure
Current – Generator Phase 2	LSS Rotational Speed
Current – Generator Phase 3	Digital Compass

Having discussed the design and build of this system with the authors of [76] and [77] it was apparent that were a number of factors which made the design challenging, the first being the lack of space within the wind turbine nacelle which was also coupled with the requirement of high data acquisition speeds. According to the previous authors an industrial computer initially seemed like the obvious choice however; the high capital costs and limited processing power combined with the bulkiness of the enclosure soon ruled this option out. It was then decided that a standard desktop Dell Optiplex would be used as this could provide the processing capability at low cost. To make it more suitable for the nacelle environment the outer casing of the PC was removed and it was fitted into a purpose built enclosure (Figure 14). This enclosure would also house the other components that would make up the condition monitoring system.

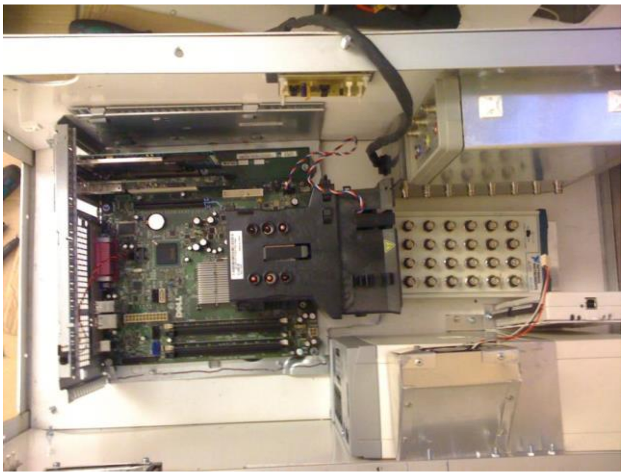

Figure 14: System enclosure unwired

The enclosure, made out of aluminium, also housed an uninterruptable power supply (UPS) which was essential to prevent sudden power loss which field experience suggests is a common occurrence within a wind turbine. The UPS used was an APC RS-800 which could provide approximately 1 hour of back-up power. This was deemed enough back-up power as power losses within a wind turbine will tend to be either very short outages i.e. seconds for a momentary power loss, or hours or even days for a grid trip or more major outage.

Figure 15: Inside main enclosure

Also, contained within the system enclosure was a switch mode power supply (SMPS). This was required to deliver a range of DC voltages to the sensors, each having different voltage input requirements.

Two essential parts of the system were the data acquisition modules. These consisted of a National Instruments USB-6218 acquisition module which was used for the low speed data acquisition and a National Instruments PCI-6251 module which was used for the high speed data acquisition. Due to the number of sensors and the requirement for two different acquisition rates (50Hz and 20 kHz) it was not possible to have a single acquisition module.

The other main components within the system enclosure were mainly focused towards signal conditioning. PT100 signal conditioner cards were used to take the signals from the PT100 temperature sensors and convert them into a voltage that could be read by the low speed data acquisition module. Frequency to voltage converters were used to convert the frequency received from the RPM and anemometer signals into voltage that the low speed acquisition module could read. A vibration sensor interface module was also located within the system enclosure and was required to obtain an accurate measurement from the accelerometers.

Separate from the main CMS enclosure is the Host PC enclosure which is located at the base of the tower. This enclosure has two main functions: to allow communications with the nacelle equipment and to receive the data from the main CMS enclosure and store it on Ethernet drives which are also located within the enclosure. Figure 16 shows the system architecture.

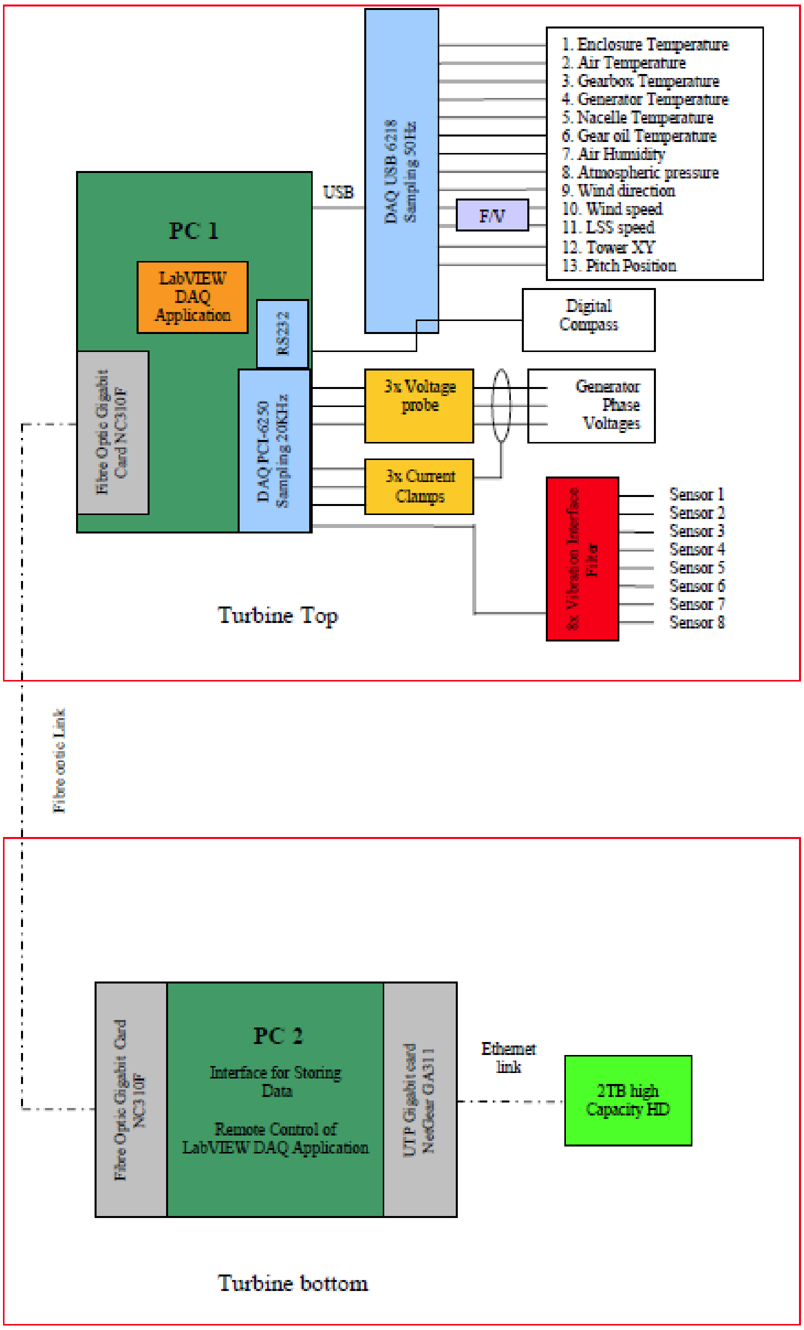

Figure 16: System Overview [76]

3.2.2 Failure Mode Effects Analysis Applied to System One

The first system was installed in the wind turbine for almost a year however was not operational for a significant proportion of that time. The length of downtime was due to system failures coupled with not being able to gain access to it due to weather restrictions. Having lost communications between the nacelle enclosure and the tower base enclosure it was decided that it was not economically viable to continue to troubleshoot issues as they arose within the wind turbine. It was therefore decided that it would be better to uninstall the system, learn from the experience and put the equipment to better use in an environment which allowed for easier CMS fault diagnosis and debugging.

The system was removed by Vestas technicians whilst they carried out routine maintenance. This avoided the need for an additional wind turbine shut down and the expense of having two Vestas technicians taken out of performing more crucial work on the wind farm.

An FMEA is a step-by-step process for identifying all possible failures within a design, product or service [142]. The purpose of carrying out the FMEA is to take actions to eliminate or reduce failures, starting with the highest priority ones [142]. Performing an FMEA is advantageous in identify high level failures however it does have its limitations in being able to include every trivial failure mode [143]. That said it is a useful tool and has been used on the first system in order to identify the causes of its failure and to allow improvements to be made to future systems based on the findings.

The first step of the FMEA is to identify the parts of the system which have failed or not functioned satisfactorily and the effects these have had. For a mechanical part this may simply be visual inspection however for an electrical part or for a larger system such as a computer this may be a lengthier process which involves testing individual pieces of electrical circuitry. It may also involve replacing known failed components or bypassing them in order to test parts of the system where the status is unknown. Having identified these parts the focus then moves onto identifying the cause of the failure or unsatisfactory performance. It may not always be possible to definitively confirm the exact cause of failure but quite often the nature of the failure leads one to the cause of the failure. For example, a cable that has snapped could be assumed to have come under too much strain. Or a corroded connector could be assumed to have been exposed to high moisture levels. Having identified the failure and the cause of the failure the aim is then to identify what can be done to prevent these failures or under performance happening again. In terms of a wind turbine CMS this usually involves selecting different component which are more suited to the task. It may also involve redesigning the architecture of the system to avoid certain problems.

This section discusses the FMEA under each of the robustness categories highlighting how the different failures of the first system allowed the five categories to be identified.

Weather Robustness

On decommissioning the CMS several factors were found that could have caused signal degradation. One of these factors was the build-up of corrosion on the pins within one of the connectors (Figure 17). It is notable that the sensor with this corrosion was located at the hub of the wind turbine where the main shaft enters the nacelle. This increased corrosion may be the result of increased moisture levels at the hub where precipitation can more easily penetrate the nacelle.

Figure 17: Connector corrosion

It was also noted that on the junction box for the weather instruments one of the connectors had signs of sparking (Figure 18). There are several explanations as to why this may have happened. One explanation and the most likely is that a build-up due to corrosion caused a short circuit between the terminals resulting in over-currents. Another explanation may be that (prior to any corrosion) moisture had seeped in, possibly due to rainfall, and this caused short circuiting between the terminals.

Figure 18: Connector sparking

An observation made when removing the weather instruments from the met mast bracket was that the mast had been struck by lightning. A lighting rod that had been welded to the met mast was no longer present and there was evidence of hot sparks from markings on the fin of the wind vane (Figure 19). It is believed that the extreme currents and heat caused by the lightning strike had caused the weld to fail and thus allow the lightning rod to break off.

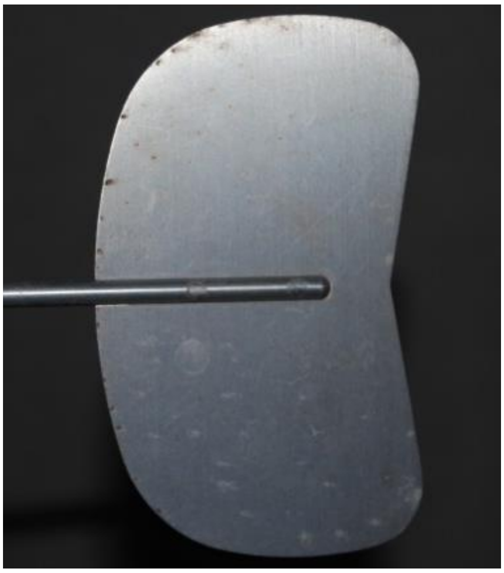

Figure 19: Wind vane following suspected lightning strike

Table 4: FMEA that identified the need for Weather Robustness

Component/ Function	Failure mode	Effects of FM	Cause of FM	Preventative action	Robustness Categories
Connector	Lost signal, Noisy data	Data loss/corruption	Corrosion from moisture ingress	Improved connector	Weather
Lightning rod	Broken lightning rod	Equipment left vulnerable to over-currents	Lightning strike, inadequate build	Stronger lightning rod, appropriate earthing	Weather

Operational Robustness

Having collected several months' worth of data it became apparent when comparing the later datasets to the initial datasets that false readings were being obtained. Initially it was not known whether the sensors themselves had failed or whether it was another issue between the sensor and data acquisition module. Upon further investigation it was found that for the PT100 temperature sensors false readings were being obtained due to loose connections entering the signal conditioning modules. These modules use spring loaded terminals to clamp the incoming wires. It is believed that high levels of vibration due to normal wind turbine operation combined with a small downward force from the weight of the wire caused these connections to work loose. It would therefore be recommended that spring loaded terminals are not used within a wind turbine nacelle environment.

On one visit to the wind turbine for data collection it was found that the entire CMS was switched off. It became apparent that there was no power from the auxiliary power supply within the wind turbine. On speaking to the wind farm site supervisor it was discovered that there had recently been a grid trip meaning that the turbine had been disconnected from the electrical grid and had been without power. This in turn had caused the circuit breakers for the auxiliary power supply within the wind turbine to trip. This meant that the UPS batteries for the CMS had been drained of all power and the CMS therefore shut down. It was not until the circuit breakers were reset that the UPS could receive power and switch the CMS back on. When a CMS is being run from an auxiliary power supply that is susceptible to power losses it is important that the power status is monitored to ensure that it can be restored as soon as possible following an outage. This issue may not always be something that can be avoided through the system design as it depends on the site's communications network but it emphasises the need for good communication between the condition monitoring team and the wind farm site supervisor.

On uninstalling the system from the wind turbine it was discovered that the fibre optic cable running between the main CMS enclosure and the Host PC had snapped. The way in which the cable was frayed suggests that the cable had snapped after coming under excessive strain as opposed to general wear and tear (Figure 20). It was therefore obvious that this break of the fibre optic cable had resulted in the loss of communications between the enclosure in the nacelle and the enclosure at the base of the tower. This was in fact the second fibre optic cable that had broken this way. It is believed that the reason for this breakage was due to a lack of slack in the cable. The fibre optic cable ran down the tower alongside the four power cables which are separated by a circular spacer (Figure 21). This spacer allows the cables to twist at the same time as the turbine yaws and prevents them from coming under excessive strain through twisting.

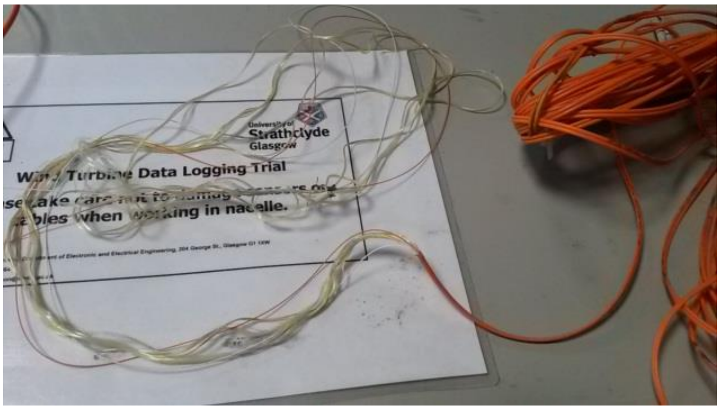

Figure 20: Frayed fibre optic cable

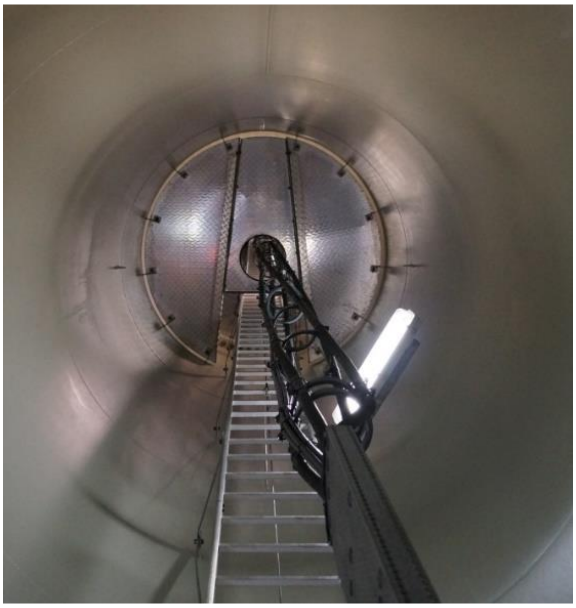

Figure 21: Wind turbine tower with power cables in centre

Fibre optic cable by its nature does not have a lot of flex in it and therefore when subjected to excessive strain will break relatively easily. To prevent the fibre optic cable from coming under excessive strain it must be installed in a way that allows it to have enough slack to prevent over straining yet be secured in the right places to avoid any one part bearing the weight of the cable below it. Where possible any new fibre optic cable being installed should follow as closely as possibly the path of the existing fibre optic cable which is used for the wind turbine control communications. The most likely location in the wind turbine for the fibre optic cable to come under excessive strain is at the yaw deck. It is therefore crucial within this area to leave sufficient slack to be taken up as the wind turbine yaws.

With the system uninstalled from the wind turbine it was brought back to the university so that it could be further tested and the reasons for its failure identified. The cabinet located at the base of the tower was tested first. This cabinet housed the Host PC which had the purpose of allowing communications with the system in the nacelle and also of receiving the data from it and storing it on an external Ethernet drive. When power was supplied to the enclosure, the PC and Ethernet drives started up as normal and all files and folders could be accessed. This enclosure is less susceptible to issues caused by the rising and falling of temperature which would be experienced by the nacelle enclosure whenever the wind turbine was shut down or started up. To protect this base cabinet from low temperature conditions a heater had been fitted inside it along with fans to draw out any moisture.

After confirming that the tower base cabinet was functioning as normal attention was moved onto the nacelle enclosure. This is the main enclosure for the CMS and houses all the crucial data acquisition hardware including a PC. On removing the enclosure cover it was found that there was a large volume of thick black dust covering everything (Figure 22).

Figure 22: Large volume of dust inside enclosure

Power was supplied to the UPS and an attempt was made to switch it on however it would not power on. The UPS supplies the power to all components of the CMS within the nacelle and therefore with it not switching on, nothing else could receive power. The battery for the UPS was replaced in an attempt to get it to switch on however it still would not, suggesting a more serious fault within the UPS.

When the CMS was designed and built a fan was fitted on top of the UPS air inlet in an attempt to increase the circulation of cool air and prevent the UPS from overheating. However it became apparent from the level of dust within the UPS that the fan had in fact caused more harm than good by drawing dust inside of it (Figure 23). Part of the reason for drawing in so much dust was due to the absence of the correct fan filter which would have prevented such a level of dust passing through. However given the excessive volume of dust, even with a filter in place, airflow would soon have been restricted as the dust saturated the filter. It is therefore believed that the dust drawn inside the UPS by the fan caused the fan to overheat, resulting in its failure. Replacing the UPS within the nacelle would have been very difficult, time consuming and economically not viable and therefore this further underpins that it was the correct decision to have the system uninstalled from the wind turbine.

Figure 23: Failed UPS due to excessive dust

To continue to test the rest of the system, the working UPS from the tower base enclosure was used to replace the faulty UPS. Power to the UPS is supplied via a connection and switch on the outside of the enclosure. The enclosure is also fused and the mains supply enters a terminal block before connecting to a slow-start relay and the UPS. On trying to switch on the UPS a clicking noise could be heard from inside and it would not switch on. This clicking noise is likely to be the automatic voltage regulator (AVR) attempting to correct the input voltage level. The UPS has an AVR boost function which uses the internal transformer to increase that voltage and an AVR trim function which uses the internal transformer to decrease the input voltage. Bypassing the enclosure external connection, switch, fuse and slow start relay stopped this clicking and allowed the UPS to switch on as normal. A voltage drop within the enclosure caused the UPS to attempt to correct the voltage however it was unable to correct it to a level that allowed it to switch on.

With the UPS now powering the rest of the system attention was turned to testing the sensors. As stated previously the signals from the sensors are acquired via two data acquisition (DAQ) modules: a high speed module acquiring at 20 kHz and a low speed module acquiring at 50Hz. On attempting to run the acquisition software it was found that the DAQ modules were not being seen by the computer. On closer inspection it was found that the DAQ modules were not powering up. To confirm this, the low speed USB DAQ module was removed and connected to another PC. Surprisingly the module powered up as normal and could be seen by the PC. On connecting it back into the CMS and after further investigation it was discovered that the reason the DAQ modules were not being seen by the CMS PC was due to an NI MAX database corruption. NI MAX is the measurement and automation explorer that allows hardware to be connected to the PC and managed. Database corruption can occur if the system is not shut down properly, which is usually caused by a power loss and in this case this corresponds to the failure of the UPS. Under normal circumstances if the UPS had simply run out of battery the system would have shut down safely prior to this. However since the UPS failed it is likely that no signal to shut down safely was received by the PC.

With the corrupted database restored the sensors could then be tested. Of the six PT100 temperature sensors it was found that only one was faulty. It was not the sensor itself that was faulty but the corresponding signal conditioning module. The cause of failure of this module is unknown however due to the other issues associated with the terminals (discussed in section 3.2.2) of this module it would not be recommended for use again for such an application.

Another notable observation was the difference between enclosures that were IP rated compared to those that were not. The enclosures that had an IP rating of 56, which prevents dust and splashing liquid, had no dust inside them at all (Figure 24) compared to those that had no IP rating (Figure 22). The reason that there were enclosures with no IP rating is because they were purpose built in-house.

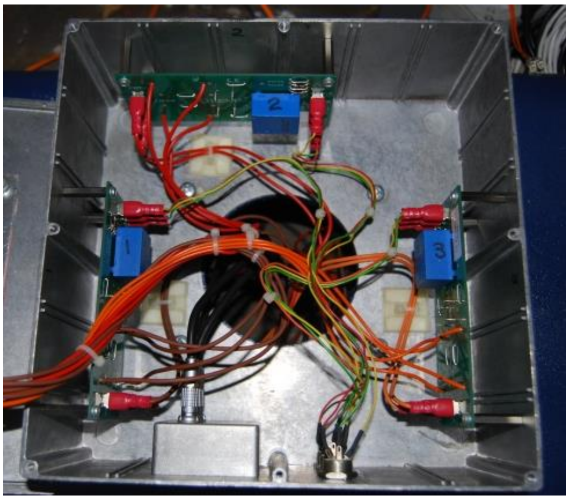

Figure 24: IP56 rated enclosure

Table 5: FMEA that identified the need for Operational Robustness

Component/ Function	***Failure mode***	***Effects of FM***	***Cause of FM***	***Preventative action***	***Robustness Categories***
PT100 Sensor	*Disconnection*	*Loss of signal*	*Vibration & spring connection*	*Improved connector*	*Operational*
Power supply	*Power loss*	*CMS shutdown*	*Grid trip*	*Better communication*	*Operational*
Uninterruptable power supply (UPS)	*Burnout*	*UPS failure, power loss.*	*Dust build up, lack of a filter*	*Use of appropriate filters*	*Operational*
Data acquisition modules	*Corruption*	*Data loss*	*Unexpected shutdown, no shutdown procedure*	*Error handling, use of shutdown procedure*	*Operational Software*
Fibre-optic cable	*Snap, break*	*Data/comms loss*	*Excess strain on cable*	*Improved routing, breakpoints*	*Operational*

Personnel Handling Robustness

Manual handling robustness is applicable at different stages of the systems' lifetime. The first stage was when the system was being tested. During this stage the sensors were connected and disconnected from the system numerous times which resulted in some fatigue to the cable where it enters the connector. It was also found that some cables were coming loose from their connectors due to the cable diameter not being a perfect fit for the connector. It is therefore essential that when cables and connectors are specified during the design that they are a suitable match for one another.

The testing stage was the only stage that resulted in issues with the system. There were no issues caused to the system by personnel at either the installation or maintenance stages. The main enclosure had been designed so that it was capable of supporting the weight of any personnel working within the wind turbine nacelle to reduce the risk of damage to equipment inside should it be stood on.

Table 6: FMEA that identified the need for Personnel Handling Robustness

Component/ Function	***Failure mode***	***Effects of FM***	***Cause of FM***	***Preventative action***	***Robustness Categories***
Connector	*Connector/ cable break*	*Signal loss*	*Poor cable/ connector match*	*Careful selection of components*	*Personnel handling*
Cable	*Snap, break*	*Signal loss*	*Repeated bending during use*	*Stronger cable /sheathing*	*Personnel handling*

Electrical Signal Robustness

As discussed in the introduction of this chapter, the wind turbine nacelle is an inherently noisy environment in terms of electrical signals. The main causes of this noise being the power cables [130] within the CMS enclosure and also the WT generator [131] along with its associated cables. The system was originally designed and built using only twisted pair cable which would not provide the level of noise cancellation that a fully shielded cable could provide. Due to the complexity of this system and the limited space within the main CMS enclosure, as can be seen from Figure 15, it was almost impossible to ensure that power cables and signal cables were kept separate. Furthermore the UPS for the CMS was also located within the main enclosure which would contribute further to noise within the signal cables.

Table 7: FMEA that identified the need for Electrical Signal Robustness

Component/ Function	***Failure mode***	***Effects of FM***	***Cause of FM***	***Preventative action***	***Robustness Categories***
Electrical signals	*Electrical noise*	*Poor signal quality*	*Cable type, cable routing*	*Shielded cable, careful routing*	*Electrical signal*

System Software Robustness

Shortly after the completion of the installation of the system and having left it acquiring data for one week it was found that the acquisition program for logging data had crashed. After some time troubleshooting the issue it was found that it had crashed due to a one of the virtual instruments (VI) (similar to a subroutine in C programming) in the software being unable to establish a serial connection with the electronic compass. Rather than the VI accepting that it could not connect to the compass and flagging an error then carrying on with the rest of the program, it became “stuck” and continued to try to connect to the compass which prevented the rest of the program from running leading to the system crashing.

This problem with the electronic compass highlighted a potential area for improvement early on. The concern was not due to the fact that the sensor was not being read but was due to the fact that the program had not handled the error well. A well designed software program should be able to handle an error in a way that allows the rest of the program to run uninterrupted rather than causing a complete system crash.

One difficulty in troubleshooting a CMS within a commercial wind turbine is the time-pressured environment brought about by the loss of revenue being accrued for every minute that the blades are not turning. Wind farm operators are very reluctant to shut down a wind turbine unless it as absolutely necessary. The wind turbine must be shut down any time access to the nacelle is required.

Troubleshooting within this time-pressured environment highlighted another area for improvement with the system software: readability. Trying to identify a problem within a large program under pressure and having not written the program was challenging. National Instrument's Labview is a graphical programming environment which prides itself on its usability and ease in which engineering problems can be implemented. This however relies on the careful use of subVIs; as discussed in the previous section, using subVIs increases the modularity of the program making it more readable and easier to debug. In this case subVIs were not used as well as they could have been which resulted in a very large and difficult to read main VI.

Table 8: FMEA that identified the need for Software Robustness

Component/ Function	***Failure mode***	***Effects of FM***	***Cause of FM***	***Preventative action***	***Robustness Categories***
Main software program	*Crash*	*Full system crash, data loss*	*No error handling*	*Error handling*	*Software*

3.3 Formulation of Engineering Design Process

Five categories of robustness have been identified through the process of carrying out an FMEA. Criteria for each category have been defined in order that the categories may be used during the design of a wind turbine CMS. Addressing the first research question of this thesis, this section will introduce and discuss the formulation of an engineering design process which integrated the categories of robustness.

An engineering design process is a formulation of a plan to aid an engineer in creating a product [144]. There are a number of variants of the steps included in the design process however the process should guide the engineer in developing a system or product which is able to perform its desired function. The design process may vary depending on the application of system or product being created. An example of this being a safety-critical system which may be defined as a system whose failure may result in danger to human life, lead to substantial economic loss, or cause extensive environmental damage [145]. A safety-critical system will require a more rigorous validation stage of the design process to significantly reduce the risk of failure.

In an attempt to aid the design process for renewable energy systems, Chandler and Matthews [146] present a solution to system design based on holistic Model Based System Engineering using SysML (System Modelling Language). By defining system interconnections decision making will be improved which will allow designs to be better tailored to the environment in which they are to operate.

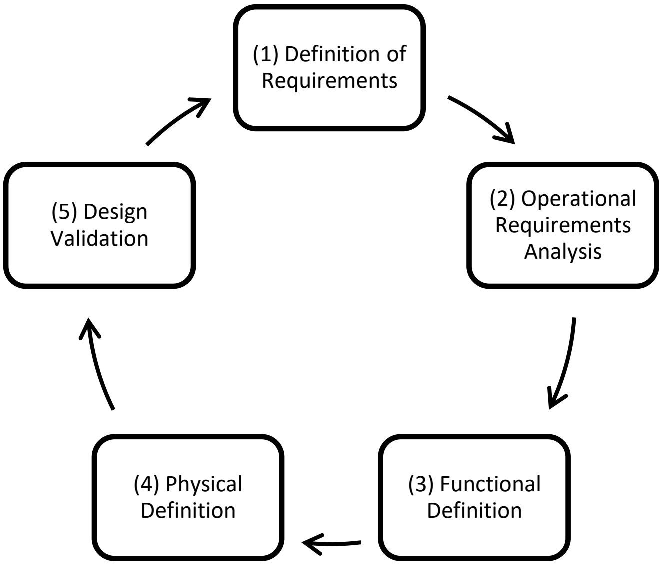

Figure 25: Systems Engineering Process Derived by Chandler and Matthews [146]. (Reproduced from [146])

Figure 25 shows the 5 stage process derived by Chandler and Matthews. This holistic approach uses all available data in order to progressively strengthen the design starting with the definition of requirements which includes data from stakeholder or market demands. The final stage of the process involves comparing system requirements with the potential system solution and it is at this stage of designing a wind turbine CMS that the five categories of robustness should be implemented.

To aid in the design of wind turbine CMS an engineering design process is presented in Figure 26. This design process incorporates the five categories of robustness which were identified through the process of an FMEA.

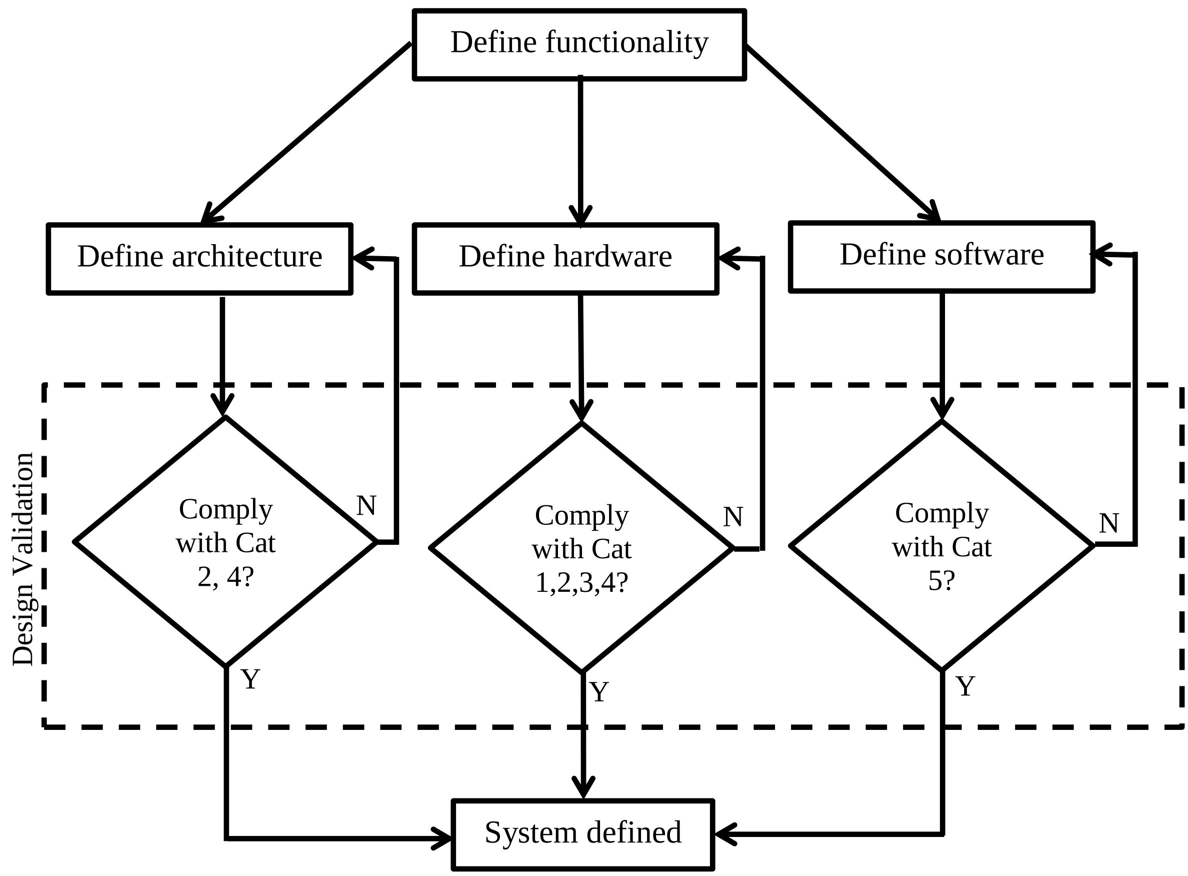

Figure 26: Design Process for implementing Robustness Categories

Defining the functionality of the system is the first step of the design process. Examples of functional requirements for a wind turbine CMS may include:

- Capture sensor data at a specified sampling rate
- Transmit acquired data to wind farm control centre for analysis
- Backup a specified volume of data locally
- Allow remote access to check system status
- Alert wind farm operator when specified thresholds are exceeded

The next stage of the design process is to define the system architecture, hardware and software design. The architecture of the system relates to the hardware layout and therefore how parts of the system are linked to other parts of the system. The hardware design identifies the actual components that are used within the system. And finally the software design is what allows each part of the system to interact in order to carry out the required functions. Although each of these areas are related to one another they are designed independently and therefore should be validated independently which is the final step of the design process.

System validation is the crucial stage which will ensure that the design specified will allow the specified functionality to be carried out satisfactorily. Not only should this stage ensure that the system can carry out the required functionality but it must also ensure that the system is designed suitably for the environment in which it has to operate. For this reason the five categories of robustness identified by the author have been integrated into this validation stage as shown in Figure 26. For the system to carry out its required functions and to operate reliably in the environment in which it has to operate:

(1) System architecture should comply with criteria for operational and electrical signal robustness
(2) System hardware should comply with criteria for weather robustness, operational, personnel handling and electrical signal robustness
(3) System software should comply with criteria for system software robustness

By using an engineering design process and more specifically the five categories of robustness within the validation stage, designers of wind turbine CMS will be able to design systems which can operate far more reliably even although they may not have any knowledge of the environmental conditions within a wind turbine nacelle. This design process addresses the first research question by aiding engineers in the design of wind turbine CMS.

3.4 New and Improved CMS for a Vestas V42 Wind Turbine

Following the experience with the first CMS system the university was involved in another collaborative project to design, build and install a CMS in a Vestas V42 wind turbine [110]. The V42 is almost identical to the V47, except for a slightly smaller generator of 600kW. The difference this time being that the system designed would have to operate in conjunction with two other systems designed and built by different project partners which added its own challenges.

3.4.1 System Overview

The system designed by the university has the task of capturing data from 29 sensors which are spread across the nacelle. These included vibration, temperature, voltage and current, and meteorological parameters. The system will also act as the master to the two other systems designed by the other project partners. This means that the system will provide a valid timestamp taken from a GPS signal, monitor the status of the UPS which supplies power to all three systems, monitor the health status of all three systems, and manage the data storage for all three systems.

One key requirement for the new system, based on the experience from the last system, was to reduce the complexity and increase robustness. The previous system required a significant number of signal processing interfaces prior to the signals entering the DAQ modules. These additional interfaces increased the complexity of the system and the number of areas in which issues could occur. The key component in the new system which allows simplification and ruggedisation is a National Instruments CompactRIO (cRIO).

The cRIO, which is a ruggedized real-time embedded industrial controller [147], was deemed to be the best option for the CMS given the acquisition requirements and the environment in which it was to operate. With the wide range of sensors to be used for acquiring data, the cRIO would allow acquisition modules to be used which the sensors could connect to directly avoiding the need for any additional pre-processing or conditioning circuitry. The requirement for high acquisition rates is achieved through the use of the built-in FPGA module. This module allows high performance data processing by implementing the program on a re-programmable silicon chip as opposed to running the program as a software application [148].

The use of a cRIO also allowed the main CMS enclosure to be significantly smaller in size. Figure 27 shows the new CMS enclosure. The cRIO can be seen located in the centre of the enclosure with its power supply sitting to its immediate right. The 24Vdc power supply for the cRIO is also used to supply power to all of the sensors. A DC-DC converter seen on the right-hand side of the enclosure is used to convert the 24Vdc in to ±12Vdc and 5Vdc required for different sensors.

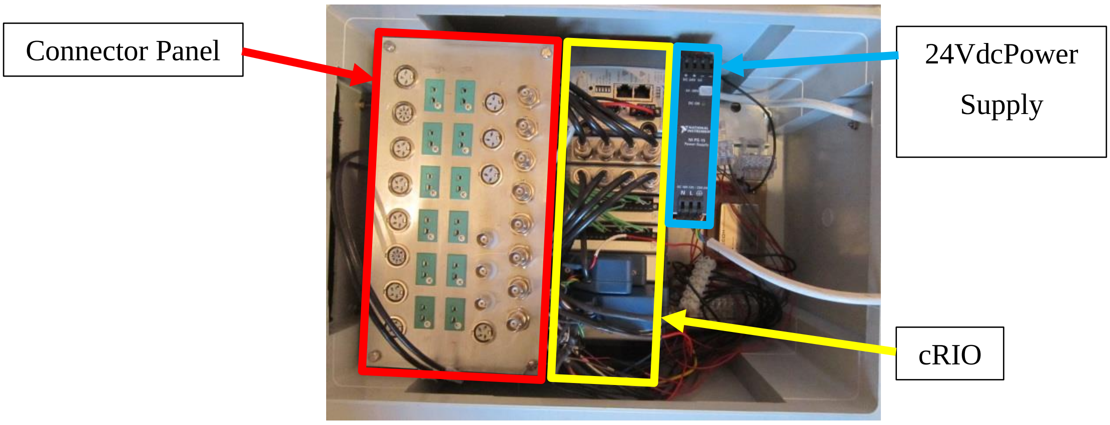

Figure 27: New CMS enclosure

3.3.2 Improvements using the five categories of robustness

Although the first CMS installed was limited in success in terms of data capture it was a very worthwhile project in terms of learning about the environment and challenges faced by a wind turbine CMS. The new system was designed and built with the five categories of robustness in mind and the improvements made are discussed in this section.

Weather Robustness

There were two main issues that occurred as a result of the weather on the system:

- Corrosion on connectors
- Lightning strike

The main enclosure for the new system was selected to have an IP rating of 66 which means it is completely dust tight and capable of withstanding powerful water jets (see Table 2). Although it is unlikely that the system will be exposed to powerful jets of water there is a chance that it could be exposed to an oil leak or precipitation dripping from the nacelle roof.

As can be seen from Figure 27 the connector panel was brought inside of the main enclosure which will reduce the chances of moisture entering at the connectors which could result in corrosion. The sensor cables enter the enclosure via a brushed entry system which although reduces the enclosure's ability to prevent water ingress from powerful jets it will still prevent large volumes of dust entering. To prevent any moisture ingress through drips from above a rubber seal with a flap which extends over the cable entrance was fitted to the enclosure.

As discussed in the previous section the lightning rod that was attached to the met mast was knocked off by a lightning strike. It was decided that for the new system it would be better not to have a lightning rod at all on the met mast. The reason for this was that unless the rod was fully capable of absorbing the full lightning strike and diverting the extreme current into the wind turbine's lightning system, it would do more harm than good by attracting a lightning strike. Since there was already a lightning rod on the wind turbine's own existing met mast, which sits higher than the new met mast, it would be better to allow it to absorb the lightning strike and direct the over-currents down the wind turbine's lightning protection system. Another precaution taken with regards to lightning strikes is that every part of the CMS equipment is well grounded so that any over-currents that they are exposed to can find an easy path to ground in order to prevent any damage to crucial parts of the system.

Operational Robustness

There were two main issues that occurred as a result of normal wind turbine operation on the system:

- Overheating due to excessive dust intake
- Snapped fibre optic cable

By locating the UPS in a separate enclosure, the main CMS enclosure has no requirement for cooling which reduces the risk of excess dust being drawn in by fans. Mounting the UPS in a separate enclosure means that the main CMS enclosure can be smaller, lighter and have reduced electrical noise. Having an additional enclosure for the UPS means that it can also be used for the networking equipment such as the network switch. The enclosure now housing the UPS is IP65 rated and has fans built into it with appropriate filters to reduce the level of dust that could enter and risk over-heating. Each of the systems are also fitted with dehumidifiers to reduce moisture levels inside of them.

As stated previously the fibre optic cable was susceptible to coming under excessive strain causing it to break and therefore prevent data from being sent to the Ethernet data storage drives. To reduce this risk the routing and fixing of the cable was revised. Break points have been added to the fibre optic cable by way of patch cables and couplers. These break points have been added at the locations most susceptible excessive strain. If the fibre optic cable comes under excessive strain the coupler will allow the main cable and patch cable to separate and avoid a breakage. In addition to the break point a spare fibre optic cable was installed but not connected. If the one cable is damaged then the replacement can be simply connected in, again reducing data loss.

To reduce the risk of data loss a 2TB USB drive has been incorporated into the main CMS enclosure and connected directly to the cRIO. In the case that the fibre optic cable is damaged as it was previously, the USB hard drive will allow approximately one months’ worth of data to be stored locally, significantly reducing the risk of losing valuable sensor data.

A final addition to the new system, to further increase reliability, is the use of three NAS (network attached storage) drives. Data from the three systems is able to write directly to these NAS drives with no dependency on the Host PC. Although the Host PC directs the three systems to write to a specific drive, they would still be able to write to the drives should the Host PC fail. All three systems in the nacelle will write to the one selected NAS drive. Once this drive is nearing capacity they will all simultaneously begin writing to the newly selected drive. Should all three drives reach capacity prior to being replaced each of the systems has the capability to store their own data locally until an empty NAS drive is installed.

Manual Handling Robustness

There were two main factors which, although they did not cause any issues, were identified as potential areas in which a fault or failure could occur.

- Connectors on the connector panel
- Wear and tear of sensor cables running across the nacelle

In Figure 27 the connector panel can be seen on the left hand side of the main CMS enclosure. On the previous system the connector panel was mounted on the outside of the enclosure. This however meant that the sensor connectors were susceptible to being knocked off or damaged whilst maintenance work was being carried out in the nacelle. For this reason it was decided that it would increase system robustness to have the connector panel inside the enclosure. The sensor connectors enter the enclosure via a brushed opening which allows the connectors to pass through but reduces the exposed area in which dust may enter.

To reduce the risk of sensor cables being damaged within the nacelle all cables have been run inside protective conduit. This will protect cables from general wear and tear which may result from any work carried out within the nacelle due to the limited space.

Electrical Signal Robustness

Two areas in which noise reduction could be improved were identified:

- Noise from the UPS
- Noise from power supplies within the CMS enclosure

The main change to the CMS to reduce electrical noise on the monitored signals was to keep the UPS separate from the main CMS enclosure. To do this a separate enclosure was used which would house the UPS and the network equipment. The UPS can introduce a significant amount of noise due to the mains supplies in and out of it. By having it separate it meant that only one mains cable had to enter the main CMS enclosure to power the 24V power supply. To further reduce electrical noise in the signals the connector panel was mounted as far away as possible from the power supplies – this is difficult given the limited space available. As with the previous system shielded cables were used throughout the system to reduce noise levels as far as possible.

System Software Robustness

System software robustness was identified as a key area for improvement in the new CMS. There were two main requirements on the new software:

- Ability to handle errors
- Ability to debug more easily

The software for the new CMS can be split into three parts. The first is the software for the Host PC, located at the bottom of the tower, which is used to communicate with the systems in the nacelle. This program will tell the three systems in the nacelle which NAS drive they should be writing data to. It will also monitor the health of each of the systems by continuously receiving a health status pulse from each of them as well as any other information about errors in any of the systems. It can then send out a status email detailing the state of each system and if any errors have occurred. As well as monitoring the health of the systems in the nacelle it will also monitor the status and volume of data on the NAS drives. Although the Host PC is required to send out key information, the systems in the nacelle are not wholly reliant on it and are still able to function should communications with the Host PC be lost.

The second part of software is the FPGA (Field-Programmable Gate Array) program. Programming an FPGA is slightly different from other programming in that it is all based on digital logic. This logic is applied on the FPGA by re-wiring the chip itself which is why such high processing speeds can be achieved. Within the FPGA program there are two main loops: one to acquire the high speed data at 10.24 kHz and the other to acquire low speed data at 50Hz. These loops are initiated and triggered to begin acquiring data by the real-time program on the cRIO controller. Within each loop data is read from the sensors, combined into an array, converted into an appropriate data type and loaded into a direct memory access (DMA) first in first out (FIFO) queue, which can be read out by the cRIO controller's real-time application.

The third and main part of the software is the real-time application that runs on the cRIO controller. This application performs a number of key tasks including: defining system configuration, interfacing to the FPGA to acquire data, handling data logging, and communicating with the Host PC. The application is designed so that it can run for long periods of time without any human interaction. The main configuration for the system is written to a text file and stored on the cRIO to be read at the initialisation stage.

A key feature in the new system software is the built-in error handling. Should any error occur, such as an FPGA overrun, an error will be flagged and sent to the Host PC. The program will then carry on acquiring data as normal and not be brought to a halt by this error. The system also handles errors that are not related to the software. For example, if communications are lost with the Host PC (possibly due to fibre optic damage) then the cRIO will attempt to find a NAS drive to write to for itself. If a NAS drive cannot be found then it will begin writing data to the local USB drive.

The new software was designed to be easy to read and allow bugs to be easily identified. This was done through the careful use of subVIs (virtual instruments) which increased the program's modularity. By careful use of subVIs, the main VI, shown in Figure 28, gives a very high level view and only by entering each subVI will a lower level view be obtained. This makes the program more readable for a user who may not fully know the workings of the system.

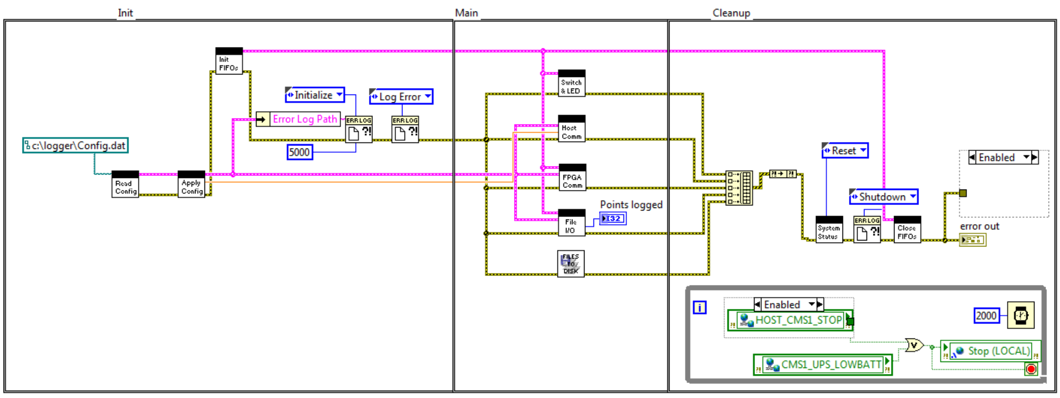

Figure 28: Main VI for new CMS

3.5 Research Methods for Undertaking Work on Commercial Wind Turbines

Obtaining operational data from commercial wind turbines for research purposes is difficult due to the commercial sensitivity surrounding wind turbine failures. The work discussed in this chapter involving the installation of two CMS in commercial wind turbines not only allowed invaluable data to be captured but also provided an opportunity to gain an insight into the challenges faced when working with commercial wind turbines on an operational wind farm for research purposes. The aim of this section is therefore to document the challenges involved and to provide advice to anyone who may want to carry out research on an operational wind turbine or farm.

The most significant factor that makes working with an operational wind turbine challenging is availability. There are different senses of this term availability:

1. Availability of a weather window which allows work to be carried out on the wind turbine
2. Availability of a weather window which the wind farm operator will be willing to lose the wind turbine's generation capacity.
3. Availability of road/track access to the wind turbine/farm
4. Availability of wind turbine technicians to accompany the person carrying out the work

Each of the availability's given above are effected by weather conditions which is what makes working with an operation wind turbine so challenging. To carry out work on a wind turbine and to climb into the nacelle to work the wind speed must be below a specified value which, given that wind turbines are situated in locations chosen for their high wind speeds, creates a challenge. There also must not be a high risk of lightning strikes during the period work is to be carried out.

It may be that the wind speed is low enough to allow work to be carried out within the wind turbine however it also relies on the wind farm operator being willing to shut down the wind turbine. If there has been a long period of low wind speeds the operator may not be willing to lose the revenue lost through shutting down the wind turbine whilst work is carried out.

Given that a weather window is available which allows work to be carried out in the wind turbine and the wind farm operator is willing to allow the wind turbine to be shut down, it must then be possible to access the wind turbine by driving on the wind farm road. Wind farms are often located at the top of hills which experience greater snowfall and wind turbines will often become inaccessible because there is too much snow on the roads. When these roads are miles long it is often not economically feasible to have them cleared. Clearing them with a machine also results in damage to the road resulting in more costly repairs.

To carry out any work within a wind turbine an authorised technician must be present. However when there are limited weather windows to carry out maintenance and repair work to wind turbines, technicians will have a large work list trying to keep as many wind turbines on the windfarm operating as possible. Work on research projects may therefore not always be of highest priority.

Although the challenges brought about by the reliance on suitable weather windows cannot be avoided they must be taken into consideration when planning work on an operational wind turbine. The following advice is given to aid in planning this work:

1. Avoid key/major work during winter months when the weather is unpredictable and there are long periods of no access the wind farm
2. Be prepared to go to work at very short notice – weather windows often become available at short notice
3. When a weather window becomes available it is essential to be well prepared so that as much work as possible can be done in a short time
4. Wind turbine downtime is an expense to the operator, therefore the operator will push to keep downtime to a minimum which add pressure in carrying out the work
5. Test, test and test again. If a system is to be installed in the wind turbine perform as much rigorous testing in as realistic conditions as is possible prior to the installation. It is extremely difficult and costly to fault find in a commercial wind turbine.
6. Prepare for all eventualities. Be prepared for things breaking, i.e. sensors, cables, brackets. Have spare hardware and plenty consumables. Take every possible tool that might be needed. Hardware stores aren't often located near a wind farm.

3.6 Conclusion

The wind turbine nacelle is a particularly harsh environment, more so that one would initially suspect. This is due to a number of factors including high vibration levels, high volumes of dust, extreme temperature fluctuations and also the risk of damage through personnel working within the nacelle. Through careful design and consideration of key factors it should be possible to design a reliably robust CMS that is capable of operating for long periods of time without human intervention whilst providing the wind farm operator with an accurate description of the state of the wind turbine's health.

Addressing the first research question of this these, five categories of robustness were introduced in this chapter: weather robustness, operational robustness, personnel handling robustness, signal robustness, and software robustness. These categories of robustness were identified through the process of an FMEA and highlight where there is a need for careful design of each aspect of a wind turbine CMS to ensure that it is not vulnerable due to the environment in which it has to operate. Through the introduction of the first CMS, which was designed without using a design process and the categories of robustness, it was evident that not considering these crucial factors lead to a system being built that was unable to operate reliably in a wind turbine nacelle. The detrimental effects included connector corrosion, overheating, and noisy signals.

The second system introduced in this chapter, which was designed using the engineering design process which incorporates the five categories of robustness, has at the time of writing, been operating reliably for 18 months and providing data that can be analysed to assess the condition of the wind turbine. Key improvements made using the categories of robustness as summarised in Table 9 included: simplification of the main CMS enclosure through the use of a ruggedized industrial controller, the use of IP rated enclosures, de-noising of signal cables through the separation of the UPS and power cables, and careful design of the software that incorporates error handling.

Table 9: Summary of improvements from System 1 to System 2

System 1	System 2
Complex design with many components	Simplified design by using cRIO
One large main enclosure	Separate enclosure for UPS and network equipment
Signal and power cables grouped together	Signal cables and power cables separated
Single unshielded fibre-optic	Shielded fibre-optic cable & spare installed
Poorly matched cable & connectors	Well matched cable & connectors
Very large unreadable software program	Simple high level main program
No error handling in software	Error handling in software
Single data storage device	3 Main storage devices and local USB backup storage

The process of installing a CMS in an operational commercial wind turbine is very challenging due to a number of factors but mainly as a result of the reliance on suitable weather windows. In addition to giving designers of CMS guidance in the design of these systems themselves this chapter also gave advice for those planning to carry out research projects with commercial wind turbines. Highlighting that meticulous preparation is key to a successful project.

4 Erroneous Data handling Techniques

4.1 Overview

One significant deterrent to wind turbine operators deploying condition monitoring systems throughout their fleet is the problems associated with false alarms. The occurrence of a false alarm may lead the operator to take unnecessary actions resulting in additional expenditure that was not required. A false alarm could also result in the wind turbine being shut down and out of service for a period of time unnecessarily until the cause of the alarm can be investigated by an on-site technician. False alarms may be caused by a sensor or software malfunction and are corrected by replacing a sensor or reconfiguring software.

This section of work presents a novel technique which is able to detect erroneous data and remove it. The technique presented addresses research questions two and three of this thesis. Firstly by showing how erroneous data can be detected in order to reduce false alarms and secondly how this data can be removed to allow the remaining healthy data to be used for condition monitoring and fault detection.

It is essential to be able to differentiate between erroneous data i.e. data which does not truly represent the parameter that is being monitored, and data that may look erroneous but is actually a fault or extreme condition within the wind turbine. Although the application in this section focuses on the removal of erroneous data outputted by an RPM sensor, the same principles may apply for removing data from any dataset where the normal operation of the machine is understood. By using multiple parameters and principles of operation for a wind turbine, confidence can be gained that the data identified as being erroneous is in fact erroneous. An example of a principle of operation could be a wind turbine's physical inability to produce rated power at a low rotational speed thus signifying an erroneous reading. By identifying true erroneous data, techniques can then be used to filter it out from the dataset so that the remaining healthy data can still be used. By reducing the number of false alarms wind farm operators will have a greater confidence in the ability of condition monitoring systems to accurately detect true faults which will increase the uptake of the use of condition monitoring systems and ultimately reduce the operating costs of wind turbines.

The technique described in this section is based on the relationship between rotor speed and both wind speed and generator output current. Using the relationship between parameters is a useful way of analysing data since certain parameters will always be directly related. The most common relationship used in wind turbine monitoring is the relationship between the power output and the wind speed known as the wind turbine's power curve. Power curves, which are provided by manufacturers, can be used for planning, forecasting, performance monitoring and control of wind turbines [149]. A typical power curve (Figure 29 [150]) can be split into 4 principle regions: below cut-in wind speed where the wind speed is too low to generate power efficiently, between cut-in and rated wind speed where the wind turbine is increasing its power output as the wind speed increases, above rated wind speed where the rotational speed of the wind turbine is controlled to maintain the rated power output, and finally above cut-out speed where the wind turbine is shut down to protect it against high wind speeds.

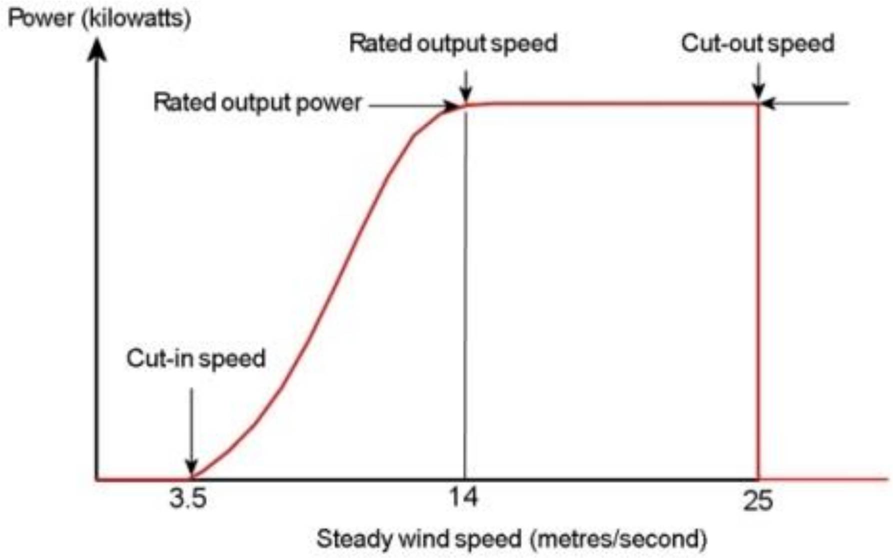

Figure 29: Typical wind turbine power curve [150]

The power curves supplied by the OEM will have been created following standard IEC 61400 [151] which indicates how to measure wind speed and power; however these power curves can be difficult to use for direct comparisons with operational wind turbines of differing ages. Manufacturer's power curves will have been developed under standard conditions using specific methods. Given that each wind turbine site can be very different in terms of terrain, wind and atmospheric conditions mean it is unlikely that the power curve for a given operational wind turbine will match that of the manufacturer. Given the necessity for an accurate power curve there have been a number of studies carried out to improve the modelling of wind turbine power curves.

The development of power curves is often categorised into parametric and non-parametric techniques. Parametric techniques are built on a set of mathematical expressions where the parameters required for the expression are found using advanced algorithms [152]. Non-parametric techniques on the other hand attempt to find the relationship between wind speed and power output with no assumption of the functional form of any distribution [149]. An algorithm developed by Thapar et al. [153] allows comparisons to be made on the output of wind turbines which have been modelled on the concept of linear variation of power, Weibull parameters, the method of least squares and cubic spline interpolation. Summarising the output of their analysis using this algorithm they state that modelling methods in which the actual power curve of an individual wind turbine is used for developing characteristic equations, by utilising various curve fitting techniques, accurately predicts the power output of the wind turbine. In particular they find that the method of least squares [154] and cubic spline interpolation [155] replicate the output of the wind turbine most accurately. The accuracy of the method of least squares was also confirmed by Kusiak et al in [156] who found that the model developed using the least squares method outperformed that which was developed using the maximum likelihood [155] approach.

Carrillo et al. [157] also review commonly used equations for modelling power curves by analysing their ability to approximate the manufacturer's power curve. The equations compared consisted of polynomial, exponential, cubic and approximate cubic power curve. The result of their analysis showed that exponential and cubic equations provided the best approximation when the coefficient of determination and the error in energy density are taken into consideration. They also concluded that the polynomial provided the worst results in terms of fitting due to its sensitivity to the values of parameters such as the wind speed.

One point apparent from reviewing the literature is that each wind turbine's power curve will be quite different from other power curves even for the same model of wind turbine experiencing similar wind conditions. Another point to note was that all analysis carried out was based on variable speed wind turbines whereas the sensor in the application discussed below is situated in a fixed speed turbine. While the power curve will not be any different for a fixed speed wind turbine, this application uses the relationship between generator current output and rotor speed which will differ significantly from that of a variable speed wind turbine. So although there are similarities to modelling power curves, this application focusses on modelling the relationship between rotor speed and generator current for which there is very little literature.

4.2 False Data Detection Model for Rotor Speed Sensor

A Hall-Effect Sensor (shown in Figure 30) was used as part of the condition monitoring system to measure the rotational speed of the low speed shaft. To obtain the rotational speed in revolutions per minute the Hall-Effect sensor was used to detect and count the holes on the rotor locking disc. By measuring the time between holes the rotational speed in revolutions per minute could be calculated.

Figure 30: Hall-Effect Sensor for measuring rotational speed

On analysing the data from the CMS it was apparent that false low rotational speed measurements were being captured. Given that the false measurements were always low as opposed to high, it indicated that the reason for the false measurements was due to the Hall-effect sensor not detecting every hole on the locking disc. The sensor was mounted using a clamp which, given the high level of vibration within the wind turbine nacelle, means it could be possible for the sensor position to move if the clamp was not secured tightly enough. For an accurate measurement this sensor must be positioned with millimetre accuracy [158]. Looking at data from different periods of time shows that the sensor moves in and out of good positions. Figure 31, which shows RPM plotted against current, shows a period where the sensor was outputting very high levels of erroneous data due to a bad position of the sensor. Figure 32 however shows a period of time where the position of the sensor is obviously in a far better position resulting in significantly less erroneous data.

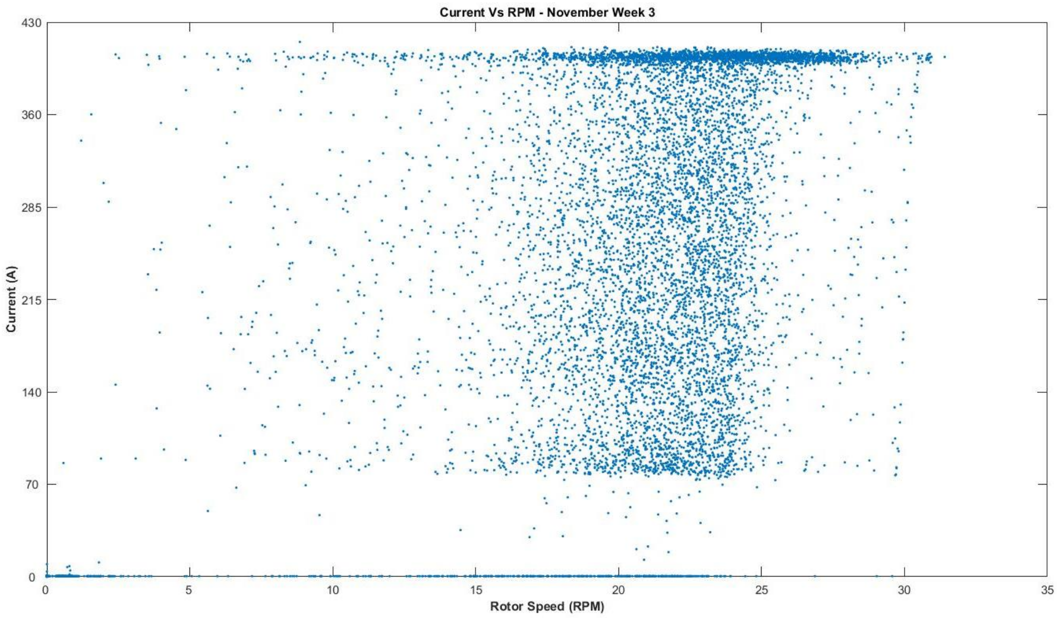

Figure 31: RPM Vs Generator Current for November Week 3

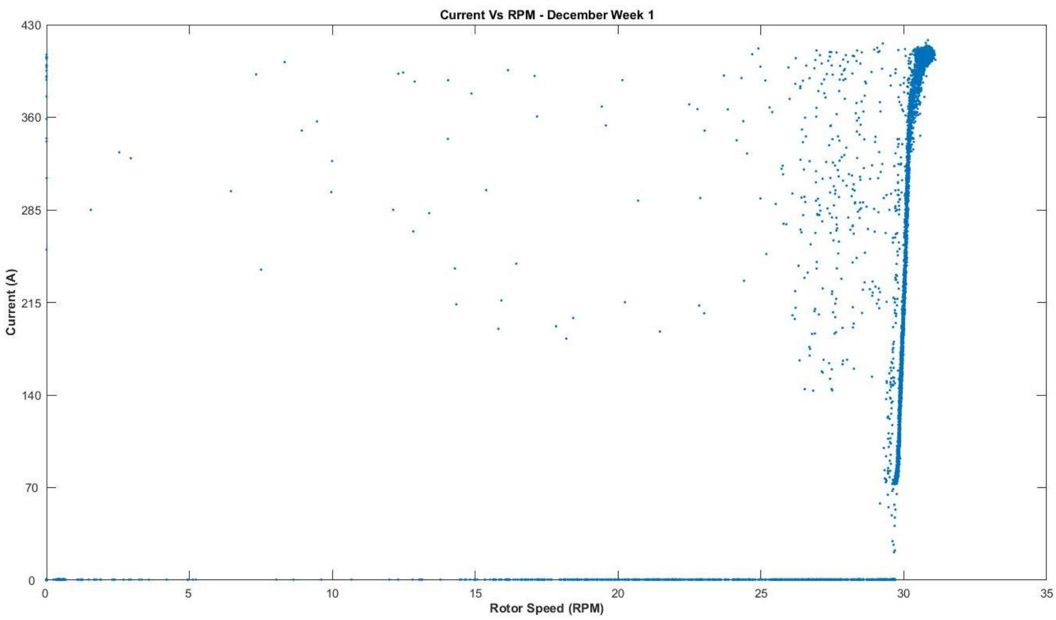

Figure 32: RPM Vs Generator Current for December Week 1

Although some of the datasets are very poor with a large number of false measurements, there is a clear difference between the healthy and false measurements when plotting RPM against generator RMS current. This has aided in the development of a normal behaviour model which was required so that thresholds could be set for detecting erroneous data. The process of how this model was developed is shown in Figure 33.

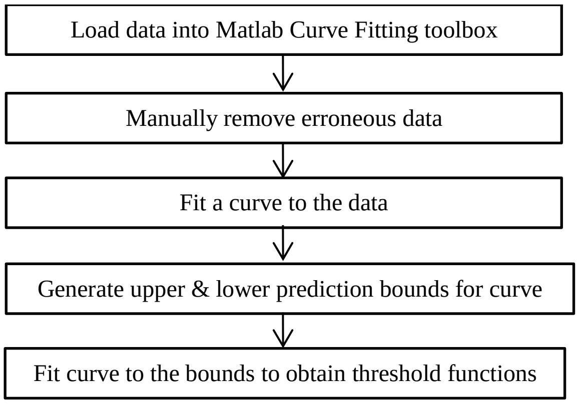

Figure 33: Flowchart for developing Error Detection model

To begin with a dataset was chosen for a period of time which had the least amount of erroneous data in it and this was loaded into the Matlab Curve Fitting toolbox. Matlab's Curve Fitting toolbox allowed different types of curves to be fitted using the least squares method (identified as the most accurate method in the literature) and the goodness of fits statistics, as shown in Table 10, compared. Based on these statistics a 4th order Gaussian curve was deemed the best curve to use due to its goodness of fit and its simplicity over some of the alternatives.

Table 10: Comparison of goodness of fit for fitted curves

Curves	SSE	R^2	Adjusted R^2	RMSE
Gaussian 4th Order	4.577E+07	0.9824	0.9822	70.97
Gaussian 5th Order	4.622E+07	0.9823	0.9822	70.98
Gaussian 6th Order	4.619E+07	0.9823	0.9824	70.63
Gaussian 7th Order	4.681E+07	0.982	0.982	71.46
Fourier 3 Terms	4.859E+07	0.9813	0.9813	72.76
Fourier 4 Terms	4.652E+07	0.9821	0.9821	71.2
Fourier 5 Terms	4.606E+07	0.9823	0.9823	70.85
Polynomial 5th Degree	6.187E+07	0.9762	0.9762	82.09
Polynomial 6th Degree	4.884E+07	0.9812	0.9812	72.94
Polynomial 7th Degree	4.859E+07	0.9813	0.9813	72.76

Prior to fitting the curve, clear outliers were manually excluded from the fitting so that it had no impact on the fitted curve. Having fitted the Gaussian curve to the data, upper and lower confidence bounds of response values of the data were then added. The bounds are calculated using $C = b \pm t\sqrt{S}$ where b are the coefficients produced by the fit, t depends on the confidence level, and S is a vector of the diagonal elements from the estimated covariance matrix of the coefficient estimates. These bounds can be added with differing confidence levels. It was found that by setting the confidence level to 99% a threshold was obtained which would be at the correct level for removing erroneous data since it excluded all the data points that were eliminated as clear outliers and included all the remaining data points. To use these prediction bounds as thresholds a function would be required for each. To obtain the function a curve was fitted to both the upper and lower prediction bounds – once again a Gaussian curve was used for the fitting. Figure 34 shows the model with the curve fitted to the data shown by the purple/pink line and the upper and lower thresholds shown by the red lines.

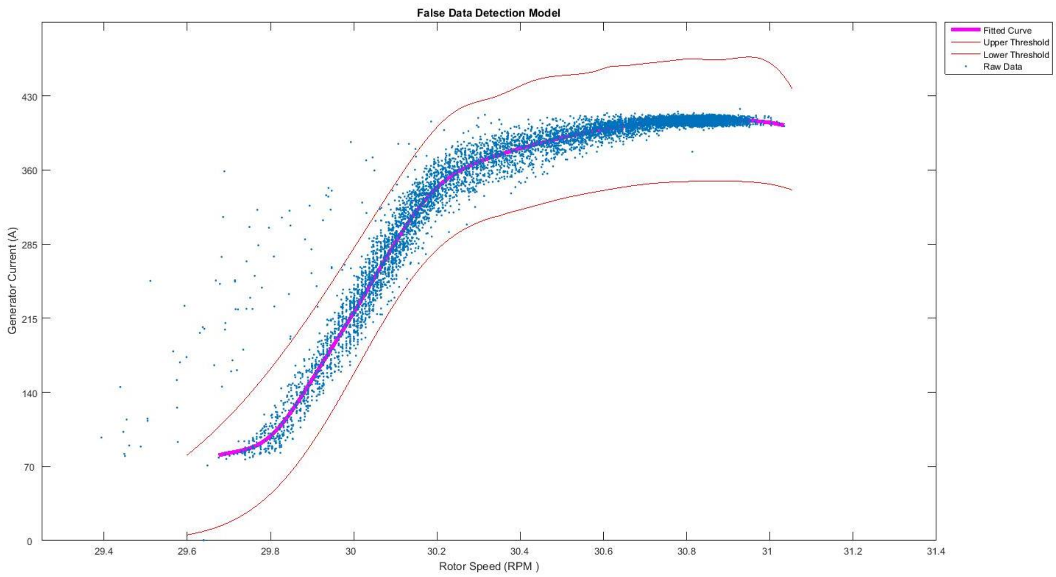

Figure 34: False Data Detection Model

Having obtained upper and lower thresholds levels for detecting erroneous data the next stage was to remove this data from the dataset. Initially the erroneous data was removed in one stage as is shown in the top box of Figure 35. Within this stage the dataset which is to have the erroneous data removed is imported into Matlab. The RPM data which contains the erroneous values along with the corresponding generator current data are taken in one data point at a time. The RPM value is used along with the functions for the thresholds to find a "healthy" range for the current value. If the current does not lie within this range then the RPM value is deemed erroneous. In addition to exceeding the thresholds to be deemed erroneous the value of the current must also be greater than 1 amp. This is because during normal operation the wind turbine can rotate between 0 and 29 RPM before it starts generating any power; therefore without this additional rule all data generated whilst the turbine is not generating power would be deemed erroneous. Having determined whether the data is erroneous or not it is then placed in either a "filtered data" array or a "false data" array.

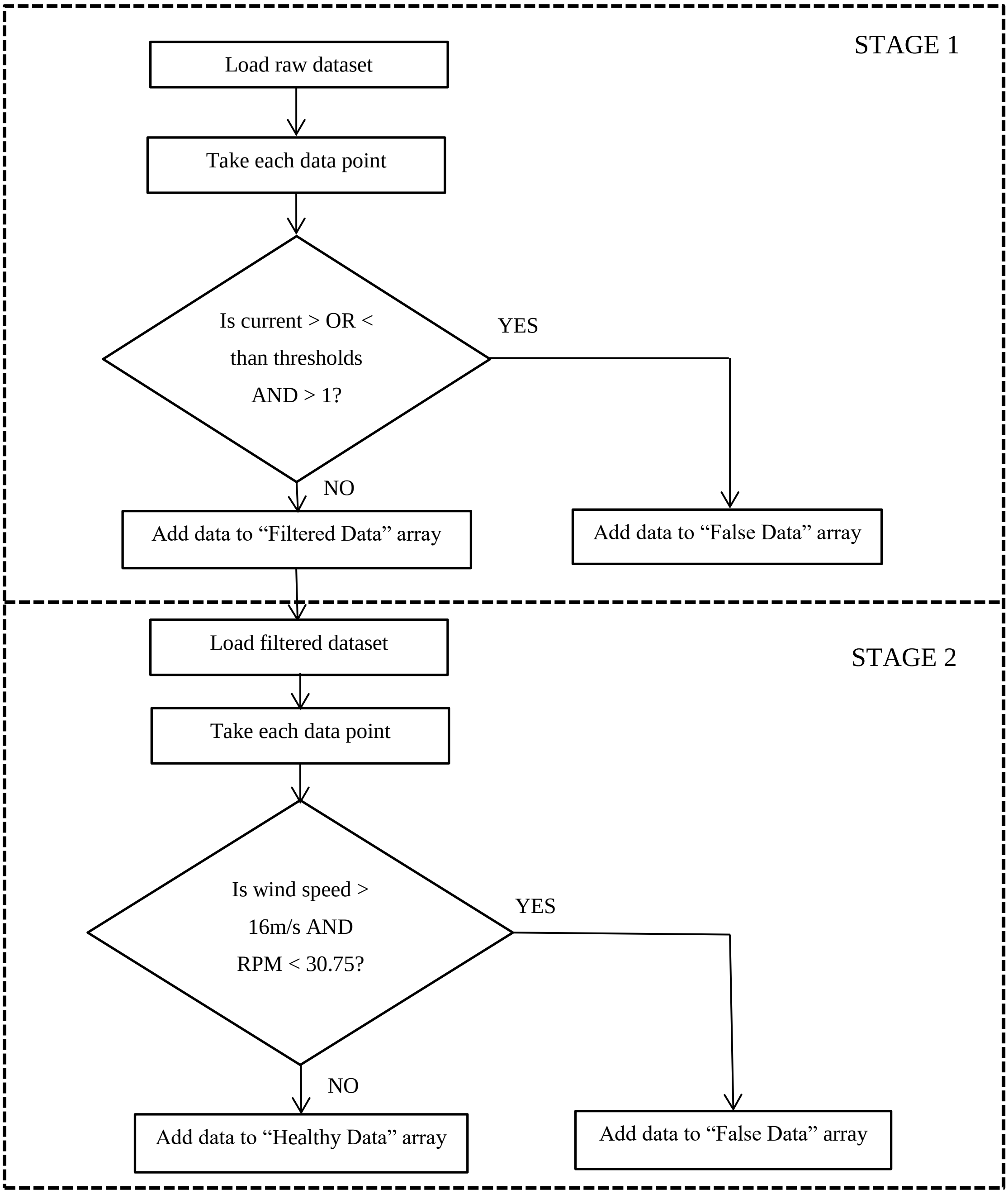

Figure 35: Flowchart showing process of removing erroneous data

After applying the model to the data initial observations seemed to show that all false data was being detected and effectively filtered out as shown in Figure 36. However when the RPM data was plotted against the corresponding wind speed measurements as shown in Figure 37 it could be seen that false data (circled) was being missed by the initial model.

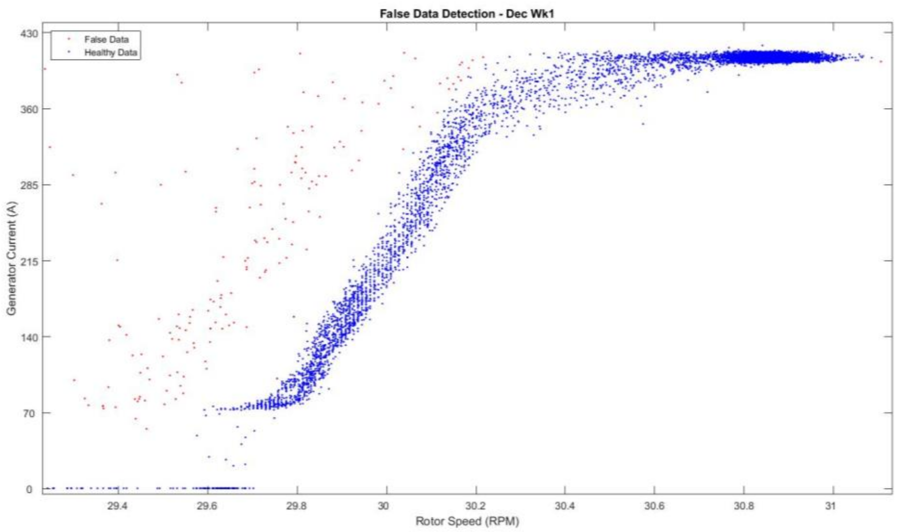

Figure 36: One Stage Erroneous Data Detection Model - Current Vs RPM

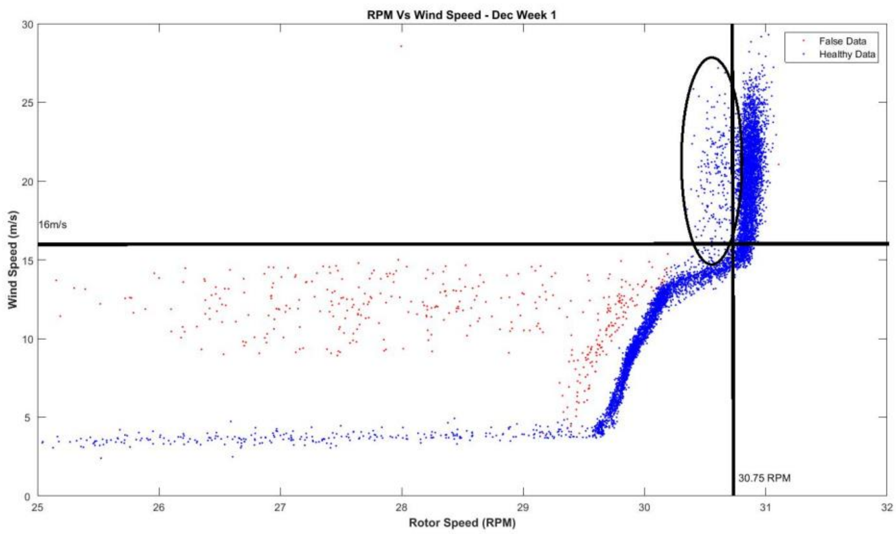

Figure 37: Filtered RPM Vs Wind Speed Data

The data being missed was erroneous low signals that were occurring when the wind turbine was operating at rated power. A second stage was added to the initial model shown in the lower box of Figure 35 that would use the RPM data filtered in stage 1 along with wind speed in order to remove the false data. This erroneous data was captured by the detection model by adding two linear thresholds to the Wind Speed Vs RPM plot as shown by the black lines in Figure 37 at a wind speed of 16m/s and rotational speed of 30.75 RPM. Therefore any data point that had a wind speed greater than 16m/s and a rotational speed of less than 30.75 RPM will be classed as erroneous.

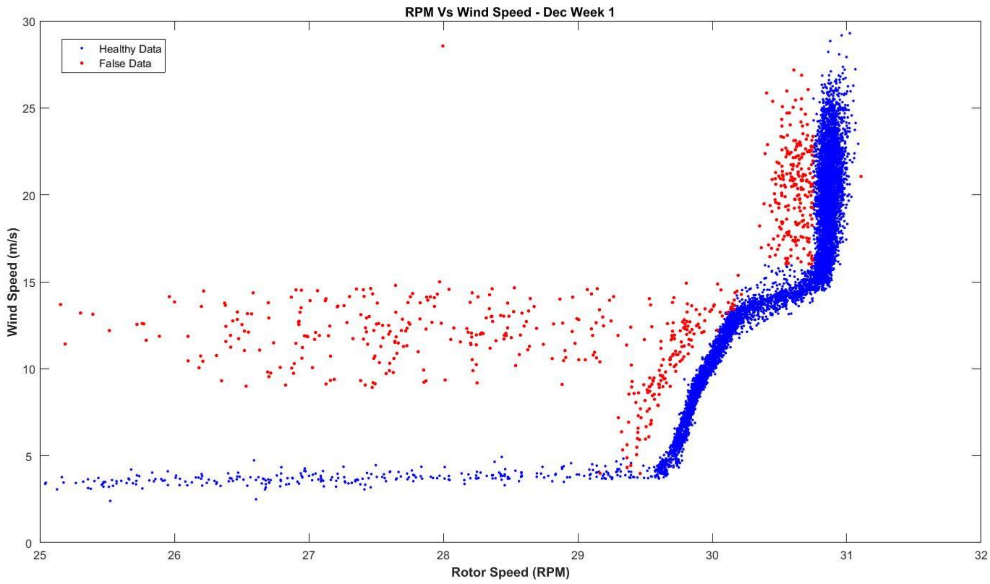

Figure 38: Two Stage False Data Detection: RPM Vs Wind Speed

Figure 38 shows the result of adding a 2nd stage to the false data detection model. It can be seen that false data in the region where the wind speed is above 16m/s is now detected and filtered. There is a small region around 15m/s where higher-variance data is not filtered by the model. In this region the wind turbine will be beginning to pitch its blades to maintain rated power. Due to the act of pitching the blades there is likely to be more variability in the rotational speed and so the data is not filtered in this region due to the risk of removing healthy data. By plotting current against RPM again as shown in Figure 39 it can now be seen that a significant level of erroneous data is now detected at rated power (2850 Amps) which was not so apparent following the first stage of the model.

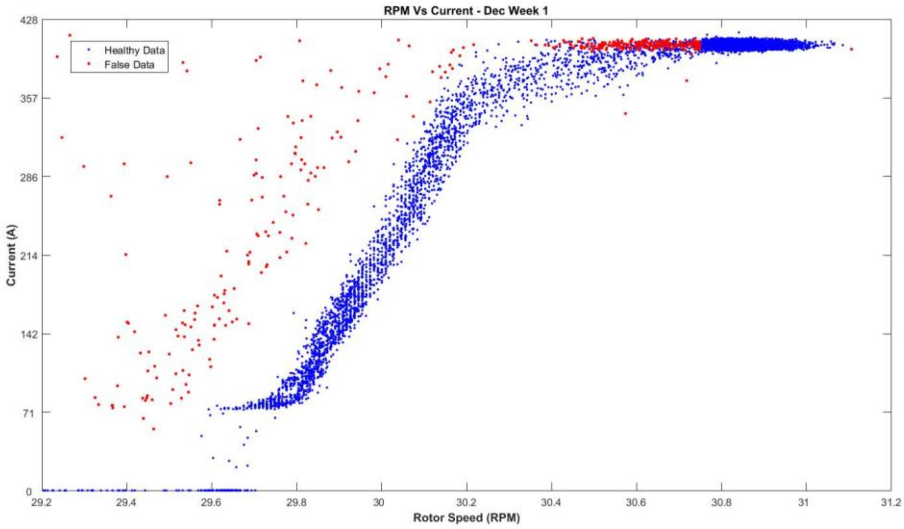

Figure 39: 2 Stage False Data Detection Model: RPM Vs Generator Current

4.3 Discussion of Results

The aim of the model presented is to remove erroneous data from a dataset. In this case the erroneous data consists of false low rotational speeds from a Hall-effect sensor. The first stage of the model uses the relationship between rotor speed and generator output current to identify the erroneous data. A wind turbine will always have a power curve which describes how the power output should vary with rotor speed or wind speed. Since the condition monitoring system used did not measure power output, the generator phase current which also has a relationship to rotor speed has been used instead.

By using the relationship between rotor speed and generator output current the erroneous data could be easily identified. There are several reasons why this relationship can be used with confidence to identify the erroneous signals. The first reason is that a wind turbine generator can only generate a certain level of output current for a given range of rotor speeds, i.e. it would not be possible for the generator to reach its rated current at half the rated rotational speed. This reason is even stronger for the wind turbine used in this case study due to it being a fixed speed wind turbine, meaning that it is designed to only generate power within a very narrow (29-31 RPM) rotational speed range.

The second reason is established by the relationship between the type of erroneous data that is occurring and the operating principles of the wind turbine. The erroneous data only ever consists of false low signals and never false high signals. It is only ever false low signals because the Hall-effect sensor can only miss holes on the rotor locking disc, it cannot count more holes than are actually present. This is very useful in terms of ensuring that the system does not filter out data that is actually detecting a true wind turbine fault. As mentioned in the previous paragraph, a wind turbine cannot generate rated current at a low RPM; however it could be possible for a lower generator current to be generated at a higher RPM if there is a fault in the generator.

For the relationship between RPM and generator current a Gaussian curve was fitted to the data and thresholds of normality defined. Due to this being a fixed speed wind turbine and operating at (or very close to) 31 RPM a simple linear threshold could be used for removing the erroneous data using the relationship between RPM and wind speed. It was found that the first stage of the model removed all the erroneous data that occurred before the turbine reached rated power output and therefore the 2nd stage of the model removes the erroneous data that occurred at rated output. Comparing Figure 36 and Figure 39 the erroneous data that was missed by the first stage of the model and not apparent in Figure 36 at rated output becomes more obvious in Figure 39.

4.4 Conclusion

For wind turbine condition monitoring systems to be cost effective they must be able to provide the wind farm operator with a reliable indication of the state of health of a wind turbine. The occurrence of false alarms or erroneous data could result in significant loss of revenue caused by unnecessary downtime. Being able to tell the difference between erroneous data and a true wind turbine fault would increase the reliability of the condition monitoring system by reducing false alarms. The model discussed in this section addresses research question two by using thresholds and rules established by the principles of operation of a wind turbine, and in this scenario more specifically by that of a fixed-speed wind turbine. The thresholds and rules that this technique relies on are set based on contextual data i.e. they are determined based on how a wind turbine operates and the physical limitations of the sensor. So for the rotational speed sensor discussed in this chapter it was known that it was not physically possible for the sensor to count more holes on the rotor locking disc than were actually present. Also, it would not be possible for a wind turbine to generate rated output power and half the rated rotational speed.

By using relationships between the faulty signal and other parameters the erroneous data was effectively detected by the two-stage model. The techniques applied in this model may similarly be used for the removal of erroneous data in other applications by using principles of operation of the machine being monitored.

5 Correlation Analysis for Faulty RPM Sensor

5.1 Introduction

Correlation analysis is a technique used to study the relationship between two or more parameters [159]. There are three types of correlation commonly used, namely, Pearson, Kendall and Spearman correlation [160] of which this section will focus on the use of Pearson correlation due to its widespread use [161, 162]. The Pearson coefficient, given below, can give a measure of the strength of this relationship.

Equation 11: Pearson's Coefficient

$$Pearson's\ Correlation\ (\rho) = \frac{cov(X,Y)}{\sigma X \sigma Y}$$

where X and Y are the two parameters, *cov* is the covariance and σX is the standard deviation of X.

A Pearson's coefficient of zero would indicate that there is absolutely no relationship between parameters, a coefficient of one would indicate that there is total positive correlation i.e. when one parameter increases, the other parameter also increases, and a coefficient of negative one would indicate total negative correlation as seen in [163]. This is a useful parameter when monitoring the health of a wind turbine as the drop in correlation between two parameters may indicate a fault or deterioration of a component of the wind turbine such as gears or bearings [164].

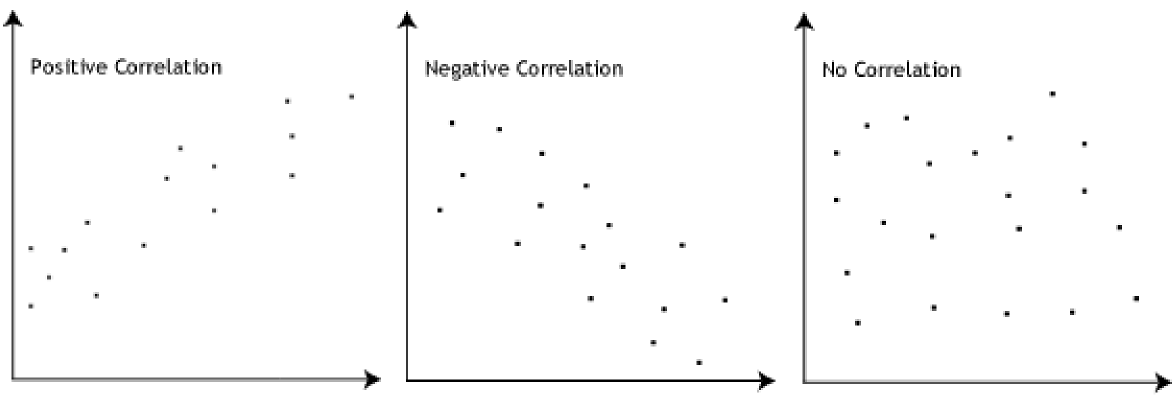

Figure 40: Pearson's Correlation [163]

The most common and simplistic way in which correlation analysis is used is to compare two parameters such as wind speed and generator power output. At a system level, a drop in correlation between these two parameters may indicate that something somewhere in the system is causing a reduction in the wind turbine's operating efficiency. It may also be used at a component level to investigate a particular piece of equipment. Zhang et al. [164] use the correlation coefficient along with clustering analysis to investigate failed components within a gearbox. The correlation coefficient is used in this case to examine the linear relationship between accelerometers for two different cases of acceleration data. Correlation coefficients were obtained to show the relationship between 12 accelerometers distributed along the wind turbine drivetrain. The analysis showed that there was low correlation between the main bearing and the low and intermediate speed stages of the gearbox indicating that there may be health issues within these areas of the gearbox, since the main bearing was known to be healthy.

Correlation is not only useful for investigating faults that have already occurred but can also be used to predict an impending fault. Since many wind turbine signals are closely correlated with other simultaneously measured signals, Schlechtingen and Santos [165] use cross-correlation (as do many others such as [6],[166],[167]) to develop the regression model shown in Figure 41 to predict a generator fault. Using linear cross-correlation, related signals and their lag with the signal to be predicted could be found. Having a strong correlation between stator and bearing temperature meant that the linear model was very accurate. Using the power output, nacelle temperature and shaft speed the number of prediction outliers could be reduced. Although a simple model, it shows how correlation can be used in effectively predicting faults.

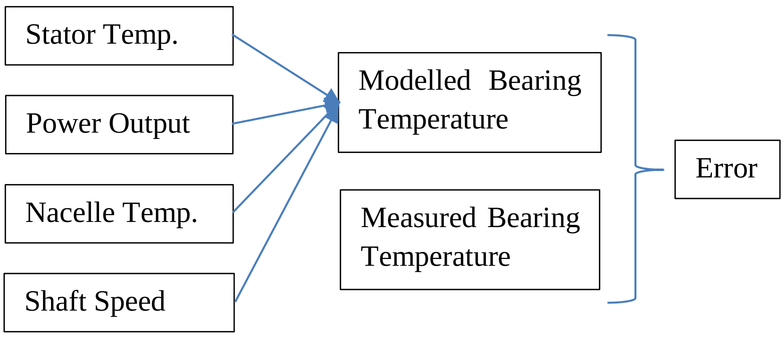

Figure 41: Regression model (reproduced from [153])

Another method which uses correlation analysis at system level is discussed in [39] where the correlation coefficient between neighbouring wind turbines is used to detect changes in wind turbine health. When the wind turbines are in a healthy state the correlation coefficient will be high however when the condition of one deteriorates the correlation coefficient will reduce. This method however does have drawbacks since the operational state of each wind turbine is very much determined by local terrain factors such as the wind direction, wind shear and wind speed at that specific wind turbine.

Although correlation analysis is a useful and simple tool for analysing wind turbine condition monitoring data the output of such analysis can be significantly affected in two ways. The first is by wind turbine downtime. When the turbine is shut down either for maintenance or simply low wind speeds the sensors will no longer output correlated data but instead will be producing uncorrelated noise. This must be therefore factored in when designing any fault detection model which uses correlation analysis, a point which has not been highlighted in any of the literature above.

The second way in which the output of the analysis may be affected, which is not identified in literature, is by erroneous data being used in the analysis, most likely from a faulty sensor, and this is the issue that will be addressed in this chapter. Although correlation analysis may be sensitive to erroneous data when trying to detect a fault, this drawback can have its advantages in that it can be used to detect erroneous data.

By understanding the relationship between different sensors and their distribution across the wind turbine, correlation analysis may be used to detect erroneous data through a drop in correlation. This is shown in this chapter through the application of two sets of data from a faulty rotor speed sensor: one set of data is erroneous due to false low measurements captured by the sensor; the second set has had the false low measurements filtered out by the Error Detection Model discussed in the previous chapter. The work in this chapter addresses the second research question by showing how the presence erroneous data can be identified. Although correlation can be used for detecting faults within the wind turbine the main focus of the technique in this application is for detection of erroneous data.

5.2 Correlation Analysis

The condition monitoring system collected data from a total of 29 sensors which were distributed across the wind turbine nacelle of a Vestas V42 600kW wind turbine. Out of the 29 sensors, nine were chosen to use in the correlation analysis because of their high likelihood of having strong correlation. The sensors chosen were:

- Hall-effect sensor measuring rotor speed of the low speed shaft
- Anemometer measuring wind speed on the nacelle roof
- Accelerometer 1 located on the main bearing
- Accelerometer 3 located on the low speed side of the gearbox casing
- Accelerometer 5 located on the forward end of the generator casing
- Accelerometer 7 located within the gearbox
- Load Pin 1 located on the gearbox port side support arm
- Load Pin 2 located on the gearbox starboard side support arm
- Generator current phase 1

Pearson's correlation coefficient was found for the following 8 pairs of sensors:

1. Rotor Speed and Wind Speed
2. Rotor Speed and Accelerometer 1
3. Rotor Speed and Accelerometer 3
4. Rotor Speed and Accelerometer 5
5. Rotor Speed and Accelerometer 7
6. Rotor Speed and Current 1
7. Load Pin 1 and Load Pin 2
8. Load Pin 1 and Current 1

Rotor speed is the sensor which was known to be outputting erroneous data in the form of false low signals as discussed in the previous chapter. By plotting rotor speed against generator output current it became very visually apparent by an obvious divide between healthy and erroneous data that the sensor was missing pulses and therefore outputting erroneous low signals. It is therefore the sensor which this analysis is focusing on with the majority of the analysis looking at this sensor's correlation with other sensors. Pairs 7 and 8 were included to be used as controls since these sensors should always have a very high correlation unless the turbine is shut down or there is a fault with these sensors.

The data for the analysis was initially captured by the condition monitoring system at 10.24 kHz for accelerometers and 50 Hz for everything else, then a mean was taken for each minute of data. The averaged data was then used to find correlation coefficients for daily, hourly and 10-minutely time periods which was done by taking the following numbers of minutely averaged data points:

- Daily – 1440 values
- Hourly – 60 values
- 10 Minutely – 10 values

Taking correlations over different time periods provides a better understanding of the data, as short term events may have a significant impact on the 10 minute correlation coefficient, but the effect will be diluted over an hourly or daily period.

The Pearson's coefficient, as given by Equation 11, was computed in Matlab for each sensor pair for the different time periods for both the raw data, which contained the erroneous measurements, and for the filtered data which had the erroneous data points removed by Error Detection Model described in the previous chapter.

The analysis was performed for 10 one-weekly batches of data from September 2015 to January 2016 with one daily, hourly and 10-minutely sample taken from each week for the analysis. This was deemed a long enough period to see how the correlation changed over time as the position of the sensor changed. It was also expected that over this period of time there would be months with greater downtime as a result of lower wind speeds and that this would have a notable impact on the correlation levels.

5.3 Results

The Pearson's coefficients that were obtained can be seen plotted in Figure 42 for the Daily, Hourly and 10-Minutely periods where the Pearson's coefficient 'r' is given on the y-axis for each week. The raw data, which contains erroneous data, is given by the blue trace and the filtered data, in which the erroneous data has been removed, can be seen by the orange trace. During normal operation the parameters that were chosen for the analysis are always likely to have some level of correlation. As expected this correlation dropped in the presence of erroneous data as can be seen in Figure 42 which shows that raw data on average has a much lower level of correlation than the filtered data.

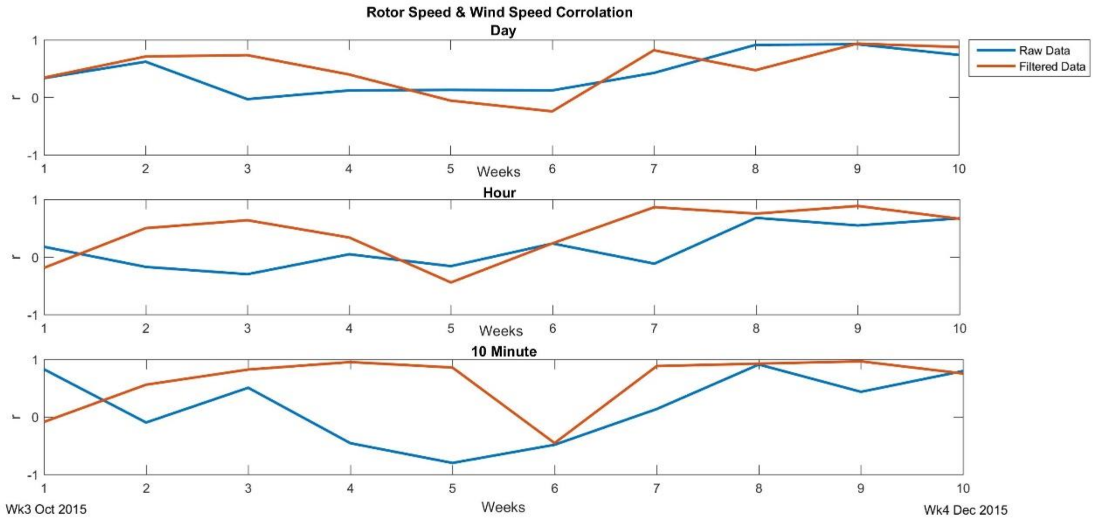

Figure 42: Pearson's Coefficients for Rotor Speed and Wind Speed

It can also be seen, as mentioned previously, that the correlation differs, sometimes considerably, depending on the time period the correlation is performed for. There are several occasions where the correlation is higher for the raw data than it is for the filtered data, for example, in week 8 of the Daily plot, where the blue trace is higher than the orange. One explanation for this is low wind speeds. When the wind speed is low and the wind turbine is operating below rated speed there is far more variation in shaft rotational speed, power output and the resulting vibrations, than in higher wind speed conditions. This increased variation causes a drop in the correlation between parameters. Another explanation for the filtered data having lower levels of correlation and for the raw data having a higher level of correlation is that when a sensor is outputting very high levels of erroneous data it means that there is not a lot of true data left for analysis in the filtered dataset after the erroneous data has been removed. If there is very little true data left to carry out the analysis on then it is more likely that the correlation level will be lower since the covariance of the parameters will most likely be lower.

The correlation between rotor speed and each of the accelerometers provides the clearest results due to the acceleration being proportional to the rotor speed as can be seen from Figure 43 where the acceleration increases with rotor speed. Taking Figure 44, it can be seen that the correlation is significantly higher for most weeks and for each correlation period when the erroneous data has been filtered out, as shown by the orange trace, which is almost always higher than the raw data, shown by the blue trace. The traces for Accelerometers 3, 5 and 7 (see Appendix) all follow the same pattern as that for Accelerometer 1 shown in Figure 44.

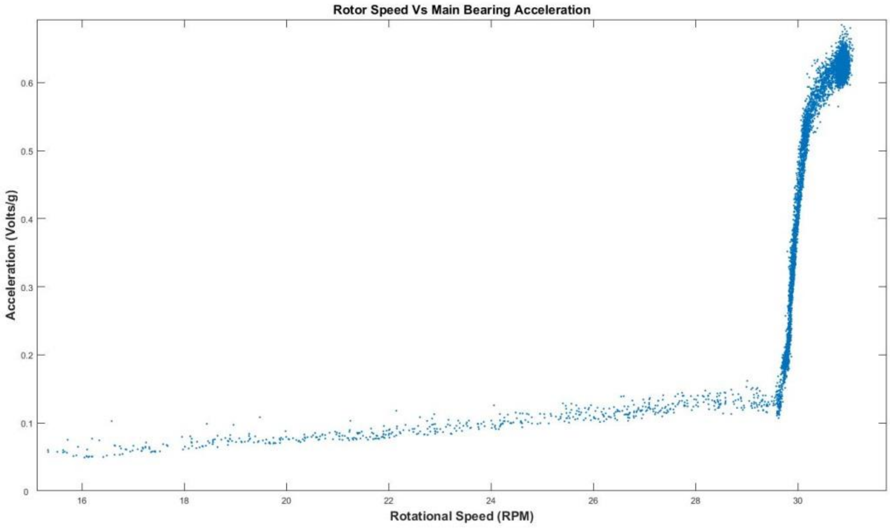

Figure 43: Rotor speed plotted against acceleration of the main bearing

Notably, at week 6 it can be seen (Figure 44) that the correlation of the filtered data actually drops significantly and is almost the same as the unfiltered data, particularly for the 10-Minutely correlations. As mentioned previously this is due to the fact that there is a very high level of erroneous data coming from the rotor sensor in this period, which results in there being less data to perform the analysis on which is likely to cause the covariance to drop resulting in lower correlation.

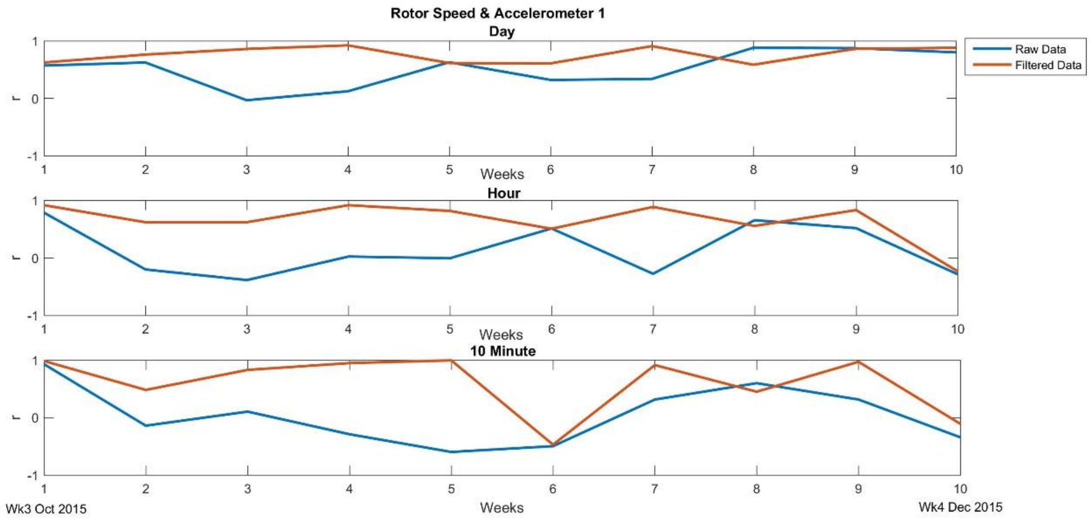

Figure 44: Pearson's Coefficients for Rotor Speed and Accelerometer 1

Figure 45 below is the output from the Error Detection Model for Week 6 which shows rotor speed plotted against generator current and the extremely high number of erroneous values being outputted by the RPM sensor in this week. There is such a high level of erroneous data (red) that there is very little healthy data (blue) left to carry out the correlation analysis on particularly for the 10-Minutely period.

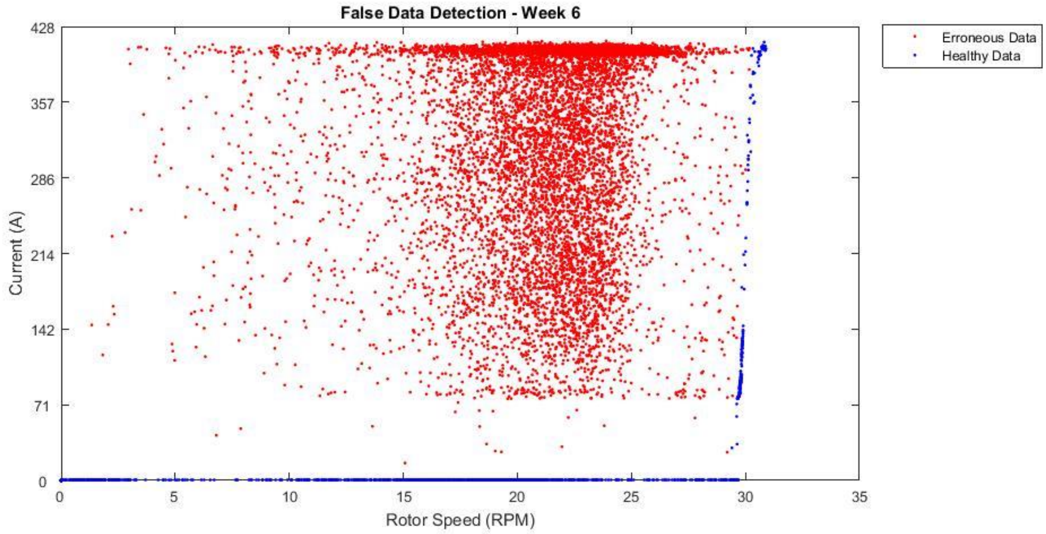

Figure 45: Rotor Speed plotted against Generator Current for Week 6

Another discrepancy in the results can be seen at week 8. Investigating additional data for this week showed that the slight drop in correlation was due to a prolonged period of low wind speed. The wind turbine will only generate power at its rated value when the wind speed is at or above its rated wind speed of 16 m/s. As can be seen from Figure 46 the wind speed is below the rated wind speed (shown by the red line) for a significant proportion of that week resulting in more variation of rotor speed, power output and vibration on the drivetrain. It can also be seen in Week 8 of Figure 44 that there is very little difference in correlation between the raw and filtered data, this is because the rotor sensor was working well during this period with very little erroneous data being outputted and therefore the raw and filtered datasets were almost the same.

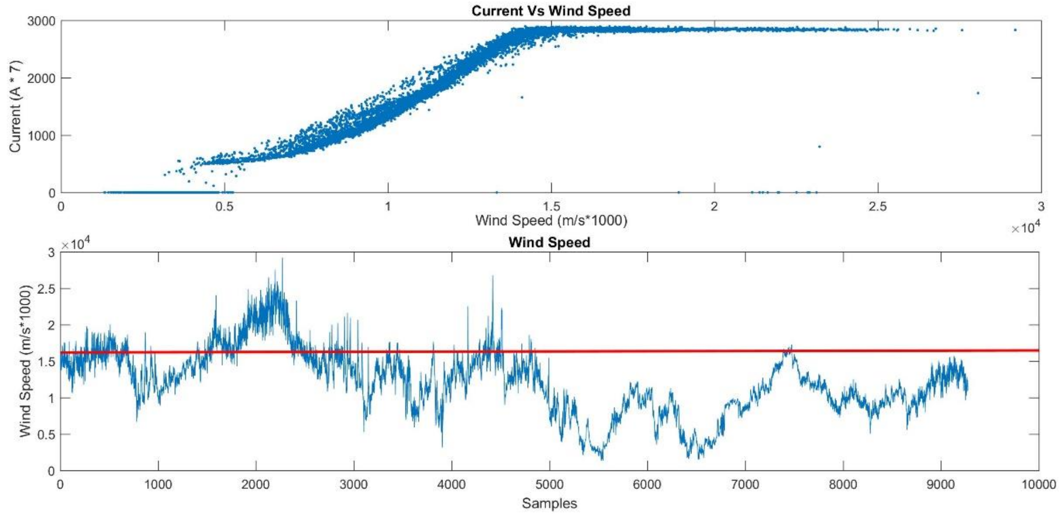

Figure 46: Wind Speed Vs Current (top) and Wind Speed (bottom) for Week 8

Two parameters which, based on their correlation, are able to provide a good insight into the health of their measurements and the health of the wind turbine itself are rotor speed and generator current. Although the data for this analysis is from a constant speed wind turbine, in general as the rotor speed increases so too does the current. Different information is also gained depending on the period of time the correlation analysis is performed over. Taking Figure 47 it can be seen from the Daily plot that the correlation level is more variable than the Hourly and 10-Minutely plots. This is because the Daily plot is more sensitive to wind turbine downtime and periods of low wind speeds (such as in weeks 2 and 8) where the wind turbine is producing power below the rated power output or producing no power at all. It is more sensitive to these events because it may include a number of these events within a day whereas the Hourly and 10-Minutely periods may miss these events entirely depending on when the sample of data was taken for the analysis. This Daily plot highlights the need for performing the analysis over different periods of time since the Daily plot at Week 5 has detected the presence of high levels of erroneous data by the drop in correlation yet this would not be so easily detected in the Hourly and 10-Minutely plots.

Looking at the plots in Figure 47 for the Hourly and 10-Minutely periods, it can be seen from the orange trace that the correlation of the sensors is considerably higher when the erroneous data has been removed. This example shows that the presence of erroneous data could be detected by a drop in correlation between these sensors. If however the data was known to be free of erroneous measurements then it may be that there is a fault with the wind turbine itself such as the generator not producing the correct current level for a given rotor speed.

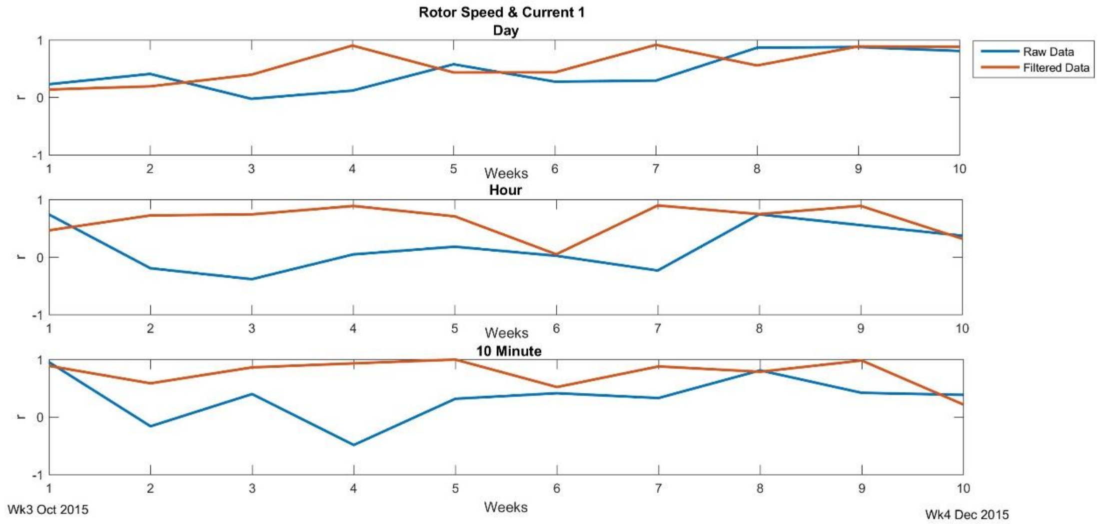

Figure 47: Pearson's Coefficients for Rotor Speed and Current

Load Pin 1 and Load Pin 2 as mentioned previously were used as a control because they should almost always be strongly correlated, except during wind turbine downtime or periods of high erroneous data. Figure 48 shows this strong correlation particularly for the analysis performed for Daily correlation. The Hourly analysis shows a drop in correlation for the raw data at week 5 which indicates that there was a high level of erroneous data. Although the Load Pin data is not erroneous the data points that are at the corresponding timestamp of the erroneous rotor speed data points are filtered out. The drop in correlation for both the raw and filtered data for the Hourly and 10-Minutely correlations in weeks 6 and 10 are caused by wind speeds being below the cut-in wind speed of 4 m/s and the wind turbine being shut down.

Load Pin 1 and Current 1 are also sensors that can be used as a control due to their high correlation with each other as can be seen from Figure 49. Comparing Figure 48 and Figure 49 both have high correlation and the only difference being that Load Pin 1 and Current 1 are negatively correlated meaning that as one increases the other decreases. It should also be noted that in both Figure 48 and Figure 49 there is a difference in correlation between the raw and filtered data at Week 5. Although none of the sensors included in these graphs are outputting erroneous data, any data at a timestamp corresponding to that of the timestamp at which the rotor speed sensor outputs an erroneous reading is removed for this analysis. Therefore once again there is less healthy data to carry out the analysis on resulting in a lower covariance and correlation.

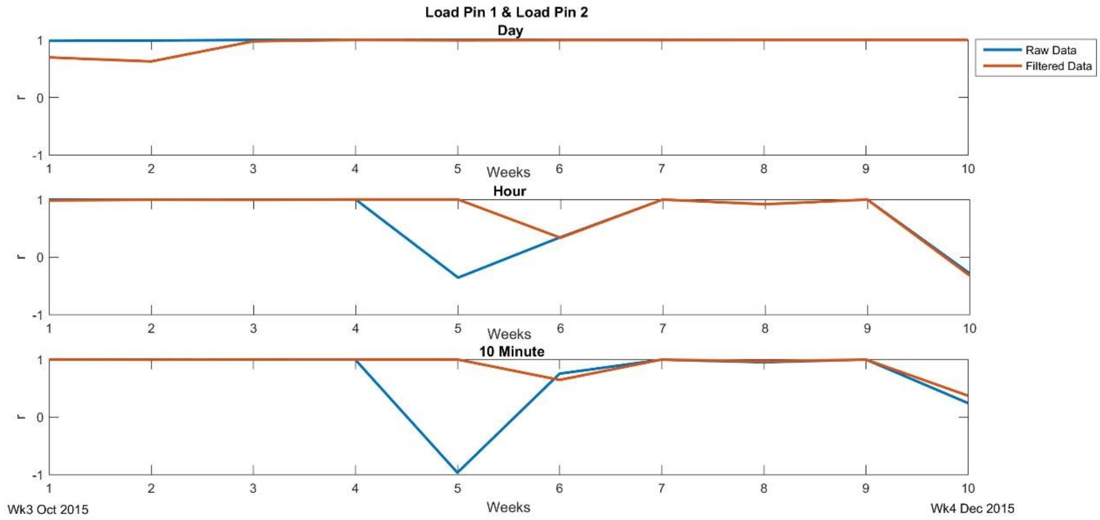

Figure 48: Pearson's Coefficients for Load Pin 1 and Load Pin 2

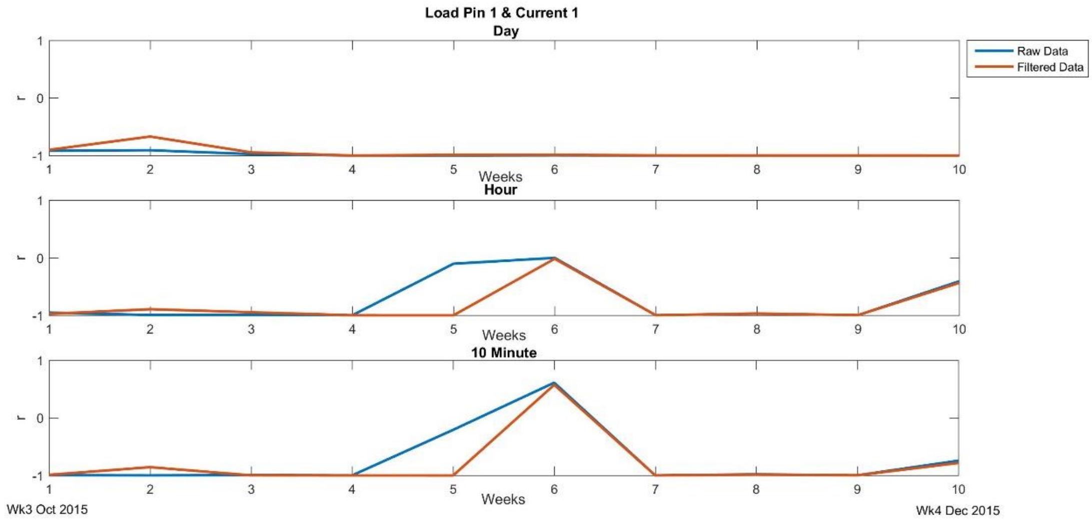

Figure 49: Pearson's Coefficients for Load Pin 1 and Current 1

Figure 48 and Figure 49 show how using sensors that are almost always very strongly correlated as controls can aid in confirming for other parameters whether the sensors are at fault or whether the change is due to normal operation of the wind turbine i.e. if the correlation between two sensors drops and the correlation of the control sensors also drop then it is reasonable to conclude that the correlation is only dropping due to normal operation such as a shutdown; however if the correlation between two sensors drop yet the correlation of the control sensors stays the same then it may be concluded that there is a fault with a sensor or the wind turbine itself.

5.4 Conclusion

Due to many wind turbine parameters being correlated with each other, Pearson's correlation coefficient is a useful measure which is able to give an indication of a change of state of operation or health within a wind turbine. Correlation analysis may not give enough information to diagnose a fault but can indicate with minimal computation that a change has occurred. This section has addressed research question two by showing how the correlation between parameters will drop in the presence of erroneous data thus allowing erroneous data to be detected and false alarms to be avoided. It has also been shown that control sensors can be used to distinguish between erroneous data and normal wind turbine operations.

Both of the techniques presented in this chapter and the previous chapter can be used to detect erroneous data however the techniques do differ from one another and there are times when one may be more suited over the other. The False Data Detection Model is more suited when the erroneous data can to an extent be determined by the characteristics of the sensor and the parameter being monitoring. For example, in the case discussed in this chapter, the rotational speed could only ever be falsely low and not high because it is not possible for the sensor to count more holes than are present in the rotor locking disc. So although this technique is very effective for a specific application it requires certain characteristics of the application. Given the correct application, this technique can be used for online erroneous data detection and removal.

Correlation analysis on the other hand provides a higher level erroneous data detection capability based on the relationship between parameters. Although this technique cannot be as accurate in terms of detecting erroneous data from a specific sensor for a specific parameter as the False Data Detection Model can, it can provide a simpler erroneous data detection method that can cover a wider variety of monitored parameters. With the correct thresholds in place for detection and rules applied that are based on the operating state of the wind turbine it would be possible to apply this technique to online monitoring.

The two techniques presented provide different levels of erroneous data detection however both are very much dependant on contextual information. Because of the variable and stochastic nature of a wind turbine it is not suitable, for example, to set a fixed threshold for a temperature sensor as it is essential when setting the threshold that the ambient temperature and the load on the generator are taken into consideration. A temperature that may be deemed high for a low generator load may only be the result of an abnormally high ambient temperature. It is therefore crucial for any error detection technique to consider the whole goings-on and operating state of the wind turbine.

Table 11: Summary of False Data Detection and Correlation Analysis techniques

False Data Detection Model	Correlation Analysis
Low level detection	High level detection
Application specific	Wider range of applications
Key information required	Simple to implement
Provides clear output	More knowledge required to interpret output
Rely on contextual information	
Provide online detection	

6 Clipped Voltage Signal Correction

6.1 Overview

Signal clipping is a term that is used in a number of different applications but generally it tends to imply that the amplitude of a signal is stopped from reaching its natural peak value and is limited past a certain threshold. One might assume that the clipping of a signal is a negative result of something going wrong; however within the field of digital communications signal clipping is a technique that is commonly being used particularly in conjunction with Orthogonal Frequency Division Multiplexing (OFDM) [168, 169], a method for encoding digital data on multiple carrier frequencies. Clipping of the OFDM signal reduces the high Peak-to-Average Power Ratio which occurs as a result of the OFDM method [170]. The method of clipping however does have its drawbacks such as causing distortion and a number of publications have focussed on these effects [171, 172].

In relation to the work in this section, clipping is seen as an undesirable occurrence with regards to the output from a sensor. Ni et al. quite rightly describe clipping, not as a fault of the sensor, but as the environment exceeding the limits of the analogue to digital convertor [173]. When discussing different system faults that data from a sensor can show, Ni et al. state that clipping may be detected as a “stuck at” fault whereby the data remains at, or close to, a certain value for a period of time.

Another way of describing the clipping of a signal from a sensor is sensor saturation, again meaning that the operating range of the sensor has been exceeded. An area where saturation can have detrimental impact is Active Noise Control (ANC). ANC systems are used to reduce the noise levels being outputted by industrial machinery through the principles of superposition, where a secondary loudspeaker creates a cancelling noise of the same amplitude but opposite phase [174]. If the reference sensor is subject to noise greater than the dynamic range of the sensor it will saturate. To study the effects of sensor saturation on an ANC system, Kuo et al. [175] model a saturated signal by nonlinearly clipping the output of the reference sensor. Through the use of a Fourier series it is shown that the clipping, or saturation, of a sensor signal produces extra harmonics on the frequency spectrum, a point which will be picked up on later in this chapter.

This chapter will focus on the clipping of signals outputted from voltage sensors that are mounted on the terminals of a 600 kW generator, one on each phase. The voltage was measured using the circuit shown in Figure 50 which incorporated an LV25P voltage transducer, which is actually a closed loop current transducer that uses the Hall Effect – a phenomenon where a voltage is induced proportional to a current which is passed through a magnetic field. Since the generator outputs approximately 400Vac at rated power this voltage had to be stepped down so that it fell within the input range of ±10V for the analogue to digital converter on the data acquisition device. The resistors on the input side of the transducer were chosen to bring the maximum input current to 10mA. Measuring the voltage across the measurement resistor Rm would give a voltage proportional to the input current. The value of Rm must be selected based on the input voltage range so that a voltage between ±10V can be measured. There is a trade-off between accuracy and range when selecting the value of Rm i.e. measuring a larger range will result in lower accuracy.

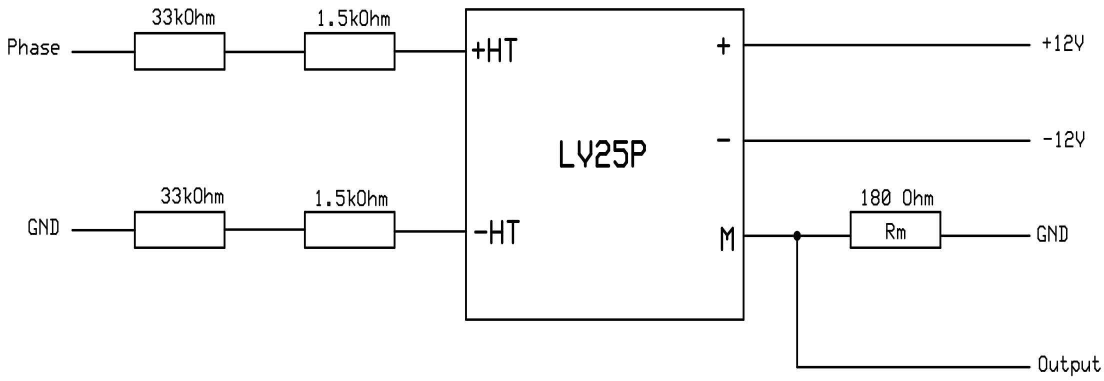

Figure 50: Voltage transducer board

On analysing the first batch of data from the system it was found that the voltage signals were being clipped when the turbine was operating at rated power which corresponds to a voltage of 400V. Without accessing the wind turbine nacelle to confirm the cause of the clipping it is suspected that the clipping is being caused by a limitation in the current draw from the power supply to the LV25P transducer. The reason for suspecting this is because the clipping is not a flat response caused by reaching a maximum range, but instead there are oscillations, as seen in Figure 51, which suggest a lack of current to the transducer.

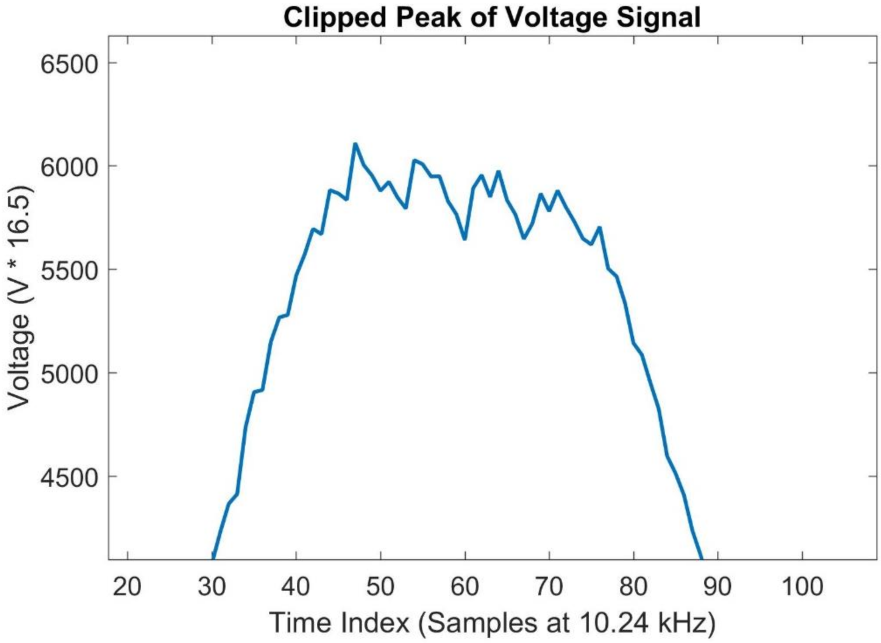

Figure 51: Clipped peak of the voltage signal

Regardless of the reason for the clipping occurring, the ability to still use the clipped data may be crucial to detecting a fault. The clipped signal itself may be required to simply detect an over-voltage or it may be that the signal is used in conjunction with other parameters for fault detection. A technique presented by Yang et al [96] uses both generator power output and rotor speed to derive a fault detection signal. To obtain the output power of the generator the voltage signal is required along with the current. Therefore if the voltage signal has been clipped this may have an effect on the output of their detection algorithm.

The current signal from a generator is a parameter widely used for detecting fault harmonics in the frequency domain, commonly known as current signature analysis [63, 176]. Crabtree et al [87] derive analytical equations for the frequency content for both line current and instantaneous power for healthy and faulty induction generators. Through the use of data from test rigs the authors show how spectra for these two parameters can be used to detect faults in the frequency domain. Once again, a clipped current or voltage signal could have an effect on the outcome of these detection methods either through harmonics being added to the frequency spectrum or through an inaccurate instantaneous power signal.

This chapter introduces a voltage clipping correction model which will allow a clipped signal to be used for analysis. Addressing research question three, this technique will allow data that contains erroneous data to continue to be used for condition monitoring. The clipped signal in this application is a voltage signal however the technique developed may be used to correct clipping in any sinusoidal signal such as current or power signals.

6.2 Clipping Correction Model

The aim of the clipping correction model was to take the raw voltage signal and replace only the data where clipping had occurred so that the corrected signal was as close to the original as possible. This is similar to the process of interpolation, a curve fitting technique, where there is the need to infer the values of a signal between discretely sampled points. An example of this is given by Barszcz and Randall [177] who use linear interpolation to resample a vibration signal at a higher sampling rate. This was done in order to obtain a higher number of samples that were needed to carry out time synchronous averaging for a three-stage gearbox with the aim of detecting a cracked gear tooth.

Time synchronous averaging, a technique that enables periodic waveforms to be extracted from noisy signals [178], also uses interpolation to resample a signal so that all samples are taken at the same point of a revolution of a piece of rotating equipment such as a gear. Decker and Zakrajsek [179] compare three different interpolation techniques used for time synchronous averaging namely: linear, cubic and spline interpolation, stating that there are two constraints whilst choosing a method – accuracy and computation time. Linear interpolation is the fastest computationally due to its simplicity; however is the least accurate. The cubic interpolation, which fits a cubic curve to the data then solves the equation for the desired point, is the second fastest and depending on the accuracy of the curve fit can be more or less accurate than linear interpolation. Finally cubic spline interpolation is the most accurate method, at the expense of computation time. This method uses a series of functions to determine the interpolated data points.

The interpolation methods described above are all used to infer a value between two discrete points. These methods of interpolation however, would not work for the clipped voltage signal discussed in this chapter since interpolation or even averaging over the clipped area would still result in some level of clipping. For this reason a method which would reconstruct the signal based on knowledge of the expected function, in this case a sine wave, had to be considered.

The correction of the clipped signal is carried out as follows:

1. Find the first data point where clipping occurs.
2. Take the X value (time index) for the two data points before and 43 data points after the first data point where clipping occurs. These are the data points which will be corrected.
3. Fit a single sine curve of the form $f(x) = \mathrm{a} * \sin(bx + c)$ to the voltage signal using the method of non-linear least squares with the data points where clipping has occurred excluded.
4. Take the X values of the excluded data points and use the function of the fitted curve to find the Y values (voltage amplitude) of the fitted curve.
5. Replace the data points where clipping has occurred with the new data points from the fitted curve.

The voltage signal that the curve had to be fitted to is a single sine wave with a frequency of 50 Hz as defined by the frequency of the local electricity network. The length of the signal used to fit the curve had to be at least 205 data points (1/50Hz * Sampling frequency of 10.24 kHz). This ensures that a whole period of the signal is used so that both a peak and trough are included - since this is the data that is needed for the correction. Strictly speaking there is no limit to the size of sample that the curve fitting can be applied to, however the accuracy of the fitted curve may decrease as the sample size increases due to variations in the signal frequency being averaged out over the length of the sample. The amplitude of the signal should vary very little as the voltage of the generator is fixed and should only ever change when the wind turbine is shut down.

Since the signal was only clipped as it approached rated power a threshold was set so that no clipping correction could be applied to the signal where it was not actually being clipped. The window size to apply the clipping correction to was chosen to be 46 data points. This window size meant a smooth transition between the original signal and the new corrected section of the signal. It was found that if too large a window size was used, i.e. greater than 46 data points, the accuracy of the correction was reduced as the transition between the raw and corrected data would be less smooth. However, it is better to err on the side of using a larger window than a smaller window since using a smaller window could risk missing part of the clipped signal as shown in Figure 52 where a window of only 15 data points is used.

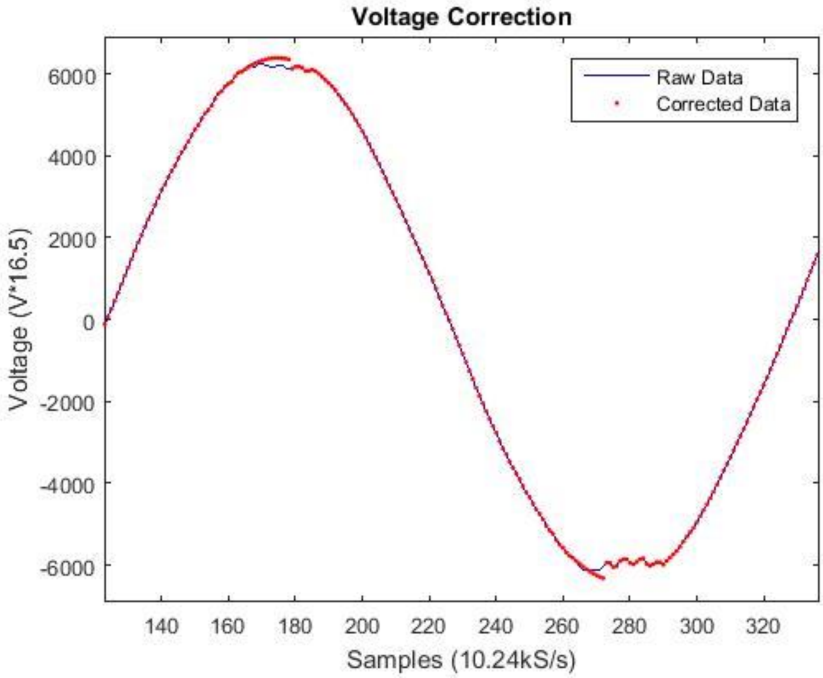

Figure 52: Corrected signal where too small a correction window has been used

The original signal which was clipped is shown in Figure 53 by the blue dotted line. The clipping of the signal occurs at an unconverted voltage of just over 6100 (which corresponds to a real voltage of just over 367V) and can be seen by the green crosses. Each green cross is a data point which is removed and replaced by the corresponding value of the fitted curve. The fitted sine curve is shown in red and it can be seen that the original signal and fitted curve align very closely.

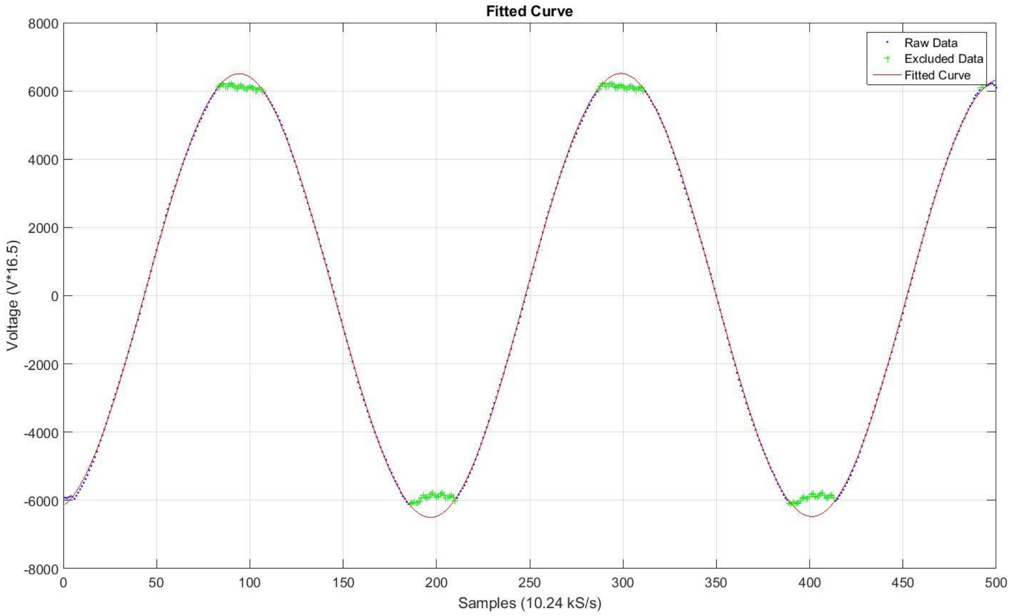

Figure 53: Clipped voltage signal with curve fitted

Using the values of the fitted curve, the points where clipping had occurred were removed and the new points inserted to give the corrected signal shown by the red dotted line in Figure 54. The raw clipped signal is shown in blue and can be easily seen at the peaks and troughs of the signal where the clipping occurs.

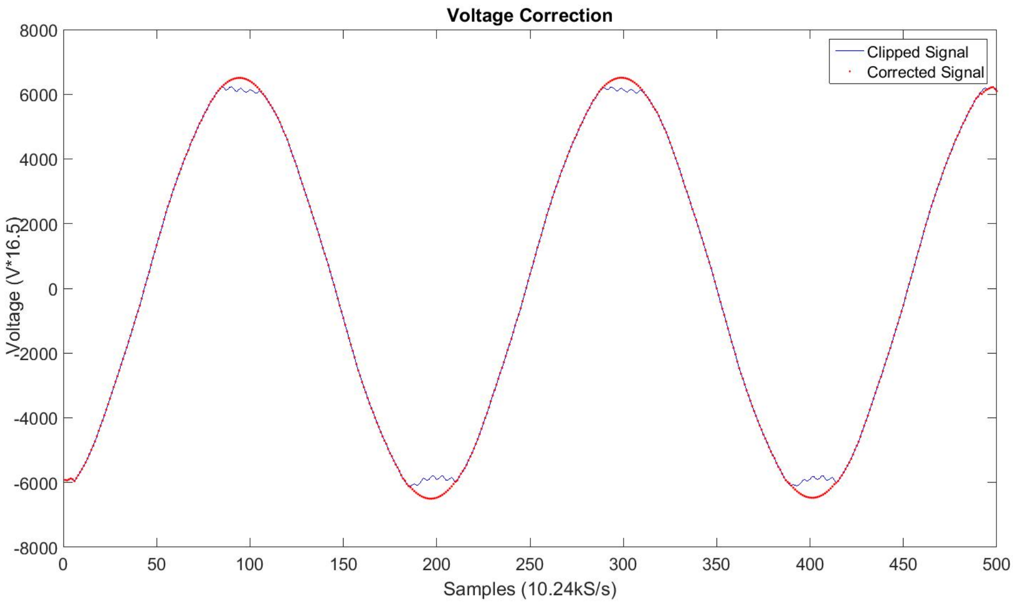

Figure 54: Clipped and corrected signals

6.3 Discussion of Results

The main aim of the clipping correction model was to repair the clipped signal so that it could still be used for condition monitoring of the wind turbine. From Figure 54 it can be seen that there is a smooth transition where the signal correction has been carried out which should mean that no harmonics in the frequency domain have been added as a result of the correction. Also since clipping only occurred approximately 22V below the expected peak value it is believed that a significant amount of information is not lost from the signal.

In an attempt to examine what effect clipping may have on the frequency domain representation of the signal, a Fast Fourier Transform (FFT) was carried out on both the clipped and corrected signals. Figure 55 below shows the spectrum for the clipped signal. As would be expected the most significant peak is located at 50Hz which is the frequency of the power grid that power is being supplied to. There are also notable, though considerably smaller, peaks seen at multiples of the grid frequency, namely 100, 150, 200, 250, 350 and 450Hz.

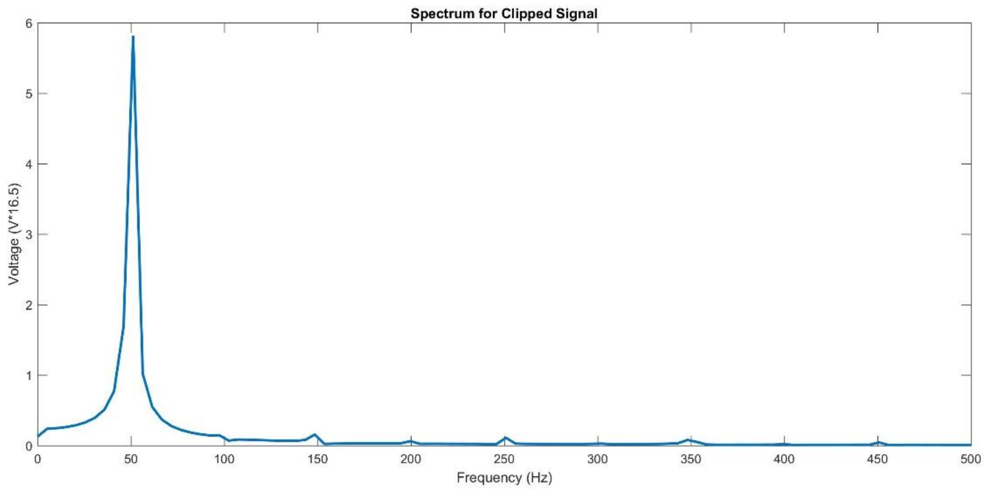

Figure 55: Frequency spectrum of clipped signal

The spectrum for the corrected signal where clipping has been removed is shown in Figure 56. When compared with the clipped signal in Figure 55 it can be seen that the amplitude of the main peak is higher for the corrected signal since clipping reduces the amplitude of the signal at each peak. It can also be seen when comparing the two spectrums that the peaks seen at multiples of the grid frequency are significantly reduced following the correction of the clipped signal. During the sections where clipping is occurring the signal oscillates at a greater frequency which will introduce higher frequency harmonics into the signal. By removing the clipped sections these harmonics are removed from the signal.

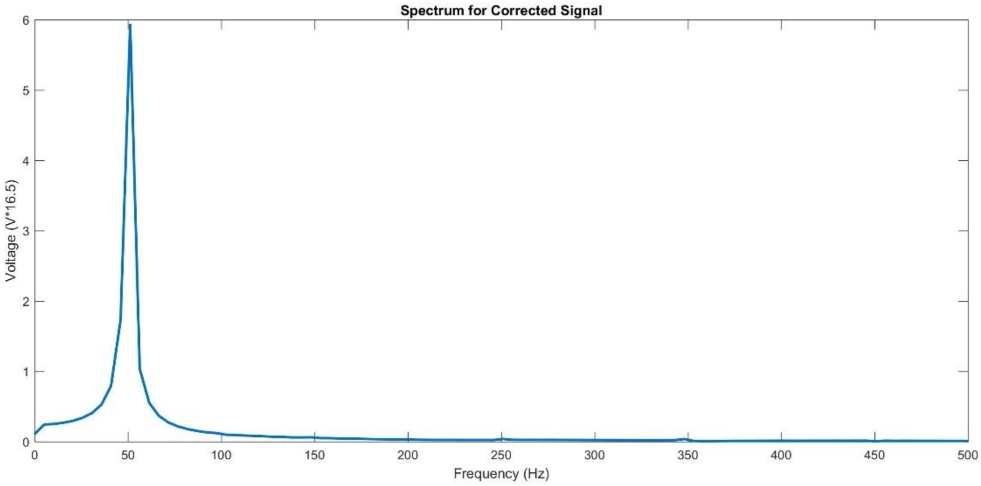

Figure 56: Frequency spectrum of corrected signal

In the case where there had been a fault with the generator such as a short circuit in a winding, a harmonic may appear in the frequency spectrum of the signal. Since the clipping correction model is only applied to the small sections where clipping occurs it is expected that it will still be possible to detect the fault harmonic. Having applied the clipping correction model it may be easier to detect the fault harmonic since the harmonics caused by clipping have been removed, thus providing a cleaner signal for fault detection. As mentioned previously, although the technique has been applied to a voltage signal in this work, it could also be applied to a current signal which is more commonly used for spectral analysis.

Instantaneous power as used in [96] for fault detection is calculated by the equation:

Equation 12: Instantaneous Power

$$P(t) = \sum_{i=1}^{3} I_i(t) * V_i(t)$$

Where $I_1(t)$ and $V_1(t)$ are the current and voltage for phase 1 at a given instant in time. Given the presence of a clipped voltage signal the power on each phase will be altered as shown in Figure 57 where the power calculated using clipped voltage data is shown by the dotted traces for each phase and the power calculated using corrected data is shown by the solid traces. The result of clipping is mainly seen as a reduction in phase power however there are some instances seen at the peaks of the waveforms where the power is higher for the clipped data.

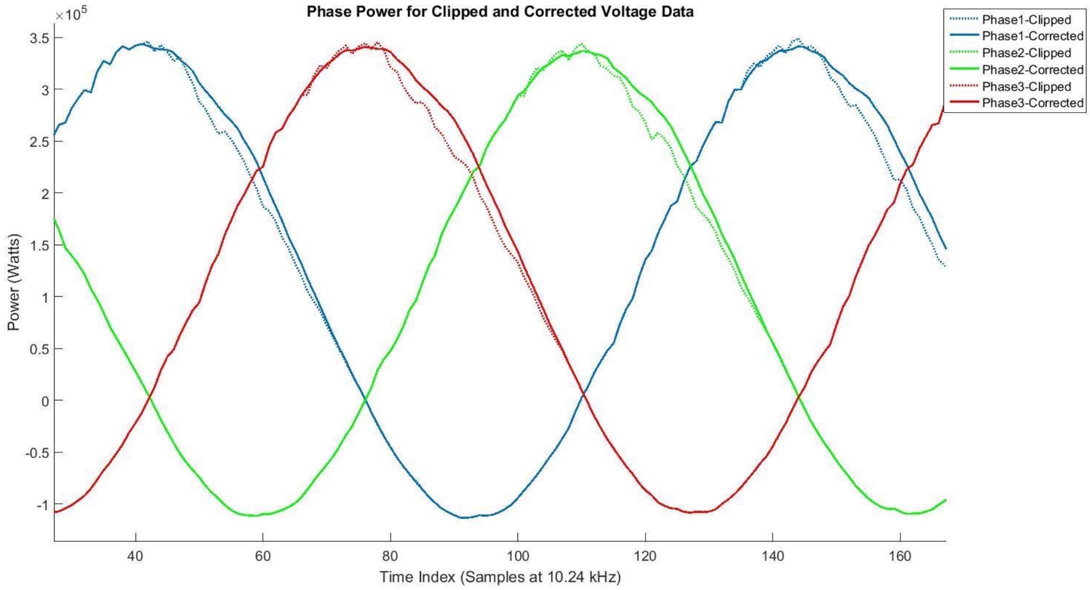

Figure 57: Phase power for clipped and corrected voltage data

The use of clipped voltage data results in an apparent reduction in instantaneous power over the majority of the signal, as shown by the red trace in Figure 58 and calculated using Equation 12. It also, at some instances, has the result of showing the power to be slightly higher than the corrected data shown by the blue trace. The main issue caused by this apparent drop in power will be the appearance of the wind turbine to be operating at reduced efficiency which could result in unnecessary costly investigative actions. A technique developed by Gill et al. [180] uses the power curve of the wind turbine and empirical copulas with the aim of being able to detect incipient faults such as blade degradation, yaw, and pitch errors. If the power curve used for this analysis was artificially altered due to an erroneous sensor reading the output of this technique could be wrongly interpreted. For example, it can be seen from Figure 58 that the instantaneous power is more variable when the clipped voltage data has been used. Gill et al. state that a pitch mechanism fault is likely to “show up as a greater variability at all wind speeds, or may lead to over or under production of power at high wind speeds” [180]. Therefore the use of clipped voltage data could be wrongly interpreted as a fault in the pitch system.

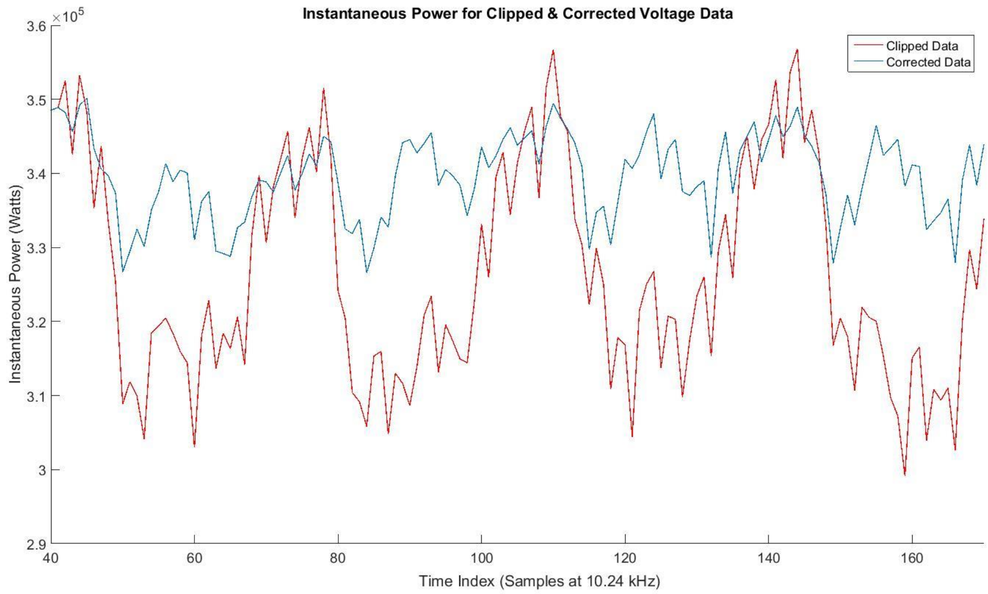

Figure 58: Instantaneous power for clipped and corrected voltage data

Transforming the instantaneous power generated using the clipped data into the frequency domain, detects the presence of a harmonic at 297 Hz, as shown in Figure 59, which is the result of clipping since it is not present in the spectrum of the instantaneous power generated using the corrected data. The presence of this harmonic may result in cause for alarm by an operator if it is not known that it is only the result of an erroneous measurement.

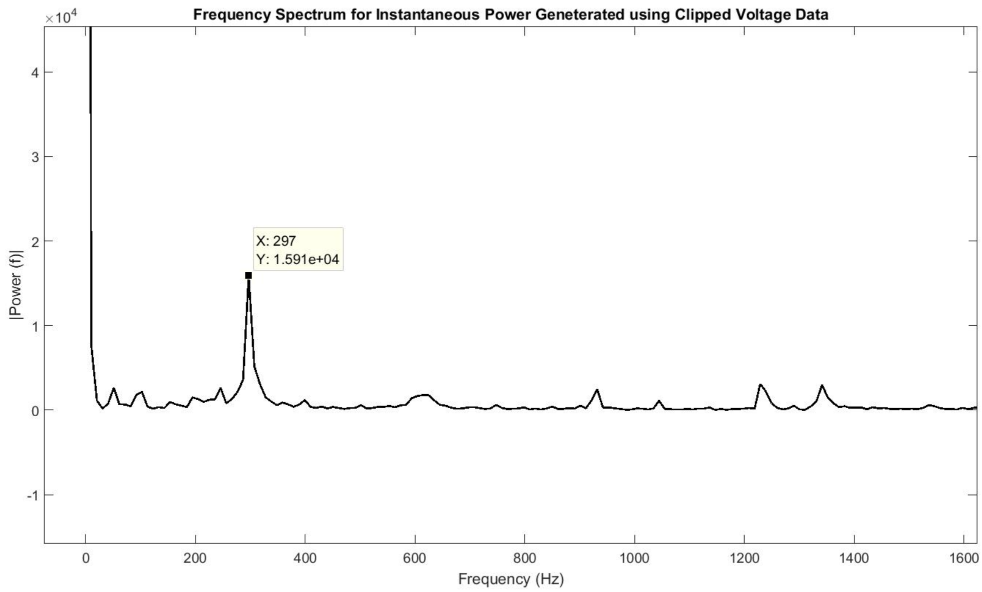

Figure 59: Frequency spectrum of instantaneous power generated using clipped voltage data

6.4 Conclusion

This section has addressed research question three by introducing a technique for the correction of a signal which has been clipped at its peaks and troughs. It may not always be possible to access the wind turbine in order to perform remedial work to stop the clipping from occurring. Also, it may be that an operator wishes to use historic data which has been clipped to investigate a particular fault or even to assess the performance efficiency of the wind turbine. Correcting a clipped signal, which potentially contains insightful information, will allow it to be used for analysis. The technique introduced here only performs the correction on the small period of data where clipping has actually occurred, therefore reducing loss of information in the rest of the signal. This section has shown that without correcting the clipping, the use of the data could potentially give false diagnoses to the health status of the wind turbine.

7 Conclusions and Further Work

7.1 Conclusions

Wind energy is a leading provider of renewable energy and is able to help meet the demands of reducing reliance on fossil fuel energy sources. However even as the most mature renewable technology, it is still hampered with reliability issues, even more so as turbines increase in size. Installing wind turbines offshore has great potential for increasing energy capture due to the more favourable wind conditions; however the further offshore they go the greater the costs of operating and maintaining them will be.

SCADA systems are currently the main way in which the health of wind turbines is monitored; however the main function of a SCADA system is for control and performance monitoring. A significant amount of work has been carried out in order to make greater use of SCADA systems and increase their diagnostic capabilities. However in order carry out detailed diagnostics through the use of more sophisticated data processing techniques, dedicated systems are required which can capture and efficiently process high frequency data. In processing this high frequency data and extracting useful information about the health of the wind turbine, operators will be better informed, allowing for more optimised maintenance and repair scheduling, and the avoidance of unplanned wind turbine downtime. This in turn will reduce O&M costs which will ultimately lead to a reduced cost of energy from wind turbines.

Although there is great potential in the use of condition monitoring systems to reduce O&M costs, it has been stated in the literature that operators have been wary of blindly adopting such systems. This may be due to high capital costs of implementing these systems or because of reliability issues such as systems giving false alarms. A number of studies have been carried out to try to quantify the benefits of implementing such systems with one stating that CMS must accurately diagnose 60-80% of potential faults to be economically beneficial.

A review of the literature identified that most of the work in developing wind turbine diagnostic techniques was done through the use of test rig data. Test rigs have the advantage of being able to provide on-demand data for a given type of fault allowing diagnostic techniques to be tested very easily. The conditions of the test however are reliant on a model which accurately depicts the conditions within a wind turbine. As accurate as the model may be, it will never truly provide the fault conditions experienced in an operational wind turbine. The lack of real fault data from an operational wind turbine was the reason that two wind turbine CMS were installed during this PhD. Through the installation of these CMS and a review of literature into wind turbine condition monitoring three research questions were defined which identified where work was need to increase the reliability of wind turbine CMS:

1. Having identified from literature that wind turbine CMS need to be more reliable, can a design process be constructed that would facilitate this through better design with an awareness for the environment in which the system must operate?
2. Given that false alarms from CMS are hindering their uptake, how could the occurrence of false alarms be reduced in order to give the operator greater confidence in the information provided by a CMS?
3. Given the occurrence of erroneous data, how could this data be removed or corrected to allow the remaining non-erroneous data to be used for determining the health status of the wind turbine?

The installation of the two CMS provided a valuable insight into the design, build and installation of CMS. It could be seen how poor understanding of the environment in which the CMS was to operate could have a detrimental impact on its reliability. Through the process of working with these CMS and carrying out an FMEA on the first system, five categories of robustness were identified and then incorporated into an engineering design process. Addressing research question one, this novel piece of work provides guidance to anyone designing a CMS for a wind turbine by ensuring that they design the system in a way that will allow it to operate reliably within the wind turbine environment.

In reviewing the literature into the reliability of CMS themselves, it was found that work which focussed on the design of CMS, primarily focussed on the functionality of the system as opposed to its long-term reliability. Functionality may be described as its ability to capture data and diagnose faults, whereas reliability is the system's ability to carry out these functions satisfactorily for an indefinite period of time without the need for human intervention. It is this need for improved reliability of CMS that the work in this thesis has addressed.

As previously mentioned, one form of poor reliability might be the generation of false alarms. False alarms from CMS are detrimental to the O&M of wind turbines as they may lead the operator to take unnecessary actions which result in additional expenditure that was not required. The occurrence of false alarms may be caused by erroneous data captured by sensors. Chapters four and five of this thesis have addressed research question two and the issue of false alarms caused by erroneous data by presenting two data analysis techniques. The first of these techniques identifies erroneous data through the use of multiple parameters and principles of operation, allowing the data to be removed from the dataset. The second of these techniques is based on Pearson's correlation analysis and shows that a drop in correlation may indicate the presence of erroneous data, or the occurrence of a fault within the wind turbine. The key to these techniques is the use of contextual data in order to allow accurate rules and thresholds to be set.

Chapter six of this thesis presented another data analysis technique, this time for repairing signals which have been clipped and therefore addressing research question three. Signal clipping may occur due to a fault with the sensor or simply because the measuring range of the parameter which it has been designed for has been exceeded. In an ideal situation, upon detecting (remotely) that a signal is being clipped, a technician could be deployed to fix or adjust the sensor. In reality however it may not be possible to access the turbine due to restrictions caused by the weather conditions or it may not be economically justifiable to deploy a technician for one sensor. Regardless of the reason for clipping, the information contained within the clipped signal may be crucial for the detection of an impending failure. To address this issue a novel technique was presented which repairs the clipped signal, but crucially, only in the periods that clipping is actually occurring so that as little information as possible from the signal is lost. It was shown that using the signal without removing the clipping could potentially result in false alarms as a result of the harmonics added from clipping.

The research presented in this thesis was carried out with the aim of improving the reliability of wind turbine CMS, as the literature identified a need for this. This has been done in two ways; firstly by improving the design of these systems and secondly through the development of data analysis techniques. Improved design will reduce the likelihood of a failure which would stop the system carrying out its intended function. Analysis techniques which can detect and remove or repair erroneous data will further increase the reliability of the system. This increase in CMS reliability will have a knock on effect of allowing wind turbines themselves to become more reliable, therefore reducing O&M costs and the overall cost of energy from wind turbines.

7.2 Further Work

In relation to the work presented in this thesis, two areas of further work in the following areas are proposed.

- False alarms were identified as an issue hindering the uptake of wind turbine CMS by operators. Therefore further work should be carried out into identifying the causes of false alarms and research applied to minimising them. To do this substantial data would be required from wind farm operators detailing false alarms and their likely cause. This would allow models to be developed similar to that in Chapter 4 which are able to detect the difference between true and erroneous data.
- As the volume of data captured by wind turbine CMS increases it will become more of a challenge to work with the data. Research should therefore be applied to improve Big Data techniques for the application to wind turbine condition monitoring. This will require substantial work into determining a framework suited to the wind farm IT infrastructure. Additionally, successful diagnostic techniques will have to be selected and implemented in a Big Data format, choosing how to categorise the map and reduce tasks.

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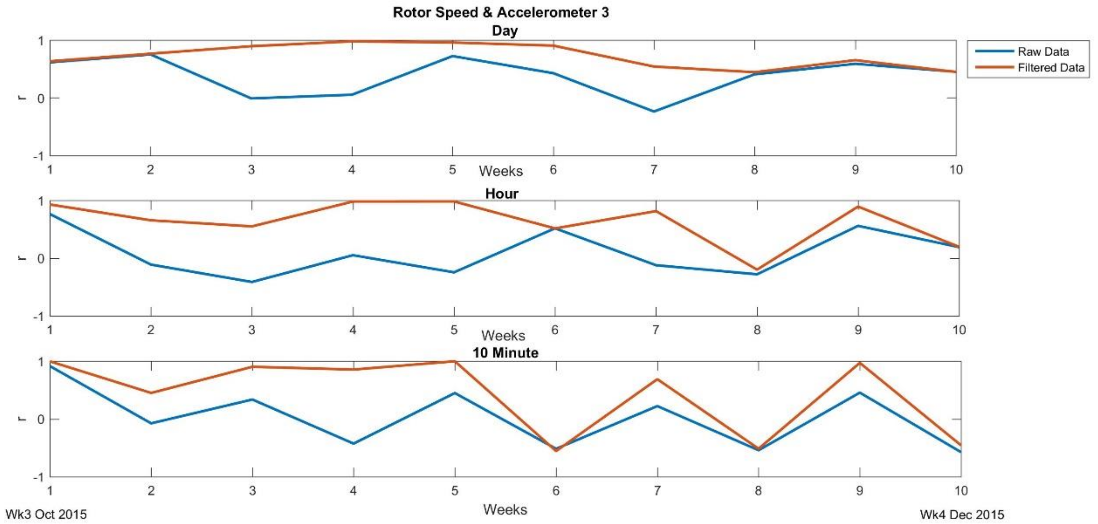
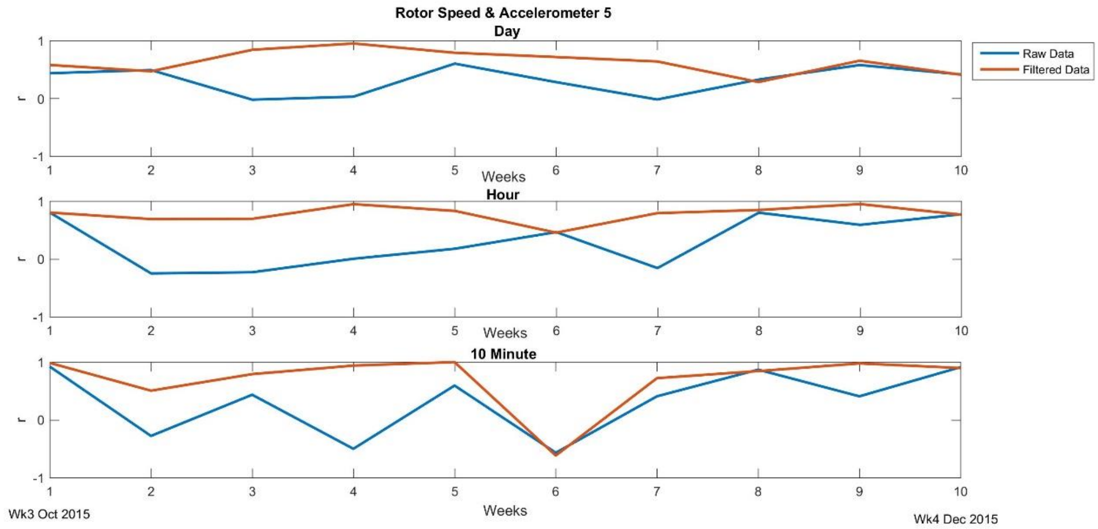
Appendix

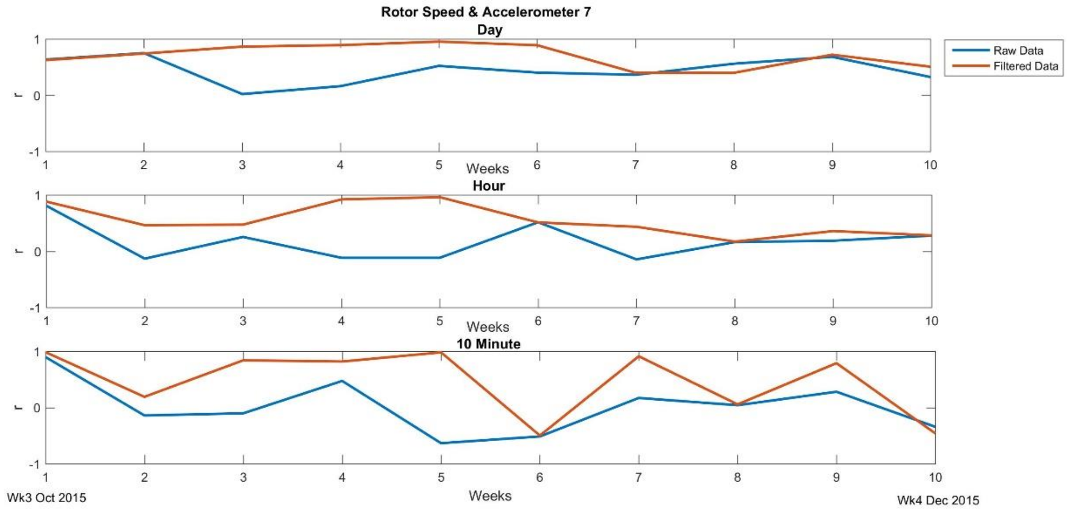
The following appendices show the correlation between rotor speed and acceleration for accelerometers three, five and seven as discussed in Chapter 0. As was discussed, there is a clear difference between the raw data and filtered data due to the acceleration being directly proportional to the rotor speed.



Appendix Figure 1: Correlation between rotor speed and accelerometer 3



Appendix Figure 2: Correlation between rotor speed and accelerometer 5



Appendix Figure 3: Correlation between rotor speed and accelerometer 7