THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Load and Risk Based Maintenance Management of Wind Turbines

Pramod Bangalore

Department of Energy and Environment
Division of Electric Power Engineering
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2016

Load and risk based maintenance management of wind turbines
PRAMOD BANGALORE

Doctoral Thesis at Chalmers University of Technology

Department of Energy and Environment
Division of Electric Power Engineering
SE-412 96 Gothenburg
Sweden
Telephone +46(0)31-772 1000

Chalmers Bibliotek, Reproservice
Göteborg, Sweden 2016

Abstract

Wind power has proven to be an important source of renewable energy in the modern electric power systems. Low profit margins due to falling electricity prices and high maintenance costs, over the past few years, have lead to a focus on research in the area of maintenance management of wind turbines. The main aim of maintenance management is to find the optimal balance between Preventive Maintenance (PM) and Corrective Maintenance (CM), such that the overall life cycle cost of the asset is minimized. This thesis proposes a maintenance management framework called Self Evolving Maintenance Scheduler (SEMS), which provides guidelines for improving reliability and optimizing maintenance of wind turbines, by focusing on critical components.

The thesis introduces an Artificial Intelligence (AI) based condition monitoring method, which uses Artificial Neural Network (ANN) models together with Supervisory Control And Data Acquisition (SCADA) data for the early detection of failures in wind turbine components. The procedure for creating robust and reliable ANN models for condition monitoring applications is presented. The ANN based Condition Monitoring System (CMS) procedure focuses on issues like the selection of configuration of ANN models, the filtering of SCADA data for the selection of correct data set for ANN model training, and an approach to overcome the issue of randomness in the training of ANN models. Furthermore, an anomaly detection approach, which ensures an accuracy of 99% in the anomaly detection process is presented. The ANN based condition monitoring method is validated through case studies using real data from wind turbines of different types and ratings. The results from the case studies indicate that the ANN based CMS method can detect a failure in the wind turbine gearbox components as early as three months before the a replacement of the damaged component is required. An early information about an impending failure can then be utilized for optimizing the maintenance schedule in order to avoid expensive unscheduled corrective maintenance.

The final part of the thesis presents a mathematical optimization model, called the Preventive Maintenance Scheduling Problem with Interval Costs (PMSPIC), for optimal maintenance decision making. The PMSPIC model provides an Age Based Preventive Maintenance (ABPM) schedule, which gives an initial estimate of the number of replacements, and an optimal ABPM schedule for the critical components during the life of the wind turbine, based on the failure rate models created using the historical failure times. Modifications in the PMSPIC model are presented, which enable an update of the maintenance decisions following an indication of deterioration from the CMS, providing a Condition Based Preventive Maintenance (CBPM) schedule. A hypothetical but realistic case study utilizing the Proportional Hazards Model (PHM) and output from the ANN based CMS method, is presented. The results from the case study demonstrate the possibility of updating the maintenance decisions in continuous time considering the changing conditions of the damaged components. Unlike the previously published mathematical models for maintenance optimization, the PMSPIC based scheduler provides an optimal decision considering the effect of an early replacement of the damaged component on the entire lives of all the critical components in the wind turbine system.

Keywords: Artificial neural network (ANN), condition monitoring system (CMS), life cycle cost, maintenance management, maintenance strategy, maintenance planning, optimization, supervisory control and data acquisition (SCADA), wind energy.

Acknowledgements

This work has been carried out at the Division of Electric Power Engineering, Department of Energy and Environment at Chalmers University of Technology, Gothenburg, Sweden within the Swedish Wind Power Technology Cetre. The financial support provided by Vindforsk and the Swedish Research Council (Dnr. 621-2014-5138), for the last two and half years, is gratefully acknowledged.

I would like to sincerely acknowledge my gratitude to my supervisor Prof. Michael Patriksson, and examinar Prof. Ann-Brith Strömberg who have guided and supported me throughout the research work.

I would like to thank Prof. Ola Calrson for his constant encouragement and for the insightful discussions during the research work.

A special thanks goes to the industrial partners; especially Thomas Svensson (Stena Renewables), Wang Zhen (Gold Wind), and Christer Pettersson (Göteborg Energi) whose experience and guidance with data and real world problems helped immensely in improving the project. I would also to like to thank Jonas Corné from Greenbyte for providing me with an opportunity to implement the results from the project to real world applications.

I would like to thank Simon Letzgus and Daniel Karlsson whose thesis work has helped in improving the work.

I also thank Prof. Lina Bertling Tjernberg for her guidance and support during the initial two and half years of this project.

A special thanks to Sara Fogelström whose administrative support in SWPTC made it possible to carry out the project without any difficulties.

I am grateful to everyone in my office; Joachim, Pinar, Nicolas, Pavan, and Daniel for the interesting discussions and arguments. I would also like to thank all my colleagues at the division of Electric Power Engineering and at the SWPTC.

I would like to thank Loredana for her continual support, kind words and encouragement which kept me going in tough times.

Finally, I would like to thank my parents for their unending love and encouragement without which nothing would have been possible.

Pramod,
Gothenburg,
September, 2016

List of publications

Appended papers This thesis is based on the following publications:

Paper I: P. Bangalore, and L. Bertling Tjernberg, "Self evolving neural network based algorithm for fault prognosis in wind turbines : A case study", *in Proc.of IEEE Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, IEEE, Durham, July 2014.

Paper II: P. Bangalore, and L. Bertling Tjernberg, "An artificial neural network approach for early fault detection of gearbox bearings", *IEEE Transactions on Smart Grid*, vol.6, no.2, March 2015, pp.980–987.

Paper III: P. Bangalore, S. Letzgus, D. Karlsson, and M. Patriksson, "A SCADA data based condition monitoring method for wind turbines, with application to the monitoring of the gearbox," submitted to *Wind Energy*.

Paper IV: P. Bangalore, and M. Patriksson, "Analysis of SCADA data for early fault detection, with application to the maintenance management of wind turbines," submitted to *Renewable Energy*.

Related papers not appended

i: P. Bangalore, and L. Bertling Tjernberg, "An approach for self evolving neural network based algorithm for fault prognosis in wind turbine", in *2013 IEEE Grenoble Conference*, IEEE, June 2013, pp. 1–6.

ii: P. Bangalore, S. Letzgus, and M. Patriksson, "Analysis of SCADA data for early fault detection with application to the maintenance management of wind turbines", accepted for presentation in *Cigre Session 46*, Paris, August 2016.

iii: G. Puglia, P. Bangalore, and L. Bertling Tjernberg, "Cost efficient maintenance strategies for wind power systems using LCC", *in Proc.of IEEE Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, IEEE, Durham, July 2014.

Preface

The Swedish Wind Power Technology Centre (SWPTC) is a research centre for design of wind turbines. The purpose of the Centre is to support Swedish industry with knowledge of design techniques as well as maintenance in the field of wind power. The research in the Centre is carried out in six theme groups that represent Design and Operation of Wind Turbines; Power and Control Systems, Turbine and Wind Loads, Mechanical Power Transmission and System Optimization, Structure and Foundation, Maintenance and Reliability as well as Cold Climate.

This project is part of Theme group 5, Maintenance and Reliability.

SWPTC's work is funded by the Swedish Energy Agency, and by three academic and thirteen industrial partners. The Region Västra Götaland also contributes to the Centre through several collaboration projects.

List of acronyms

ABPM	Age Based Preventive Maintenance
AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Interference Systems
ANN	Artificial Neural Network
CBPM	Condition Based Preventive Maintenance
CM	Corrective Maintenance
CMS	Condition Monitoring System
FMEA	Failure Mode Effect Analysis
IID	Independent and Identically Distributed
KPI	Key Performance Indicator
LCC	Life Cycle Cost
MAE	Mean Absolute Error
MHD	Mahalanobis Distance
MLE	Maximum Likelihood Estimation
MTTF	Mean Time To Failure
NARX	Non-linear Auto-Regressive network with eXogenous input
O&M	Operation and Maintenance
PCA	Principal Component Analysis
PHM	Proportional Hazards Model
PM	Preventive Maintenance
PMSPIC	Preventive Maintenance Scheduling Problem with Interval Costs
RCAM	Reliability Centered Asset Maintenance
RCM	Reliability Centered Maintenance
RLE	Residual Life Estimation
RPM	Rotations Per Minute
SCADA	Supervisory Control And Data Acquisition
SEMS	Self Evolving Maintenance Scheduler
SWPTC	Swedish Wind Power Technology Center
WT	Wind Turbine

Contents

Chapter 1

Introduction

1.1 Background

Global energy demand is set to grow by 37% by 2040 compared to 2015 ([1]). At the same time the future of global energy systems is uncertain due to volatile political situation in the Middle East, which still remains the main source of cheap oil. Electricity is the fastest growing form of energy. However, the power sector still contributes the most towards a reduction of fossil fuels in global energy mix. An estimated 7200 GW of new capacity needs to be installed by the year 2040, in order to keep pace with the growing demand, while the existing, aging power plants need to be replaced. The strong growth of renewables in many countries could raise their global share by one third by the year 2040. The share of renewable generation in the countries which are member of OECD (Organisation for Economic Co-operation and Development) may increase up to 37%, whereas developing nations like China, India, Latin American and Africa could see a doubling of the share of renewables in their energy mix ([1]).

Wind power has been one of the most promising new sources of renewable energy during the past decade. The industry has seen a steady growth, and it can be expected that the growth shows similar trend in the future. Thanks to a strong development of technology, wind turbines have increased in size from a few kW to multiple MW. Furthermore, higher wind speeds have motivated installing larger wind turbines off-shore. Consequently, this has also led to a situation where failures in wind turbine components result in higher revenue losses and also frequent maintenance becomes impractical and expensive.

In recent times, maintenance management in wind turbines has gained significance and the focus has been to improve the wind turbine reliability and profitability. Traditional methods like Reliability Centered Maintenance (RCM), which have proven to be successful in other industrial applications, are being investigated for wind turbines. The RCM method, motivates focusing the preventive maintenance activities on those components, which might be the cause of concern for the reliability of the entire system. Preventive maintenance can be broadly classified into two categories: age based preventive maintenance (ABPM) and condition based preventive maintenance (CBPM). The CBPM strategy has the advantage of a better utilization of the life of the components compared to the ABPM strategy, and hence, can be beneficial in the long run. However, to achieve an effective optimal condition based maintenance requires an efficient condition monitoring system and a practical mathematical optimization model. In this context, a maintenance management framework is presented in this thesis; it provides guidelines to (i) create a robust condition monitoring system using the data stored in the SCADA system, and (ii) use the signals from condition monitoring systems to achieve optimal condition based maintenance.

1.2 Problem overview

Wind turbines are complex electromechanical systems, which are continuously subjected to harsh operating conditions. Furthermore, wind turbines are, generally, located at remote locations to take advantage of higher wind speeds. Hence, major failures in wind turbines, which are more frequent than desirable, are expensive to repair, cause losses in revenue, and may also cause long downtimes. Furthermore, as wind power reaches utility scales, it will be expected to have reliability and availability performances close to conventional power generation. This situation has lead to an increased focus on developing advanced asset management methods, which ensure lower maintenance costs and higher availability of wind turbines.

The development efforts in the area of wind turbine asset management can be divided into two main areas, namely

I: the improvement of existing, and development of new, condition monitoring methods, and

II: the development of mathematical models for optimal maintenance planning.

1.2.1 Wind turbine condition monitoring systems

Visual inspections and vibration analysis have been the most commonly applied condition monitoring methods to wind turbine systems. Visual inspections are labor intensive and can identify only limited types of failures ([2]); they also cause downtimes, and hence frequent inspections are not desirable. Vibration analysis has been successful in condition monitoring of rotating equipment in industrial applications, however, it requires additional sensors. Furthermore, a study conducted by the National Renewable Energy Laboratory (NREL) found that the average detection accuracy of the existing vibration monitoring systems is only about 50%; see [3] for details. In addition to the development of condition monitoring tools using vibration signals, new methods using a variety of sensor measurements have been developed in the past few years; see for example [2,4]. In recent times, condition monitoring based on measurement data from the wind turbine SCADA system has been in focus, and a variety of methods have been developed for the same; those in [5–8] are a few prominent examples in this area. The analysis of SCADA data has become lucrative, as it presents an opportunity to monitor not only mechanical, but also electrical components in the wind turbines. Machine learning methods, like artificial neural network (ANN), have proven to be effective in extracting information from large SCADA data sets, which has been demonstrated in [5–8]. However, they have not yet been widely adopted for real world applications. ANN is a black box modeling method, and hence it does not incorporate any physical understanding of the system being modeled. Furthermore, there exists an inherent randomness in the training of ANN models due to the non-convex optimization used while deciding the synaptic weights ([9]). These issues have seldom been addressed in the context of wind turbine applications and, consequently, ANN based condition monitoring methods are still under-utilized.

1.2.2 Mathematical models for maintenance optimization

The mathematical models for maintenance optimization can be divided into two broad categories, based on the type of statistical failure rate models that they utilize for optimizing the maintenance decisions; ABPM and CBPM optimization models. The schedules resulting from the ABPM optimization models stipulate replacements of components based on failure rate models derived from historical failure times, while the corresponding CBPM schedules utilize the failure rate models based on information from condition monitoring systems. The ABPM strategy provides an expected number of replacements for a component over the life of the system which can be useful for financial planning purposes. Furthermore, age based statistical failure rate models are easier to create, as they need as input only the historical failure times for the components. However, replacement of components following such a maintenance schedule might lead to under-utilization of the useful lives of the components. The CBPM strategy, on the other hand, has the advantage of providing a maintenance schedule based on the health of the component, thereby providing an opportunity for maximizing the consumption of the component life. However, condition based failure rate models are difficult to create as they require detailed information from the condition monitoring systems. Moreover, the CBPM strategy does not provide an estimated number of replacements during the life of wind turbines. Hence, a hybrid maintenance strategy which can take advantage of both maintenance strategies is desirable.

1.3 Previous work

In this section a brief literature review is presented, which covers the two main topics of this thesis: the condition monitoring from SCADA data, and mathematical models for maintenance optimization.

1.3.1 Condition monitoring from SCADA data

The SCADA system is an integral part of all modern wind turbines: it records various mechanical quantities like temperature, rotational speed, etc., and electrical quantities, like current, voltage, power, etc. Relevant data from the SCADA system can be extracted at any point of time and can be used to estimate the health of selected wind turbine components. Researchers have published different methods and approaches for using SCADA data for condition monitoring; a few examples are found in [5–8,10–18]. Mathematical modeling methods like artificial neural networks have been frequently utilized for the analysis of SCADA data, as they have the capability to model highly nonlinear relationships and can easily be adapted to large-scale applications. The methods presented in [5–8] are the most prominent examples of application of artificial neural networks to wind turbine condition monitoring using SCADA data.

A software tool named Intelligent System for Predictive Maintenance (SIMAP) was presented in [5]. The SIMAP tool is divided into six modules responsible for normal behavior modeling, anomaly detection, health condition assessment, failure diagnosis, preventive maintenance scheduling, and maintenance effectiveness assessment. The normal behavior module utilizes a multiple layer ANN model for predicting a parameter value based on the selected input parameters. The ANN model output is compared with the measured value in real time, and a difference outside confidence bands, defined by the normal behavior model, is termed as an anomaly. The diagnosis of a failure is performed with a fuzzy expert system in the diagnosis module, which holds knowledge about different failure modes for the component being monitored. The health assessment module is used to categorize the component condition as either good, bad or very bad. Furthermore, a preventive maintenance action is scheduled with the objective to minimize the cost of maintenance. However, the case study presented in [5] shows that the system is able to detect the failure (approximately) 26 hours in advance, which might be sufficient to avoid a catastrophic failure, but not for an effective CBPM optimization. Furthermore, the maintenance decisions do not consider the effect of an early replacement of the damaged component, on the life of the wind turbine.

A similar ANN based anomaly detection technique for early fault detection in wind turbines was presented in [6]. The case study presented showed that the ANN models are capable of detecting deviations in the component behavior as early as six months before the eventual failure. The anomaly detection is based on observing an increase in the frequency of errors between the actual and modeled parameter values. This method of anomaly detection can become impractical when it is applied to a large number of wind turbines. In order to make the ANN based CMS method practical and scalable, it is desirable to have an automated anomaly detection which triggers an alarm when the error between the actual and modeled parameter values exceeds a predefined threshold.

The multilayer feed-forward ANN normal behavior models of various configurations with different number of neurons in the hidden layer and different input configurations were investigated in [7], for condition monitoring application in wind turbine system. The case study with 10 sec. SCADA data illustrated that the method is able to predict faults about 1.5 hours before the eventual failure. The detection of an anomaly close to the actual failure does not allow any kind of maintenance planning. Moreover, anomaly detection based on values of error between the modeled and the actual parameter value might, in some cases, not be sufficient for an early detection of anomaly in the component.

In [8], condition monitoring using Adaptive Neuro-Fuzzy Interference Systems (ANFIS) is presented along with a method to define a threshold value for anomaly detection. The standard deviation of the errors during the training period is used to define the threshold. However, the ANN models could be skewed, resulting in larger errors at certain operating points. Such a situation could lead to false alarms if the threshold value is decided based solely on the distribution of the errors during the training period, and without considering the correlation between the errors and the operating point.

The ANN based CMS developed in this thesis intends to address each of the above mentioned shortcomings. The approach presented in this thesis utilizes the sensor measurement data stored in the SCADA system as well as the SCADA generated alarms and warnings for condition monitoring of critical components in the wind turbine.

1.3.2 Mathematical models for maintenance optimization

A thorough understanding of the reliability of wind turbines is highly desirable to formulate an optimal maintenance management strategy. However, wind power installations, for the most part, are comparatively new in the field of bulk power production. The installations are yet to reach an end-of-life scenario, which means that definitive reliability analysis of wind turbines is a difficult task. Different methods for reliability analysis of wind turbines have been proposed in the literature. A reliability analysis method based on failure statistics collected from publicly available data has been presented in [19]. The method focuses on reliability analysis for incomplete data sets. Funded under the European Unions' seventh framework, the ReliaWind project was formulated with an aim to improve the design, maintenance and operation of wind turbines. Within ReliaWind project a reliability analysis procedure for wind turbine applications has been outlined in [20], which provides guidelines for performing reliability evaluation of wind turbines.

The difficulty of assessing wind turbine reliability is also augmented by the fact that wind turbine failure statistics are not freely available. In the absence of data, which is required for accurate reliability predictions, the only sources are publications which present data about failures in wind turbines. In [21], failure statistics for Swedish wind turbines during the years 1997–2005 were published. This was one of the first publications on wind turbine failure statistics; the industry typically does not publish similar data. Furthermore, in [22] publicly available databases from Germany and Denmark were presented, with results from a reliability analysis on a sub-assembly level. A summary of results presenting the failure rates for various components in the wind turbine was presented in the final project report from ReliaWind project in [23]. In order to achieve a practical maintenance schedule with mathematical optimization models, it is necessary to accurately estimate the reliability of various components in the wind turbine.

Considering that the reliability of wind turbine components can be estimated with acceptable accuracy based on historical failure times, an ABPM strategy can be initiated. Various mathematical optimization models have been developed for making optimal ABPM decisions. A mathematical model for ABPM optimization using probabilistic failure rate of various components was introduced in [24]. This basic ABPM optimization model was one of the earliest works in maintenance optimization applied to wind turbine applications. The basic model was developed further in [25] by allowing a preventive replacement when maintenance opportunities arise; this is often referred to as *opportunistic maintenance optimization*. Opportunistic maintenance becomes especially attractive for offshore wind farms, where access to wind turbines is expensive, and in harsh weather conditions even impossible. The opportunistic maintenance optimization model, presented in [25], was further developed in [26] for applications of planning maintenance resources, like number of maintenance personnel, number of shifts, number of transport vehicles, etc. An ABPM approach similar to the opportunistic maintenance, and referred to as maintenance grouping, was presented in [27]. The maintenance grouping approach provides an optimal schedule where components with similar expected failure times are optimally grouped.

The ABPM optimization allows the planning of preventive maintenance of various wind turbine components over the expected life of a wind turbine. However, the maintenance decisions cannot be updated in real time based on the information from the condition monitoring system. Today, condition monitoring systems have become mandatory for multi-MW wind turbines in most countries. The next major step in improving asset management will be the integration of information from condition monitoring systems with the maintenance optimization process, and hence leading to the CBPM strategy.

Researchers have developed various mathematical models for CBPM optimization, considering that a certain type of health information will be available from the CMS in the future. A number-dependent preventive maintenance strategy was presented in [28], for optimizing maintenance of blades in offshore wind turbines; the optimization model was formulated to find the optimal number of observable damages in the turbine blades, which should be allowed before initiating either a PM or a CM activity. An approach for CBPM applied to wind turbine blades using CMS information was presented in [29]; different condition monitoring strategies were compared from a Life Cycle Cost (LCC) perspective and an optimum strategy for blade monitoring was suggested; the model assumes that information from the CMS can be used to specify the state of the blades into one of the four defined categories used in a Markov model. A risk-based maintenance optimization framework using Bayesian theory was presented in [30]; the framework proposed a theoretical component deterioration model, which utilizes information from the condition monitoring system and considers the stochastic operating conditions for maintenance scheduling. A method to utilize the values of vibration signals from the CMS system for historical failure and suspensions to predict the remaining useful life of components was presented in [31]; the maintenance interval is decided by simulating the maintenance cost per unit time for different maintenance intervals and different failure probability thresholds. A statistical approach for using the vibration signals from condition monitoring system with the proportional hazards model (PHM) was presented in [32]; a control limit policy was developed to optimize the threshold for CBPM; this model was extended for a multi-component application in [33].

The mathematical models for maintenance optimization presented above, take advantage of either the ABPM or the CBPM strategy. However, none of them explicitly presents an option where both maintenance strategies can be utilized. In this thesis a mathematical model has been developed that provides an initial ABPM schedule, which can be used for financial planning, and provides an optimal CBPM schedule in real time based on information from the condition monitoring systems about an impending failure in a component. This mathematical model for maintenance optimization and the proposed maintenance management framework can aid in improved asset management over the life of the wind turbines.

1.4 Aim of the thesis

The main aim of the thesis is to develop a framework, which provides guidelines for utilizing operation and maintenance (O&M) data to achieve an optimal maintenance of wind turbines. The work has, specifically, focused on developing an ANN based method for condition monitoring using data stored in the SCADA system. Various issues that limit the applicability of the ANN based condition monitoring in a real world application are discussed and mitigation techniques to improve the confidence in the output of the condition monitoring activity are developed and presented. Furthermore, a mathematical model is presented, which provides an optimal ABPM strategy with the possibility to update the maintenance plan based on information from the condition monitoring system, resulting in an optimal CBPM strategy.

1.5 Main contributions of the thesis

The main contributions from the thesis are listed below.

1. A maintenance management framework referred to as Self Evolving Maintenance Scheduler (SEMS) has been proposed in this thesis, which provides guidelines for utilizing O&M data from various sources towards optimal maintenance of various critical components in the wind turbine. The description of the SEMS framework is provided in Chapter 3.

2. An ANN based condition monitoring method is proposed in this thesis. This method utilizes sensor data stored in the SCADA system along with SCADA generated alarms and warnings for monitoring of critical components in the wind turbine. Various issues related to ANN modeling; like selection and filtering of training data, post-processing of the output from ANN model to improve confidence in the condition monitoring system, and a procedure to update the models after replacement of the monitored component are discussed in the thesis. The ANN based condition monitoring system is presented in detail with various case studies in Chapter 4.

3. A mathematical model for maintenance optimization is proposed in this thesis. This mathematical model provides an initial ABPM schedule and provides an optimal CBPM schedule in real time based on information from the condition monitoring systems. The mathematical model for maintenance optimization is presented in Chapter 5, along with case studies demonstrating the advantages of the proposed optimization model.

1.6 Thesis structure

The thesis is organized as an introduction to and summary of the attached papers.

Chapter 2 provides an introduction to the concepts of ANN and provides relevant information about the reliability models utilized in the thesis.

Chapter 3 introduces the concept of maintenance management and presents the proposed maintenance management framework.

Chapter 4 presents the ANN based condition monitoring method with application results from case studies.

Chapter 5 presents the mathematical optimization model with case studies.

Chapter 6 presents the thesis conclusions and proposes future work.

Chapter 2

Theoretical background

This chapter provides the theoretical background of the concepts and methods used in the thesis. The basics about artificial neural networks are described. Relevant mathematical equations used for training the neural networks are discussed. Furthermore, a brief introduction to reliability theory is presented, with relevant information about the statistical models used in the thesis.

2.1 Theory of neural networks

The brain functions in ways that let us interact with our immediate surroundings. For example; vision is one of the functions of the brain, wherein an image input from the retina of the eye is processed to let us perceive, understand, and interact with the object being visualized. All this processing takes a matter of milliseconds. The human brain, even in early stages of growth, has the capability much greater than today's fastest computer in terms of performing complex information processing. The brain comprises of millions of neurons connected in a particular manner, the interaction of which in a specific sequence produces the desired results. These connections are established early in life through a learning procedure, commonly referred to as *experience*. The Artificial Neural Network (ANN) models intend to mimic the structure of the brain in order to model real world non-linear systems. The main similarities between the brain and the ANN is the knowledge acquisition through experience or learning processes and the retention of the knowledge with the inter-neuron connections, characterized by synaptic weights ([34]).

2.1.1 Model of a neuron

A neuron is the fundamental building block of an ANN. The function of the neuron is to generate an output based on a given set of input variables. The weighted sums of the inputs and the bias are passed through an activation function which decides the output of the neuron, as shown in Figure 2.1.

The input variables $u_1, u_2, \ldots, u_n$ are multiplied with their respective synaptic weights $w_1, w_2, \ldots, w_n$ and are summed with the bias value b. The bias values are treated in the same manner as weights. The bias could take a value equal to -1 or 1, which shifts the activation function either to left or right, respectively. $\Phi(\cdot)$ is the activation function, which decides the final output y from the neuron. The mathematical representation of a neuron, depicted in Figure 2.1, can be described as follows:

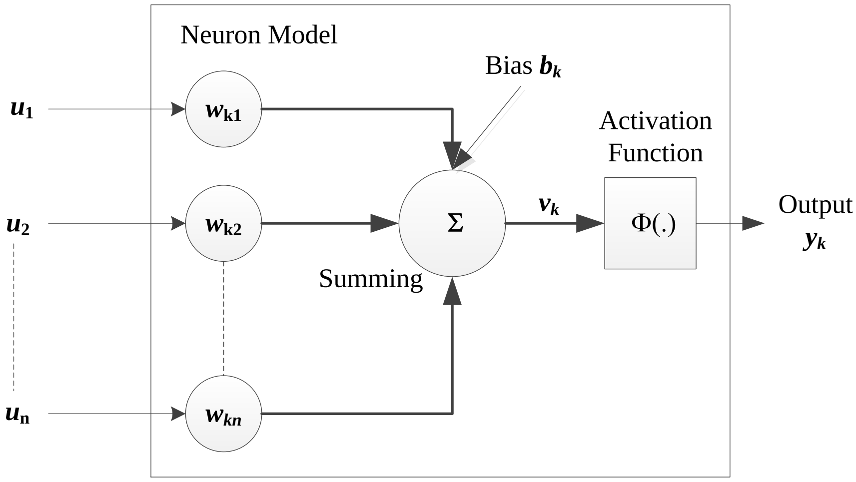

Figure 2.1: Model of a typical neuron

$$v = \sum_{j=1}^{n} w_j u_j, \tag{2.1a}$$

$$y = \Phi\left(v + b\right). \tag{2.1b}$$

2.1.2 Activation function

The output of the neuron is defined by the activation function $\Phi(\cdot)$. In this section two types of activation functions, respectively called the threshold activation function and the sigmoid activation function, are described.

Threshold function

The threshold activation function is defined by (2.2) and illustrated in Figure 2.2, below. The threshold function can have output either 1 or 0, depending on the induced field v. Threshold functions are often used in the output layer of ANN, where binary classification of the input is required.

$$\Phi(v) = \begin{cases} 1, \text{ if } v \geq 0, \\ 0, \text{ if } v < 0. \end{cases} \tag{2.2}$$

Sigmoid function

The sigmoid function is a non-linear activation function defined by (2.3) and illustrated in Figure 2.3. The sigmoid function is one of the most common activation functions used in neural networks, when a non-linear classification is required. The slope of the sigmoid function can be varied by the slope parameter a, and as $a \to \infty$ the sigmoid function tends to the threshold function. In contrast to the threshold function, which can assume a value of either 0 or 1, the sigmoid function can assume any value between 0 and 1.

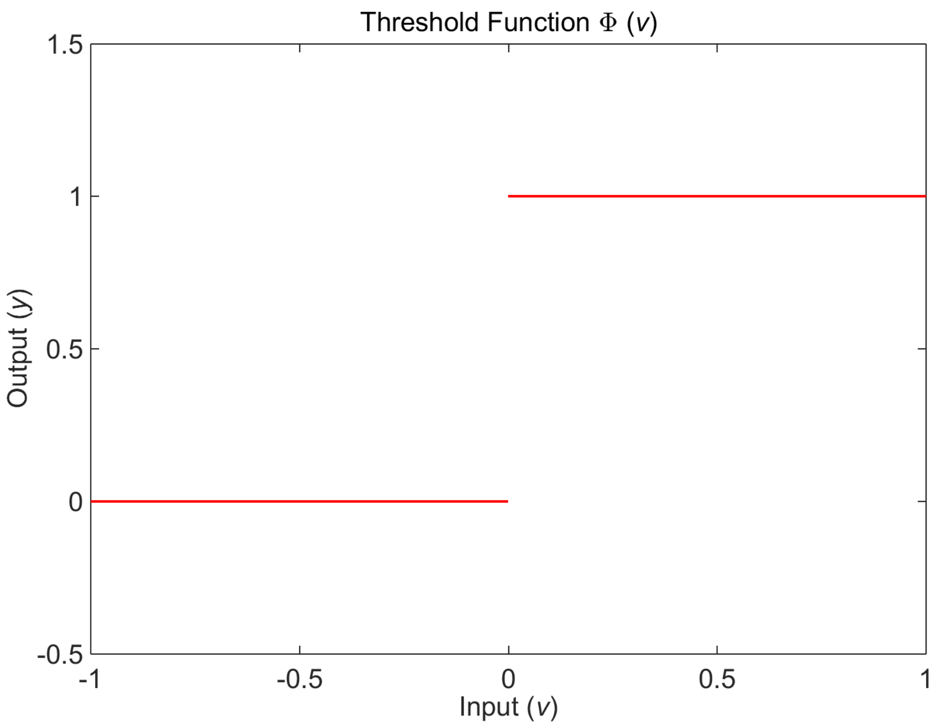

Figure 2.2: The threshold type activation function

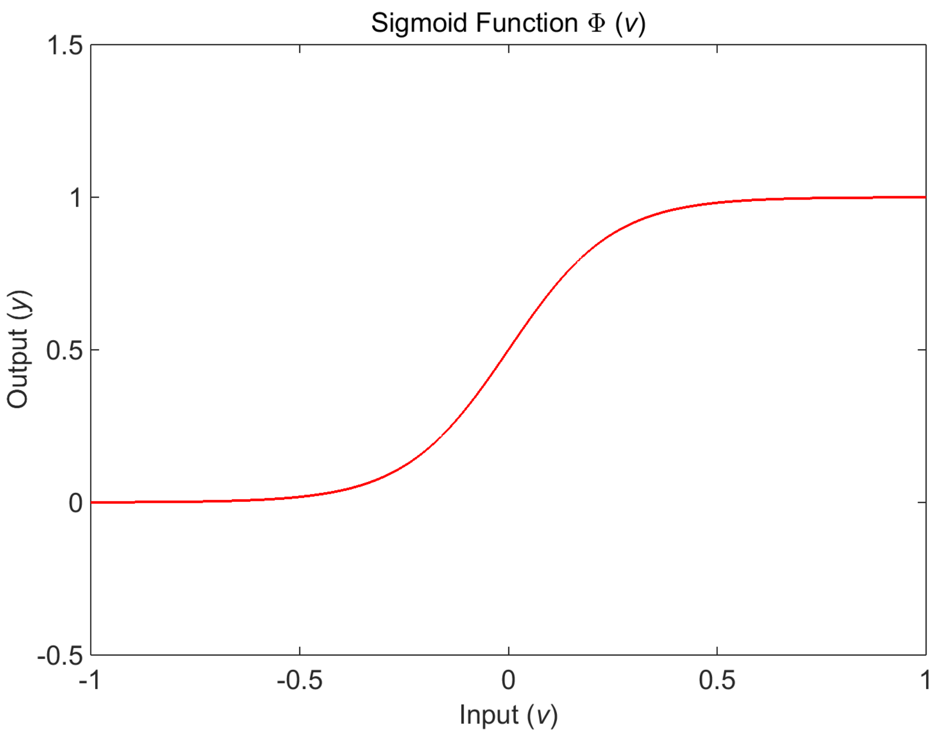

Figure 2.3: The sigmoid activation function

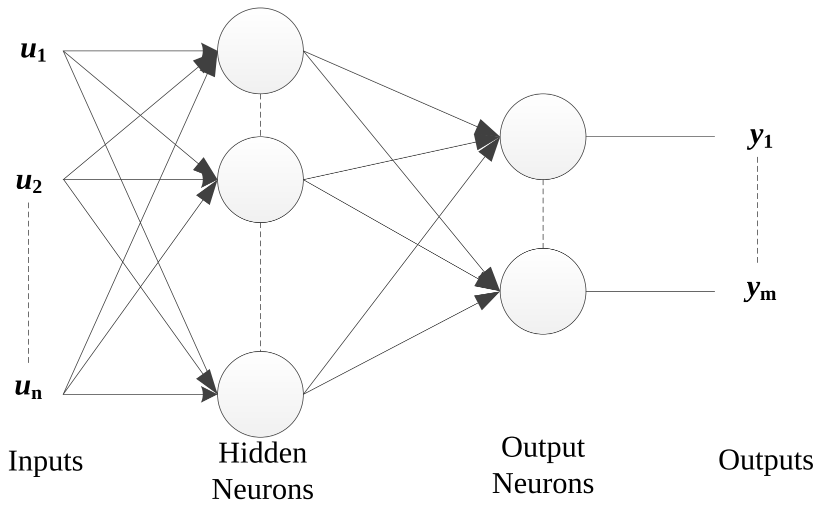

Figure 2.4: Structure of a multilayer feed-forward network

$$\Phi(v) = \frac{1}{1 + \mathrm{e}^{-av}} \tag{2.3}$$

2.1.3 Neural network architectures

The input/output relation for a neural network is strictly dependent on the network configuration, which consists of the information about the number of neurons in the different layers and their inter-connections. In this section two main types of network configurations, which are relevant for the specific application with wind turbine SCADA data, are discussed.

Multilayer feed-forward network

The multilayer feed-forward ANN configuration has at least three layers: the input layer, the hidden layer, and the output layer. A schematic representation of a multilayer configuration is shown in Figure 2.4. All the layers between the input and the output layers are referred to as hidden layers. Generally, the non-linearity in the input/output relationship is directly related to the number of layers in the network. Theoretically, there is no limit on the number of hidden layers; however, one hidden layer was found to be sufficient for an accurate modeling of various parameters in the wind turbine system.

Multilayer recurrent networks

In contrast to the feed-forward neural networks, the recurrent neural networks are characterized by at least one feedback loop. Figure 2.5 shows a schematic representation of a recurrent neural network. The neural network exhibits a feed-forward structure through the hidden layer of neurons. Furthermore, the delay units make the behavior of the neural network non-linear. This class of neural networks has shown better performance in terms of accuracy for different applications, as compared to the traditional feed-forward neural networks, as reported in [35–37].

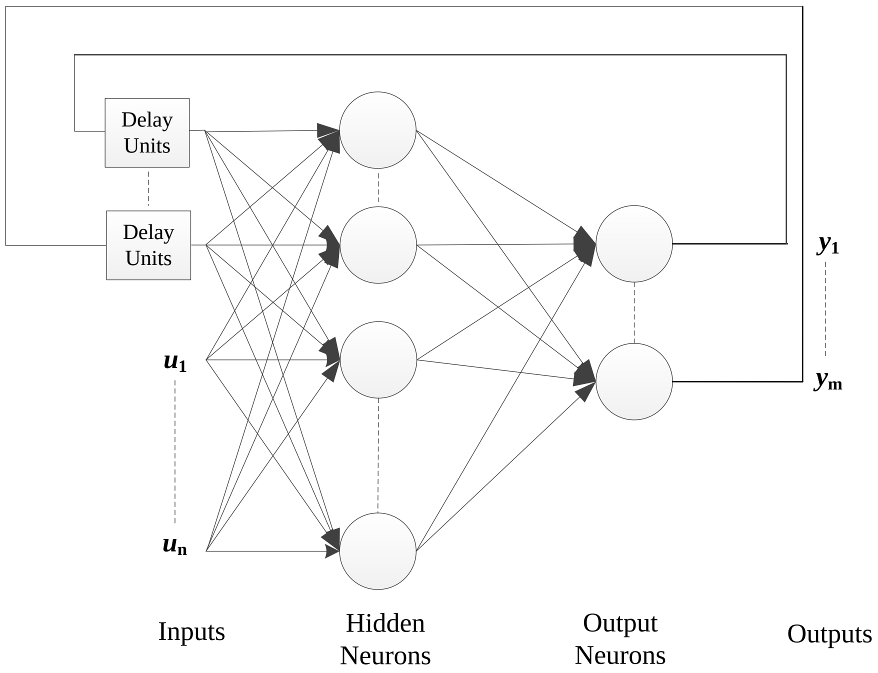

Figure 2.5: Structure of a multilayer recurrent network

2.1.4 Learning methods

For a given neural network the information about the relationship between the inputs and outputs is stored in the synaptic weights, which decide the output of each individual neuron. These synaptic weights are realized through a learning process, wherein the neural network is presented with a data set, called the *training data set*, and the network learns the relationship between inputs and outputs in this training data set. The learning methods can be classified into two categories: supervised and unsupervised learning. A labeled training data set with an output defined for each set of input variables is required for the supervised training, while an unsupervised training can be performed with unlabeled data. Supervised learning is applied when labeled data can be obtained; it is useful for modeling the underlying function of the input/output relation.

Supervised learning

Learning achieved through a pre-defined set of inputs and outputs, which are representative of the environment or system being modeled, is termed supervised learning. Supervised learning is represented schematically in Figure 2.6. A data set, consisting of samples of input vectors and their respective desired outputs, is extracted from the environment or system, which is to be modeled. This pre-defined training data set is considered to have knowledge about the environment or system and acts as a teacher to the ANN. The initial ANN model includes no information about the environment or system being considered; i.e., the values of the free parameters in the model (the synaptic weights w) are undecided. The intention of the teacher is to transfer the knowledge in the training data set to the ANN model; i.e., to decide the values of the synaptic weights. During the training process, the knowledge transfer is achieved through the influence of the error signal and the training

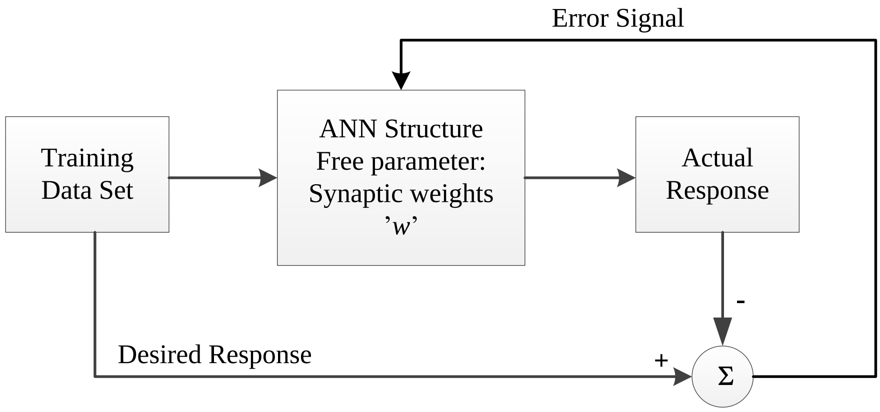

Figure 2.6: The supervised learning method

samples. The error signal is defined based on the difference between the output of the ANN model and the desired response, which is stored in the training data set.

The supervised learning of ANN models can be divided into three stages; the training, the validation, and the testing. Consequently, the pre-defined data set which represents the behavior of the environment or the system to be modeled, is divided into three parts referred to as training data set, validation data set, and test data set, respectively.

The training data set is utilized for deciding the synaptic weights of the ANN model, which is an iterative process with an aim to make the ANN model replicate the behavior of the environment or the system with high accuracy. The training of the model is essentially a minimization problem, wherein the objective is to minimize the performance measure with the synaptic weights and biases as variables. Standard minimization algorithms like steepest descent can be used for the ANN model training. However, more advanced minimization algorithms have been developed for training the ANN models, and one such training algorithm, called the Levenberg–Marquardt training algorithm, is discussed later in this chapter.

The validation data set contains data that have not been presented to the ANN model during the training process. Generally, during initial phases of training the error between the ANN modeled parameter values and the actual values reduces, for both the training and the validation data sets. However, at some stage the error value continues to reduce for the training data set but starts increasing for the validation data set, due to over-fitting of the data by the ANN model ([34]). At this stage the network training is halted and the network weights and biases, which correspond to the minimum validation data set error are saved as the final ANN model.

Finally, the test data set which the trained model has not seen previously is utilized to assess the performance of the trained ANN model.

Unsupervised learning

Unsupervised learning is achieved without a pre-defined training data set. The fact that the learning is achieved without any teacher, as opposed to supervised learning, makes it an unsupervised learning method. This method of learning is used mainly when it is impossible, or difficult, to construct a training data set, representing the environment or the system being modeled. Unsupervised learning is, hence, achieved through unlabeled samples of inputs and outputs, which are easily available for any environment or system. Data clustering applications often use unsupervised learning methods.

2.1.5 Levenberg–Marquardt training algorithm

The synaptic weights w are updated for a given structure of ANN, based on the training algorithm adopted. In this subsection, the Levenberg–Marquardt ([38,39]), training algorithm (LMA) is presented; it is one of the most common algorithms used for training moderately sized ANN models. It has the combined advantage of the convergent steepest descent algorithm and Newton's method, which usually is fast near an optimum; further details about these optimization algorithms can be found in [40,41]. The LMA is more efficient than the conjugate gradient algorithm for neural networks with less than 100 neurons ([42]). Hence, as the number of neurons required for the modeling within this thesis is less than 100, the LMA has been used for training of ANN models.

The input/output relationship for an ANN model can be represented as

$$y = F(U; w), \tag{2.4}$$

where F is the non-linear approximation function from the ANN model, which emulates the relationship between the inputs U and the output y. The input vector U consists of M input parameters, $(u_1, \ldots, u_M)$, which are used to model one output parameter y.

Consider a training set $(U(i), d(i))_{i=1}^{N}$, with N, sample points. $F(U(i); w)$ is emulated by the ANN model, $d(i)$ is the value of the desired output corresponding to the inputs $U(i)$, and the matrix w is a $K \times M$ weight matrix, where K is the number of neurons in the hidden layer. The network training is achieved by minimizing the loss function $\mathcal{E}$ defined as

$$\mathcal{E}(w) := \frac{1}{N} \sum_{i=1}^{N} [d(i) - F(U(i); w)]^2. \tag{2.5}$$

According to the LMA the weight vector is updated according to $w := w + \Delta w$, where

$$\Delta w = [H + \lambda I]^{-1} g, \tag{2.6}$$

H denotes the Hessian matrix approximation defined by (2.7) below, and g denotes the gradient vector defined as per (2.8). I denotes an identity matrix with dimensions same as H and λ is a positive scalar parameter used to interpolate between Newton's method and the steepest decent method.

$$H = \frac{1}{N} \sum_{i=1}^{N} \left[\frac{\partial F(U(i), w)}{\partial w}\right] \left[\frac{\partial F(U(i), w)}{\partial w}\right]^{\mathrm{T}} \tag{2.7}$$

$$g = \frac{\partial \mathcal{E}(w)}{\partial w} \tag{2.8}$$

Notice that if the value of λ in (2.6) is 0, then the update in Equation (2.6) corresponds to Newton's method, while if $\lambda \gg 1$, then the update is similar to the corresponding outcome of the steepest decent method. Whenever the utilization of the update in (2.6) leads to a sufficient decrease in the objective value, the value of λ is kept low; otherwise an increase in the value of λ will ultimately yield a steepest descent-like step.

2.1.6 Performance and generalization property of the trained model

In order to achieve an efficient supervised learning, the training data set should be carefully chosen such that it represents only the normal operating conditions of the component being modeled. An approach for the selection of the training data set is presented in [43], and later applied to a case study in Paper I of this thesis. Furthermore, three approaches to filter the training data, which enable elimination of data which might reduce the ANN model performance are presented in Chapter 4. The selected training data set is then randomly divided into the training, validation, and test data sets.

In order to assess the trained ANN model, the model generalization property, which is defined as the ability of the model to neglect the insignificant aspects in the training data set ([44]), is calculated. A model with poor generalization property will produce large errors when presented with data which is not present in the training data set, and hence such a model is not desirable. In order to quantify the generalization property of a network, a Generalization Factor (GF) is defined as follows:

$$\mathrm{GF} = \sigma(P_{\mathrm{train}}, P_{\mathrm{test}}, P_{\mathrm{val}}), \tag{2.9}$$

where σ is the standard deviation for a vector containing the values of the performance parameters from the training (P_{train}), test (P_{test}), and validation stages (P_{val}) of the ANN model learning process, respectively. In Chapter 4, the application of the generalization factor for the selection of an appropriate ANN configuration is demonstrated.

In this thesis the Mean Absolute Error (MAE) is used as the performance parameter. The MAE parameter is defined as

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |y(i) - d(i)|, \tag{2.10}$$

where, N is the total number of samples in the data set, $y(i)$ is the i^{th} value of the ANN model estimated parameter, and $d(i)$ is the corresponding value of the parameter provided to the model in the training, validation, and test data sets.

2.2 Reliability theory

Reliability can be defined as the "*Ability of an item to perform a required function, under given environmental and operational conditions and for a stated period of time*" ([45]). Various models can be used to estimate and predict the future reliability of a component. Reliability models created using historical failure times can be termed as *age/time based* reliability models ([45,46]), whereas models created using signals which depict the current condition of the component can be termed *condition based* reliability models ([47,48]). The condition based models can be further divided into *data driven models*; see for example [32,49], and *physics based models*; see for example [50].

2.2.1 Reliability function

The reliability of a component can be understood as the probability that the item does not fail, or, it survives, in a time interval $(0, t]$, and is defined as

$$R(t) = 1 - F(t) = \Pr(T > t), \quad \text{for } t > 0, \tag{2.11}$$

where $F(t)$ denotes the cumulative probability of failure of the component at time t. The cumulative distribution $F(t)$ is derived from the probability density function $f(t)$, according to

$$F(t) = \int_0^t f(u)du. \tag{2.12}$$

A more detailed description of reliability theory can be found in [45,47].

2.2.2 Mean time to failure

The expected life of a component is referred to as the Mean Time To Failure (MTTF); it is calculated from the probability density function according to

$$\text{MTTF} = \mathbb{E}(T) = \int_0^\infty t f(t)dt. \tag{2.13}$$

The MTTF of a component can be utilized to schedule a preventive replacement, and one such maintenance optimization model is presented in [51]. Furthermore, MTTF has also been utilized for opportunistic maintenance optimization; for example, see [52].

2.2.3 Hazard function

The hazard rate equals the probability of a component failing in the time interval Δt. Considering that recorded failure times for a large number of components n is available, a small interval Δt can be utilized and the hazard rate can then be estimated as

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T < t + \Delta t)}{\Delta t R(t)} = \frac{f(t)}{R(t)}. \tag{2.14}$$

In this thesis the hazard rate is utilized along with the PHM model, presented later in this chapter, to estimate the cost of a given maintenance schedule. Further details about the application can be found in Paper IV and Chapter 5.

2.2.4 Weibull distribution

The Weibull distribution is one of the most common probability distribution functions used to model the component failure times. A two parameter Weibull distribution with shape parameter $\beta > 0$ and scale parameter $\alpha > 0$ is characterized by the following:

$$f(t) = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} \mathrm{e}^{\left(-\frac{t}{\alpha}\right)^\beta} \quad t > 0; \tag{2.15a}$$

$$R(t) = \mathrm{e}^{\left(-\frac{t}{\alpha}\right)^\beta}; \tag{2.15b}$$

$$h(t) = \beta\frac{t^{\beta-1}}{\alpha^\beta}; \tag{2.15c}$$

$$\text{MTTF} = \alpha\Gamma\left(\frac{1}{\beta} + 1\right), \tag{2.15d}$$

where $\Gamma(x) = \int_{-\infty}^{+\infty} \mathrm{e}^{-y}\mathrm{y}^{x-1}dt$ is the Gamma function ([53]).

The shape parameter β provides a possibility to represent decreasing ($\beta < 1$), constant ($\beta = 1$) or increasing ($\beta > 1$) failure rates, which are, generally, related to the different stages of a component's life. The historical failure times of a component can be used to estimate the shape and the scale parameter of its Weibull distribution. Methods for parameter estimation are presented in [22,46]. The ABPM optimization within the maintenance management framework is demonstrated in Chapter 5 of this thesis, with Weibull distributed failure times for the wind turbine main bearing, rotor, gearbox and generator.

2.2.5 Gamma distribution

In many cases the stochastic process of degradation, like crack growth, can be represented by the Gamma process; see for example [48]. The Gamma distribution with shape parameter β and scale parameter α is characterized by the following:

$$f(t) = \frac{1}{\alpha^{\beta}\Gamma(\beta)} t^{\beta-1} \mathrm{e}^{-\frac{t}{\alpha}} \quad t > 0; \tag{2.16a}$$

$$R(t) = \sum_{x=0}^{\beta-1} \frac{1}{x!} \left(\frac{t}{\alpha}\right)^{x} \mathrm{e}^{-\frac{t}{\alpha}}; \tag{2.16b}$$

$$h(t) = \frac{f(t)}{R(t)}; \tag{2.16c}$$

$$\mathrm{MTTF} = \alpha\beta; \tag{2.16d}$$

see also [45].

The Gamma distributed failure times are used in Paper IV to demonstrate the application of the condition based probabilistic failure rate models in the maintenance management framework.

2.2.6 Proportional hazards model

The Cox PHM has been frequently applied within statistics in the medical sciences to examine the effect of covariates on the hazard rates; see [54]. The hazard rate for a PHM model can be modeled (as shown in [55]) as

$$h(t; z(t)) = h_o(t)\psi(z(t)), \tag{2.17}$$

where $h_o(t)$ is the *baseline hazard rate* and $\psi(\cdot)$ is the link function that is used to update the baseline hazard rate, depending on the value of the covariate $z(t)$. The procedure to create the PHM model and its application to maintenance optimization has been demonstrated in [32]. A hypothetical case study with the PHM model applied to CBPM optimization is presented in Paper IV and Chapter 5. The output from the ANN based CMS is utilized as a covariate to update the failure probability, based on which the maintenance schedule is then adjusted.

2.2.7 Estimation of the failure distributions

The approximation of the parameters for the statistical models which represent the failure rate of a component is a non-trivial task. Different methods can be applied to a given data set to estimate the type and the parameters of the probability distribution that fit the failure data. *Probability plotting* is a method where special graphs are used to estimate the parameters for a defined distribution for a given data set. More information about probability plots with examples and explanation can be found in [46,47]. The Maximum Likelihood Estimation (MLE) method presents an analytical solution for the estimation of the parameters for a given statistical model. The total likelihood is defined as the joint probability distribution of the data, as

$$L(p; \mathrm{DATA}) = \prod_{i=1}^{n} L_i(p; \mathrm{data}_i), \tag{2.18}$$

where $L_i(p; \mathrm{data}_i)$ is the probability or likelihood of observation i, data_i is the data for observation i, p is the vector of parameters to be estimated, and n is the total number of observations in the set DATA. The parameters for the statistical model are derived from the set DATA by maximizing the function $L(\cdot)$ over $p \in \Phi$, where Φ is a family of distributions and p is the vector of parameters for the distribution. In most cases, historical failure data for wind turbines is available as interval censored data; see for example [20]. In such cases, the probability of the event is defined as

$$L_i(p) = \int_{t_{i-1}}^{t_i} f(t)dt = F(t_i) - F(t_{i-1}); \tag{2.19}$$

where $F(\cdot)$ is the cumulative distribution function defined in (2.12), see [47].

For a given data set $L(p)$ can be seen as a function of p. The likelihood of finding the probability distribution that fits the data is maximized by finding values of p for which the function $L(p)$ is maximized. The MLE method can also be used together with Bayesian statistics (discussed in detail in Chapter 13 of [45]), wherein a prior information about the distribution is utilized and is updated based on the information from the new data.

2.2.8 Renewal process

The *renewal process* models the replacements (renewals) of a component. It is a counting process with Independent and Identically Distributed (IID) inter-occurrence times with distribution function $F(t)$, reliability function $R(t)$ and probability density function $f(t)$ ([45]). The inter-occurrence times are considered to be independent as it is assumed that the wind turbines are non-repairable systems and that the condition after maintenance is as good as new.

Generally, the number of renewals in a certain time interval is estimated using a recursive procedure, as it is difficult to obtain a closed form expression of the number of renewals for complex distribution functions like the Weibull distribution. Consider time being represented by discrete steps $t = 1, \ldots, T$. In order to estimate the expected number of renewals after time T, we assume that the value of the renewal function, $W(t)$, is known for all $t = 1, \ldots, T-1$, and $W(0) = 0$. The underlying probability distribution, $f(t)$, is known for all $t \geq 0$; for example it is known that the component failure times follow a Weibull distribution. Then the renewal function $W(\cdot)$ can be estimated as

$$W(T) = \sum_{t=0}^{T-1} (1 + W(T - t - 1)) \int_{t}^{t+1} f(s)ds; \tag{2.20}$$

see [46].

In Paper IV and Chapter 5 the expected cost of maintenance in a given time interval is estimated utilizing the renewal process, where a large number of failure times are simulated based on the underlying reliability functions of the components.

Chapter 3

Maintenance Management Framework

This chapter presents a classification of different types of maintenance strategies and introduces the concept of maintenance management. Furthermore, the proposed maintenance management framework is presented along with a discussion. The material in this chapter is most strongly connected to Papers I, II and IV.

3.1 Introduction

Maintenance can be termed as an activity carried out with an aim to restore or maintain a machine or a system to a state in which it can perform its intended function. Figure 3.1 presents a common classification of maintenance strategies (adapted from [56]).

A CM activity is performed following a failure event and a PM is performed prior to a failure event. A PM activity can further be classified as an ABPM or a CBPM, depending on the type of information utilized to make maintenance decisions. A condition monitoring system, like vibration monitoring or visual inspections, is a pre-requisite for CBPM, whereas information about component failure probabilities is required for the utilization of an ABPM strategy. The CM strategy has the advantage of providing a complete utilization of the useful lives of the components, but it is expensive as it may require unscheduled maintenance activities. The ABPM strategy is comparatively less expensive, on account of the possibility of providing an optimal schedule of maintenance activities, but it does not completely utilize the useful lives of components. The CBPM strategy then presents a better option, as it provides an opportunity to schedule the maintenance, and at the same time ensures a better utilization of the component lives. However, a successful CBPM strategy requires information from condition monitoring systems as well as good probabilistic models for estimation of remaining useful life of components.

Maintenance management can be understood as the process of building an optimal maintenance policy considering the advantages and disadvantages of the different maintenance strategies. Generally, the maintenance policy is decided with an aim to minimize the Life Cycle Cost (LCC) of the asset. LCC is the total discounted cost of investment and operational expenditures over the life for a system. A simplified LCC model for a maintenance strategy is given by (taken from [57])

$$\mathrm{LCC} = C_{\mathrm{inv}} + \sum_{t=0}^{T} \left[C^t_{\mathrm{CM}} + C^t_{\mathrm{PM}} + C^t_{\mathrm{PL}} + C^t_{\mathrm{ser}}\right] (1+\delta)^{-t}, \tag{3.1}$$

where C_{inv} denotes the initial investment cost for a maintenance strategy, which might include cost of maintenance crew, equipment, etc. C^t_{CM}, C^t_{PM}, and C^t_{PL} represent the cost of corrective

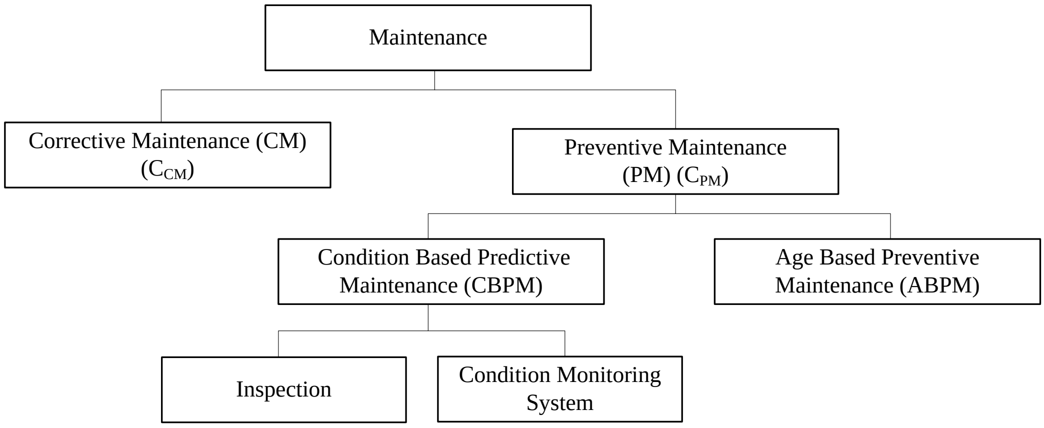

Figure 3.1: Classification of maintenance strategies

maintenance, preventive maintenance and production loss, respectively, during the year t, and C^t_{ser} is the additional costs, like administration costs, which are not accounted for in the other cost items. The total expected life of the system is T (years) and δ represents the discount rate, which is calculated based on a defined interest rate. Maintenance management aims to find an optimal balance between the various cost parameters, such that the LCC of the maintenance strategy is minimized.

3.2 Reliability centered maintenance

The Reliability Centered Maintenance (RCM) methodology was introduced in the 1960s in the civil aviation industry, with an aim to improve the reliability of the systems using focused maintenance; see [58] for details about the RCM methodology. Since then, the RCM has been successfully adopted in several fields of application. The RCM stipulates a detailed Failure Mode Effect Analysis (FMEA), including an analysis of the cause of each failure mode on the critical components of the system. In addition, RCM also seeks to answer the question as to what preventive maintenance activities can be performed to avoid such failures. RCM provides a systematic approach to establish minimum maintenance limits. However, RCM is a qualitative approach, and hence does not provide a quantitative output; it was extended to include a quantitative analysis in [59]. The application of the extended methodology, referred to as Reliability Centered Asset Maintenance (RCAM), to wind turbines is demonstrated in [60]. In principle, the RCM and RCAM methodologies can point towards bottlenecks in the system with respect to the reliability of the system.

As both the RCM and RCAM methodologies suggest, the maintenance management of the asset should be initiated with an effort to understand its reliability. Preliminary information about the system reliability can be collected using historical failure times, which might be available through the maintenance reports. In this thesis, information from maintenance reports for a population of 28 wind turbines located in different areas of South and Central Sweden is utilized. The data corresponds to 73 wind turbine years, and an analysis to estimate the downtime caused by each subsystem of the wind turbine is performed. A total of 728 maintenance work orders are analyzed, and the failures are grouped into categories based on the subsystem responsible for the failure. The average downtime for each subsystem per year per wind turbine is estimated as

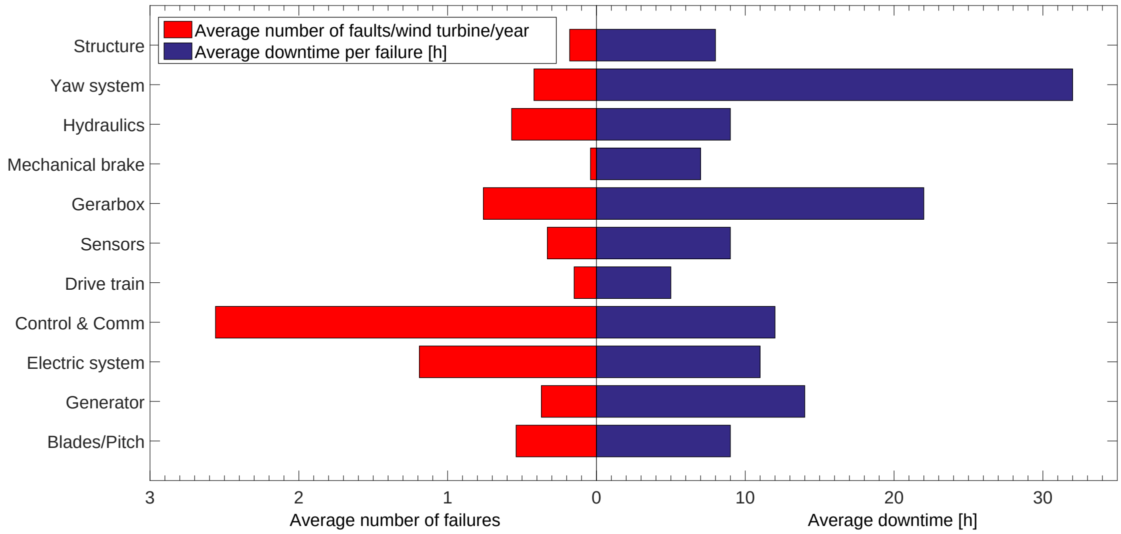

Figure 3.2: The average number of failures and downtime per failure for different subsystems for the wind turbine population under consideration

$$D_j := \frac{\sum_{t=1}^{T} d_{jt}}{\sum_{t=1}^{T} n_t I_t}, \quad j \in \{1, 2, \ldots, N\}; \tag{3.2}$$

here, D_j is the downtime for subsystem j per wind turbine per year, d_{jt} is the downtime caused by subsystem j in the time interval t, n_t is the total number of wind turbines operating in the time interval t, I_t is the length of the time interval t, and N is the number of subsystems in the wind turbine. The result of the analysis is presented in Figure 3.2.

The analysis of the failure data lead to a realization that the communication system is a cause of concern, suffering from frequent failures. The communication system could be improved, however, there is not much that can be achieved with PM other than ensuring that the firmware in each wind turbine is up to date. The electrical system and the gearbox are responsible for the most downtime, next to the communication system. These results are in agreement with previously published surveys of wind turbine reliability in [20–22]. This information can be used to improve the maintenance for the electrical and the gearbox systems by applying CMSs and opting for either age based or condition based preventive replacements.

3.3 Data collection

A systematic collection of data is of utmost importance for applying methods such as RCM and RCAM. However, at present, standardized procedures for data collection and reliability analysis are not available for wind turbines. Manufacturers follow their own standards, and consequently the type and extent of data available depend largely on the make of the wind turbines. The IEC 61400 standards have been issued for wind turbine design requirements, but do not explicitly discuss the issues of maintenance and reliability data. There are a few national and international initiatives which have focused on the aspect of wind turbine reliability. Wind turbine reliability analysis methods have been outlined in [23], which was an output from the ReliaWind project within the European Union's Seventh framework program. The ReliaWind project also issued one of the first taxonomies, specifically applicable for wind turbines. A study, undertaken by Elforsk, has demonstrated the data requirements for various levels of reliability analysis for wind turbines ([61]). The report is produced based on experiences from other electricity generation systems like hydro and nuclear. The IEA-Wind Task-33 is working on formulating recommended practices for reliability data collection and analysis for wind power O&M planning, and will issue a resulting report in 2016. The IEA-Wind recommended practices document will cover the most important aspects of data collection in wind turbines.

3.4 Self-Evolving Maintenance Scheduler framework

The aim of the proposed framework is to provide an approach for the utilization of information from different sources of data, such as SCADA, maintenance and inspection reports, CMS, etc., for optimal maintenance planning. The outline of the proposed SEMS framework is provided in Figure 3.3. A summary of the framework is presented as follows:

1. Following an analysis, such as RCM, the information about critical components and the applied condition monitoring methods is generated. The critical components will be included in the SEMS framework for continuous maintenance management.

2. An ABPM schedule is produced from the SEMS framework for the critical components, based on reliability models created using historical failure times.

3. The CMSs, including the SCADA data based CMS proposed in this thesis, provide information about any deterioration in the components being monitored. Consequently, the signals from the various CMSs are combined in order to improve the effectiveness of the condition monitoring activities.

4. Following an indication of a deterioration from any of the CMSs, an inspection is initiated, which determines the correctness of the diagnosis from the CMS.

5. The results of the inspection may initiate a maintenance planning to decide the best course of action given the probabilistic failure model of the damaged component. A CBPM optimization is performed considering the effect of an early replacement of the damaged component on all the critical components in the wind turbine over the entire lifetime of the system. Furthermore, the maintenance opportunities arising due to condition based preventive replacement of one component are optimally utilized to perform age based preventive replacement of other critical components.

6. As a general procedure each maintenance activity generates a maintenance report. The information from this report will be utilized to update the SCADA data based condition monitoring models, as the replacement of monitored components necessitates an update in the ANN model, as described in Paper I. Furthermore, the signals from the CMS of the component affected are stored in order to improve the probabilistic failure models.

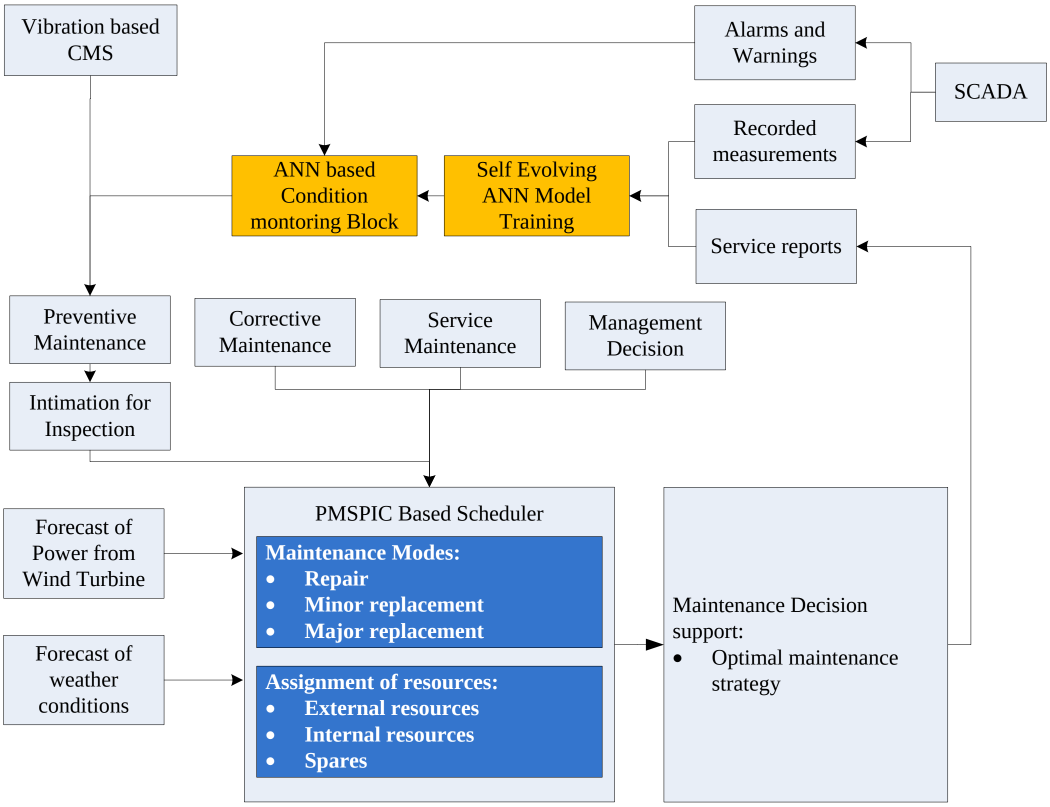

Figure 3.3: SEMS management framework

Chapter 4

ANN based condition monitoring

This chapter briefly describes different features of the SCADA system. The approach for condition monitoring using data stored in the SCADA system is presented. Various issues with the ANN models are discussed and suitable mitigation measures are presented. Case studies are performed to validate the condition monitoring method. The material in this chapter is most strongly connected to Papers I, II, and III.

4.1 The wind turbine SCADA system

The SCADA system is an integral part of all modern wind turbines. The aim of SCADA is to make it possible to remotely control and monitor wind turbines. A general structure of SCADA is shown in Figure 4.1. The SCADA system provides the user with two levels of access:

1. Control Access: through this access the user can start/stop as well as manipulate the operating parameters in the wind turbine.
2. Monitoring Access: through this access the user can get an instantaneous status update on the operating conditions of the wind turbine as well as access to historical measurement data.

The SCADA system records parameters like wind speed, wind direction, ambient and nacelle temperatures, lubrication oil temperature and pressure, and different bearing tem-

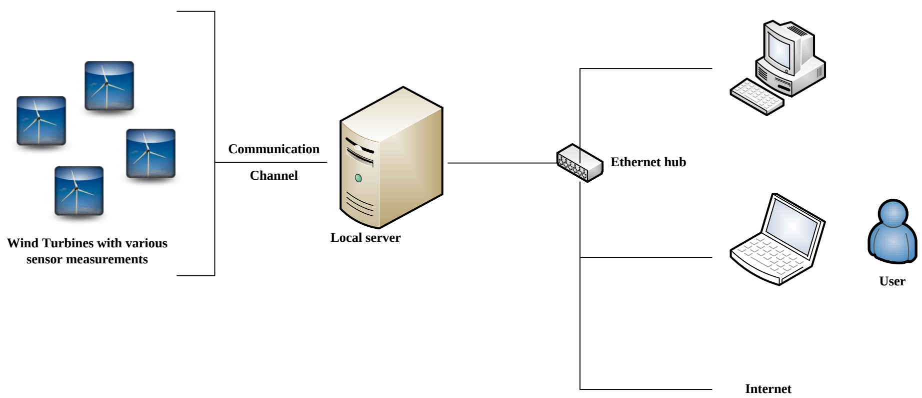

Figure 4.1: A schematic representation of a typical SCADA system for wind turbines

peratures for wind turbines. In addition to these measurements, electric quantities like voltage, current, frequency, and power factor are also measured and recorded. These measurements are stored as a 10-min average value[1] on the SCADA server. Furthermore, the SCADA system generates alarms and warnings based on pre-set threshold values, which indicate out-of-normal operation in the wind turbine. Each SCADA alarm is mapped to a status which assigns the responsibility of the downtime to an entity. The wind turbine status information is utilized for an availability calculation at the end of each month. In most modern wind turbines, the availability is calculated internally and reported as an output from the SCADA system. Hence, it becomes important to have a good understanding of the SCADA alarms and warnings.

The main function of an alarm is to make it possible to avoid the operation of components under highly stressed conditions, which otherwise may reduce the operating life of components. An alarm results in a shutdown of the wind turbine and an acknowledgment of the alarm is required for a restart. The alarms can be acknowledged in three different ways as described below.

- Auto-acknowledge: The wind turbine controller automatically acknowledges the alarm, and restarts the wind turbine when the condition causing the alarm no longer exists. There is a maximum number of auto-acknowledge occasions, after which the alarm has to be acknowledged remotely.
- Remote-acknowledge: The alarm has to be manually acknowledged at a remote location (for example, the control center), in order to restart the wind turbine. The main function is to inform the operator that a component might require an inspection.
- Local-acknowledge: The alarm has to be acknowledged manually at the wind turbine. These alarms are mainly related to the safety of operations, for example, the alarm generated in the fire safety system.

The main function of warnings is to inform the operator that an attention is needed to a particular component. A warning is generated in a situation when there is no immediate danger of damage to the component, but the rate of reduction in the life of the component could be higher than normal. The warning could be, for example, a low oil level indication, which may not be critical but needs some attention. A warning could result in an alarm if no attention is given, which will lead to a shutdown of the wind turbine. A typical SCADA system could have upwards of 500 possible alarms and warning signals. At present, there is no standard available which stipulates a certain terminology to be used for the SCADA warnings and alarms. Hence, it is difficult to associate alarms and warnings to a certain assembly or sub-assembly of a wind turbine. A simple approach for associating the SCADA alarms and warnings to a wind turbine assembly or sub-assembly is presented in Paper II. The intention of the activity is to improve ANN based CMS by analyzing the alarms and warnings together with the output from the CMS while monitoring the wind turbine components.

4.2 ANN based condition monitoring method

An intelligent analysis of the recorded SCADA data can indicate certain types of failures in critical components in advance. A method utilizing ANN for creating normal behavior

[1] In addition to the 10-min average values, some wind turbine SCADA systems also provide 10-min minimum, maximum, and standard deviation values.

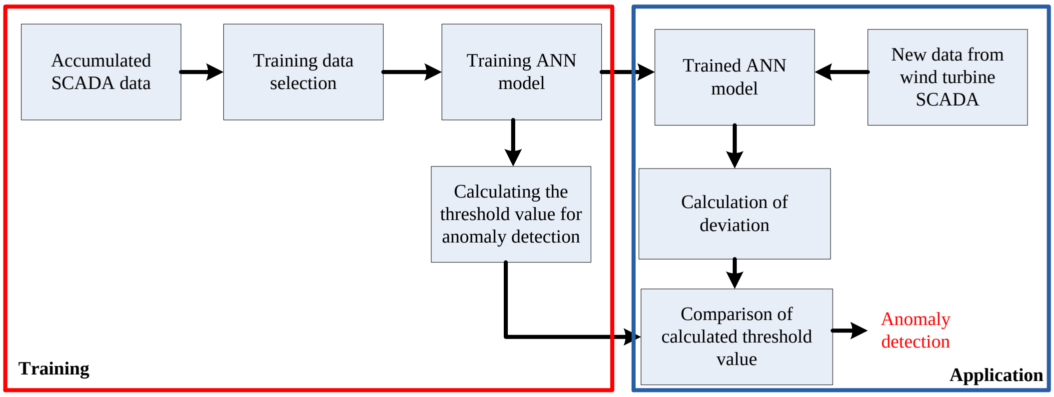

Figure 4.2: A schematic representation of an ANN based condition monitoring method

models for critical components in wind turbines is proposed in this thesis. The schematic representation of the method is shown in Figure 4.2. The condition monitoring method using SCADA data can be divided into two blocks. The block on the left in Figure 4.2 presents a one-time process, during which the ANN model is trained to emulate normal operating conditions in the monitored component. The block on the right presents the continuous application process of anomaly detection and condition monitoring.

The training of the ANN model is performed using the data from a period during which there have been no recorded failures in the wind turbine. In the application stage, the trained ANN model is used to estimate the modeled parameter values, which are compared to the actual measured values recorded in the SCADA system, and the errors are calculated. The calculated error values are compared to the threshold values and any error values higher than their thresholds are considered anomalies.

The process of building ANN based normal behavior models can be divided into the three sub-tasks

1. specification of an ANN configuration,
2. input/output parameter selection, and
3. data pre- and post-processing.

Together they represent an iterative development process, each step of the which is discussed in detail in the following sections.

4.3 Configuration of ANN models

An artificial neural network typically consists of an input layer, a number of hidden layers, and an output layer. The configuration of the ANN carries the information about the number of nodes in the input layer, the number of hidden layers, the number of neurons in each hidden layer, and finally the number of neurons in the output layer. The performance of the ANN model, for a given application, depends largely on the configuration. However, there are no known methods to optimize the configuration of an ANN model. Furthermore, several configurations could be applied to the same application ([34]). The configuration of the ANN model should be determined based on the knowledge about the data and the

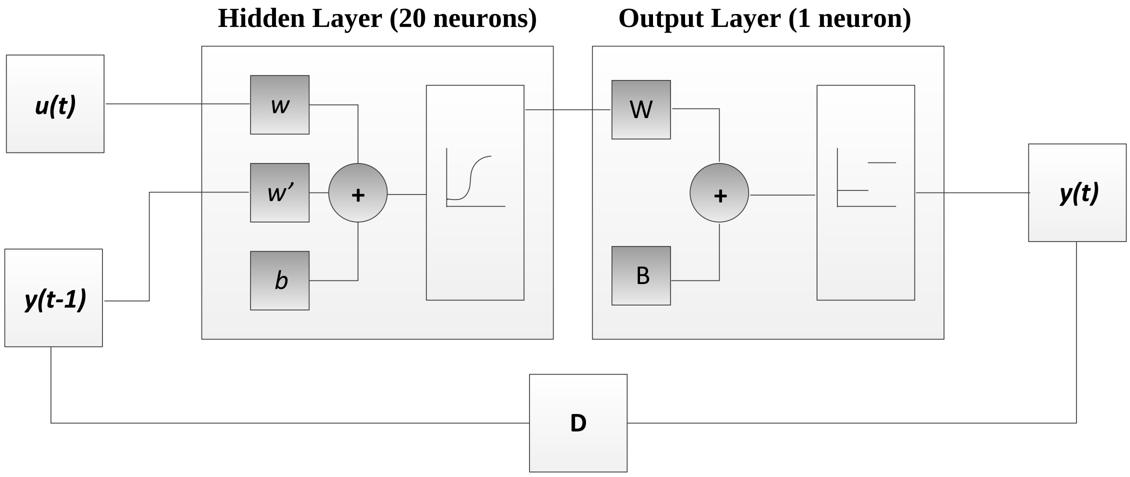

Figure 4.3: A schematic representation of the NARX ANN model configuration

source, and as suggested in [9], it is an experimental process where different configurations should be tested in order to realize the most suitable one.

The application of auto-regressive multilayer feed-forward neural networks in [5] and [6] has shown the suitability of this configuration for wind turbine applications. The Non-linear Auto-Regressive ANN with an eXogenous input (NARX) configuration is a variation of the auto-regressive ANN model, and the difference between these two configurations can be found in the manner the delayed output values are used in the model. In the auto-regressive ANN configuration presented in [5] and [6], the delayed output parameter value $y(t-1)$ is extracted from the SCADA system and is combined with the input vector $u(t)$, while in the NARX model the regressive input value is the value estimated by the model itself as shown in Figure 4.3. Unlike the auto-regressive ANN configuration, the NARX configuration provides a possibility to isolate the influence of an anomaly in the component being monitored on the output of the ANN model. Furthermore, an analysis performed in [62], where three configurations - the feed-forward ANN with one hidden layer, the feed-forward ANN with two hidden layers, and the NARX model with one hidden layer - were tested with application to data from different wind turbines, also showed that the NARX ANN configuration is the best among the investigated options. These results are also in line with the observations made in [36] and [37].

In order to demonstrate the process of investigation of different ANN configurations, two types of neural networks are considered here: a multilayer feed-forward network with one hidden layer, shown in Figure 2.4, and the NARX model with one hidden layer shown in Figure 2.5. A sample model to predict the power produced from the wind turbine is utilized to investigate the effectiveness of the two neural network configurations. The 10-min average values of wind speed, ambient temperature, pitch angle and the wind speed standard deviation are used as the inputs, and the power produced by the wind turbine is the output. A feedback delay of one time unit is utilized in the NARX network, which means that the output parameter value at time instant $t-1$ is utilized while estimating the parameter value at time instant t. In total 50 ANN model instances are trained for each configuration of neurons, and the average performance and generalization factor (GF),

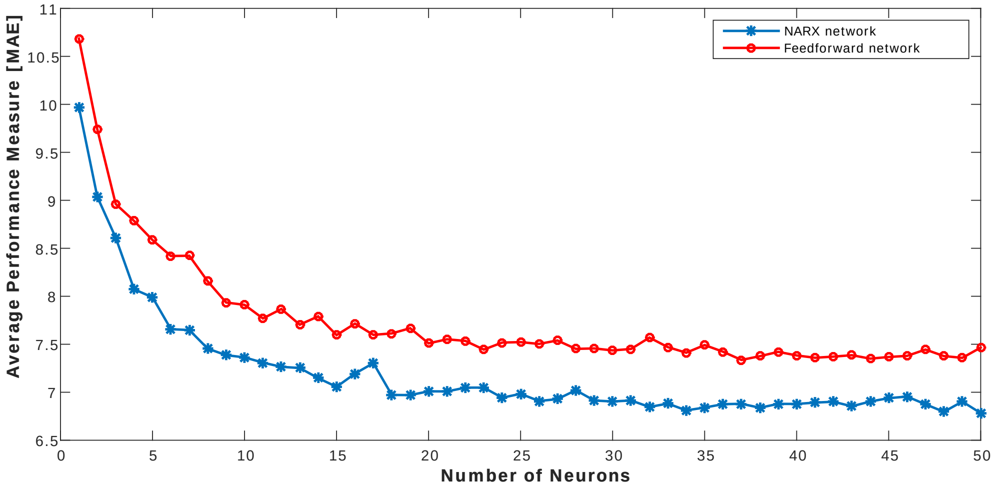

Figure 4.4: Average performance measure (MAE) for different configurations of ANN

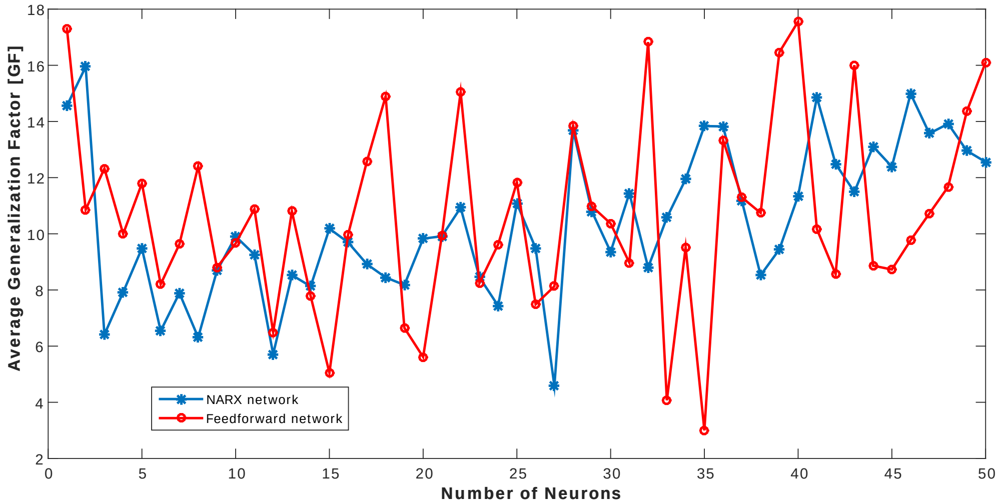

Figure 4.5: Average generalization factor for different configurations of ANN

defined in (2.9), is recorded for each configuration. Figure 4.4 and 4.5, respectively, show the average performance measure, which is the mean absolute error (MAE), defined in Equation (2.10), and the average generalization factor for NARX and feed-forward ANN with up to 50 neurons in the hidden layer.

It can be observed that the performance improvement is not significant with more than 20 neurons in the hidden layer. The generalization factor, which is defined as the standard deviation of performance during the training, testing, and validation stages, has a higher value for all configurations of the feed-forward neural network as compared to the NARX neural network. A higher generalization factor of the feed-forward network indicates that the ANN model is prone to over-fitting the data, which is not desirable. Hence, from this brief analysis it can be concluded that for the given application, the NARX network with 20 neurons in the hidden layer is an acceptable option.

4.4 Parameter selection

The selection of the correct input and output parameters plays an important role in the success of ANN based condition monitoring. The normal behavior ANN models should be accurate in estimating the output parameters as well as be able to correctly recognize failures and prevent false alarms when applied as a condition monitoring system. Since the ANN modeling is a data driven approach, which lacks any physical understanding of the system, the selection of model parameters has to be done carefully based on domain knowledge.

The output parameter of the model should be chosen such that most of the common failure modes of the monitored component directly impact the modeled parameter. For example, condition monitoring of the gearbox bearings can be achieved by creating normal behavior models for bearing temperatures. Furthermore, the modeling of the gearbox lubrication oil temperature, or pressure measurements, can aid detecting gearbox faults that do not originate in the bearings. The output parameter selection is followed by the selection of suitable input parameters. An approach based on data mining methods was presented in [7], which resulted in 18 input parameters being selected to model one output parameter. In [63] input parameter selection was achieved by analyzing the effect of each parameter on the performance of the ANN model, where 19 input parameters were selected to model one output parameter. However, a large number of inputs increases the risk of over-fitting by the ANN models; such models can lead to sub-par performance during anomaly detection ([64]). Hence, as demonstrated in [5] and [6], the domain knowledge and physical understanding of the parameter being modeled can be beneficial in selection of the correct input parameters.

The case studies presented in Section 4.8, discuss the application of the proposed ANN based CMS method for monitoring of wind turbine gearboxes. Hence, the discussion presented here is limited to the selection of input parameters for ANN models which are used for gearbox monitoring.

The gearbox bearing and lubrication oil temperatures values measured by the SCADA system are important from a condition monitoring perspective, as the most common failure modes in the gearbox will, potentially, manifest themselves into a deviation from the normal operating values. Hence, normal behavior models for the gearbox bearing and lubrication oil temperatures are utilized to achieve condition monitoring of the gearbox.

The gearbox bearing and lubrication oil temperatures are directly connected to the nacelle and ambient temperature values, and there exists a state of thermal equilibrium between these temperatures under normal operating conditions. The ANN normal behavior model can be used to emulate this thermal equilibrium condition, and any disturbance in the equilibrium may then indicate an anomalous operation in the gearbox. Consequently, the ambient and nacelle temperature measurements are utilized as input for the ANN normal behavior models. Furthermore, the temperatures inside the nacelle are directly related to the power being produced by the wind turbine, as the electrical and mechanical losses are proportional to the power produced; this concept was also exploited in [18] for the monitoring of wind turbine gearboxes. Hence, power produced from the wind turbine will also be included as an input to the ANN normal behavior models. The wind turbines utilized for case studies in this thesis have a mechanical pump, mounted on the low speed side of the gearbox, for the lubrication oil system. Hence, the flow of lubrication oil will depend on the rotational speed of the main shaft and, consequently, the rotational speed is also included as an input for the ANN normal behavior models. However, it should be noted that utilizing a parameter which is highly correlated with the output parameter could lead to a situation where the ANN normal behavior model correctly predicts the abnormal operating condition; one such case is demonstrated in Paper III. Furthermore, in order to analyze the effect of

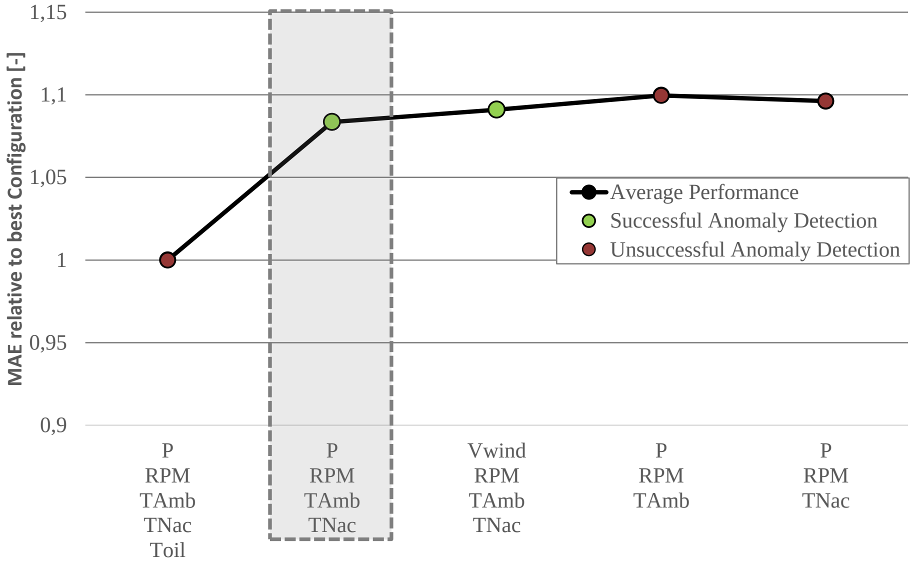

Figure 4.6: Performance of ANN models with different input configurations

different inputs on the model performance, various models were trained and tested with application to a case study with data from a wind turbine which had experienced a failure in the gearbox. The results of the study for a selection of few models are shown in Figure 4.6.

The analysis revealed that the best performing models are not necessarily the most well suited for anomaly detection purposes. In this situation, it is important that different input configurations are investigated and validations be carried out to ensure that the model is able to catch an anomalous operation as well as prevent false alarms.

A list of ANN models that can be created for condition monitoring of various wind turbine components, based on extent of data available from a typical wind turbine SCADA system is presented in Appendix B.

4.5 Data filters

The ANN models learn the input/output mapping based, solely, on the data provided during the learning stage. Hence, for the success of ANN based condition monitoring, it is important that the training data is free from errors. In the real world, however, there seldom exists a perfect data set, and often SCADA data is found to be discontinuous and to contain inconsistencies. These inconsistencies lead to inaccuracies in the ANN models and hence need to be dealt with in an appropriate manner. Three types of filters are presented here which can be applied to remove data points which might reduce the performance of the ANN models.

4.5.1 General filter

Malfunctions in the SCADA communication system, sensors or signal processing errors, and standstill during maintenance and repair actions lead to missing or faulty data points. The following three simple rules are suggested for filtering the missing and garbage data:

1. Filter out all data vectors where one or more of the considered input or output parameter values are missing.

2. Filter out all data vectors which correspond to a situation when the wind turbine is not producing any power.

3. Filter out all data vectors where one or more parameters have a value higher than a predefined threshold. In this thesis, the threshold values are decided based on manufacturer specifications. (For example, all measurements with a gearbox bearing temperature higher than 90°C were filtered out).

4.5.2 Cluster filter

Wind turbines are subjected to highly variable operating conditions, and have a non-linear operating characteristic, and hence it is difficult to detect outliers by setting simple threshold values. Moreover, during power curtailment conditions the wind turbine operation cannot be considered as normal as it is producing less than normal power; however, curtailment cannot be classified as a fault condition. The cluster filter is used to remove data outliers and data corresponding to curtailment conditions from the training data set.

The clustering method belongs to the unsupervised machine learning category, wherein an unlabeled set of data is divided into different clusters based on the selected criteria. Clustering presents a suitable solution to the problem of the classification of wind turbine SCADA data, and has been demonstrated to be successful in [65]. The approach presented in [65] illustrated the advantage of clustering applied to the wind power curve for detection of faults. This approach has been extended here and the clustering method is applied to a multidimensional data set which consists of all the input parameters of the ANN model. The algorithm for cluster filter is described in Algorithm 1.

Algorithm 1 The algorithm for cluster filter

1: Decide the maximum number N of clusters
2: Use the clustering method to assign a cluster number $n \in \{1, \ldots, N\}$ to each input data vector D_i, $i \in \{1, \ldots, \text{length(Dataset)}\}$, in the training data set
3: Find the centroid $C_n, n \in \{1, \ldots, N\}$, for each cluster
4: Calculate the Mahalanobis distance MHD_i, $i \in \{1, \ldots, \text{length(Dataset)}\}$, of each data vector D_i^n from its cluster center C_n
5: Estimate the probability distribution for the Mahalanobis distances in the vector MHD
6: Eliminate those data vectors, whose probability of occurrence is lower than a threshold value

The training data set is divided into N clusters utilizing Ward's minimum variance algorithm, described in [66]. According to Ward's minimum variance algorithm the clusters are decided to minimize the inner square distance, calculated over Euclidean space, between cluster centers. The number of clusters N is decided based on a the understanding of the behavior of the wind turbine, such that each cluster represents a different operating condition. The criterion utilized for deciding the number of clusters is presented in Table 4.1, based on which the training data set is divided into 12 clusters.

In the next step, the Mahalanobis distance (MHD), discussed in Section 4.6, is calculated for each data vector in the training data set from its cluster center. The case study presented in Paper III demonstrated that the MHD values of the training data set can be well represented by the log-logistic distribution.

Table 4.1: The criteria for deciding the number of clusters

Operating parameter	Interval 1	Interval 2	Interval 3	Interval 4
Wind speed [m/s]	$0 \rightarrow 5$	$5 \rightarrow 8$	$8 \rightarrow 11$	$11 \rightarrow 25$
Ambient temperature [°C]	$-30 \rightarrow -3$	$-3 \rightarrow 5$	$5 \rightarrow 30$	–

The main aim of cluster filtering is to remove the data corresponding to abnormal operating conditions, and power curtailment conditions that might exist in the training data set. Consequently, a probability threshold of 2.5% is chosen, and data vectors with a lower probability of occurrence are filtered out. The probability threshold is selected based on the knowledge that power curtailment, even though possible, is not a common practice for the wind turbines considered for case studies, and hence a low threshold value is acceptable since only a small amount of training data might be affected due to power curtailment. It should be noted that during the application of ANN normal behavior models for condition monitoring, power curtailment might lead to false alarms. The modern wind turbine SCADA systems include signals which indicate if a power curtailment has been initiated. Hence, it is suggested to include the SCADA signals with information about power curtailment along with ANN based CMS method. Such an integration would allow the operator to make better decisions about the alarms from the CMS system which could occur during power curtailment in the wind turbines.

4.5.3 Missing data filter

The NARX ANN configuration is characterized by at least one feedback loop between the output and the input. In the ANN models used in this thesis, the feedback loop is adjusted such that the ANN model considers the value of the output at time instant $t-1$ to estimate the output at time instant t. Hence, it is important that continuous data is available during the training and application stage when using NARX models. However, due to communication issues, on occasion continuous data might not be available and such discontinuous data can cause false alarms during the condition monitoring stage. One such case is presented in Paper III. In order to rectify the problem, a missing data filter is implemented, which is designed to ensure that at least three hours of continuous data is available for a parameter vector to be considered during the training and application stages. The data vectors which do not fulfill this criterion are eliminated from the training and application data sets. In addition to the filtering of the missing data, it is important to inform the ANN model that a data vector has been removed and that there is a break in continuity of information. In order to transfer this information to the ANN model, a missing data input parameter is utilized, which is defined as

$$\mathrm{MD}_i = \begin{cases} 1, & \text{if } \mathrm{Timestamp}_i - \mathrm{Timestamp}_{i-1} > 10 \text{ min}, \\ 0, & \text{otherwise}, \end{cases} \tag{4.1}$$

where $\mathrm{MD}_i,\ i \in \{2, \ldots, N\}$ (N is the total number of samples in the data set) is a new input parameter which transfers the information of continuity of data to the ANN model. The effect of including the missing data parameter value on the output of the ANN normal behavior model is presented with a case study in Paper III.

The implementation of each of the above mentioned filters removes certain data points from the training and application data sets. Based on applications to various case studies,

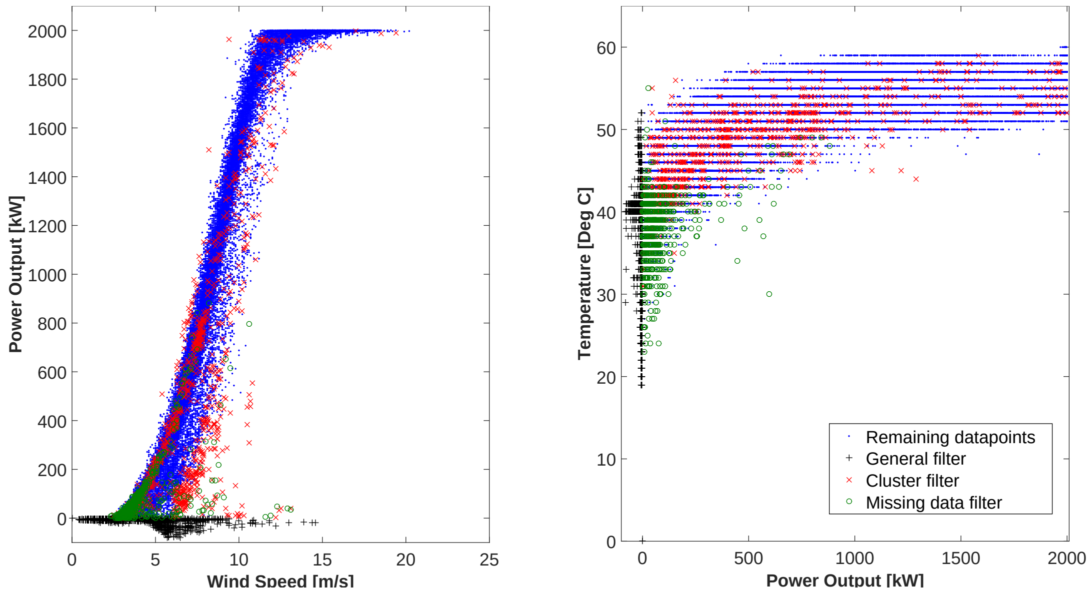

Figure 4.7: A pictorial representation of data removed from the training data set due to filtering

Table 4.2: The performance measures for generator bearing temperature model

Filtering method	Average % loss of data	Applied to training data set	Applied to application data set
General filter	15–25	Yes	Yes
Cluster filter	2.5	Yes	No
Missing data filter	1–5	Yes	Yes

presented in the Appendix and the appended papers, it was found that the filters eliminate about 20–30% data depending on the quality of the data sets. Figure 4.7 shows the layout of the filtered data, and Table 4.2 presents the amount of data removed due to each filter. The effect of filtering on the performance of the ANN normal behavior models is presented in Paper III along with a comparison of the performance of the NARX model with previously published methods.

4.6 Data post-processing

The purpose of creating ANN normal behavior models is to be able to detect anomalies in the operation of the components being modeled. Various methods have been suggested by different researchers for anomaly detection using ANN models. In [5] a confidence band is defined, and an error value outside the confidence band is then termed an anomaly. The probability distribution of errors during the ANN model training is, in [8], used to create threshold values for anomaly detection. In [6] an increase in the frequency of errors between the predicted and measured parameter values is used as an indication of anomaly. In Paper II it is shown that, for certain type of failures, it will take longer to detect an anomaly with the method using the Root Mean Squared Error (RMSE), derived from the ANN model estimated and measured parameter values. Furthermore, setting a threshold based on the distribution of errors during the ANN model's training might not be sufficient, as the model

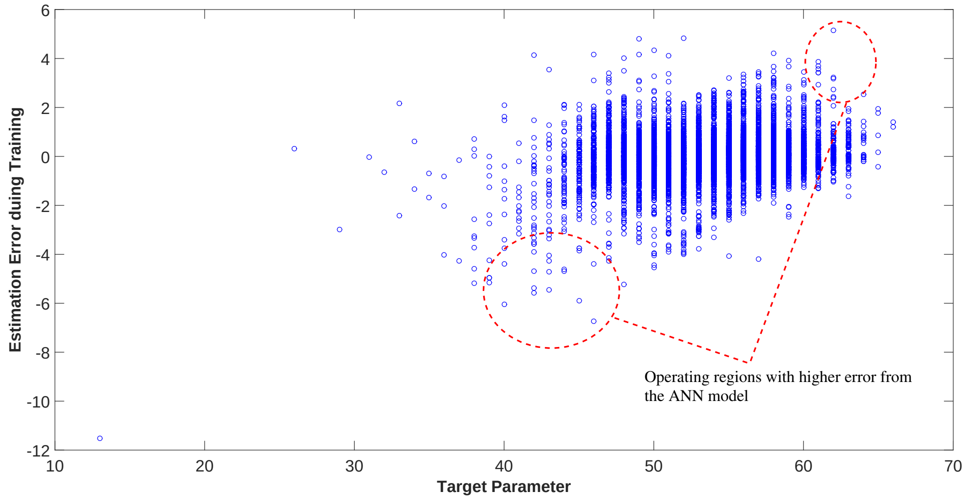

Figure 4.8: A pictorial representation of modeling errors from the training stage

might be skewed and prone to be inaccurate at some operating points, as shown in Figure 4.8, where a higher error can be seen for target parameter values around 40 and 60. Hence, in order to consider the dependance of the operating condition on the ANN model output, an approach using the Mahalanobis distance measure is used in this thesis.

The Mahalanobis distance is a unit-less distance measurement, which has the ability to capture correlations of variables in a process or a system, and is defined as

$$\mathrm{MHD}_i = \sqrt{(X_i - \mu)\, C^{-1}\, (X_i - \mu)^T}, \quad i = \{1, \ldots, m\}, \tag{4.2}$$

where MHD_i is the Mahalanobis distance measure for the i^{th} observation vector $X_i = [X_{i1}, \ldots, X_{im}]$, where m is the total number of parameters. The vector $\mu = [\mu_1, \ldots, \mu_m]$ is the vector of mean values and C is the covariance matrix. The Mahalanobis distance has been applied successfully to capture outliers in different fields of application; see for example [67,68].

A conceptual representation of the Mahalanobis distance is presented in Figure 4.9, where the points with coordinates $(1, -1)$ and $(-1, 1)$, represented by yellow dots, show a higher distance measure compared to the points with coordinates $(-1, -1)$ and $(1, 1)$, represented by bold blue dots. The Mahalanobis distance is effective when the data is distributed in elliptical space, which is the case for the distribution of errors relative to the target parameter, as shown in Figure 4.8. Hence, a methodology using Mahalanobis distance which considers the distribution of errors in relation to the target values during training period was developed and is presented in Paper II.

In addition to the Mahalanobis distance approach for anomaly detection, it is important to consider the inherent randomness in the ANN model training process. The training of a ANN models is, in general, a non-convex optimization problem ([9]). The training might stop at a local optimum, when the performance parameter is minimized; however, the generalization capability of the model might not be good. During the application of the ANN based CMS method to case studies, it was realized that the ANN models trained with the same data behave differently when there is an indication of an anomaly in the monitored component, as can be seen in Figure 4.10, where the difference in the anomaly measure from derived from the output of the ANN model varies widely among the five models.

A sensitive model, like Model 1 in Figure 4.10, will be prone to false alarms and an insensitive model, like Model 4, might not detect the anomaly; both situations are undesirable.

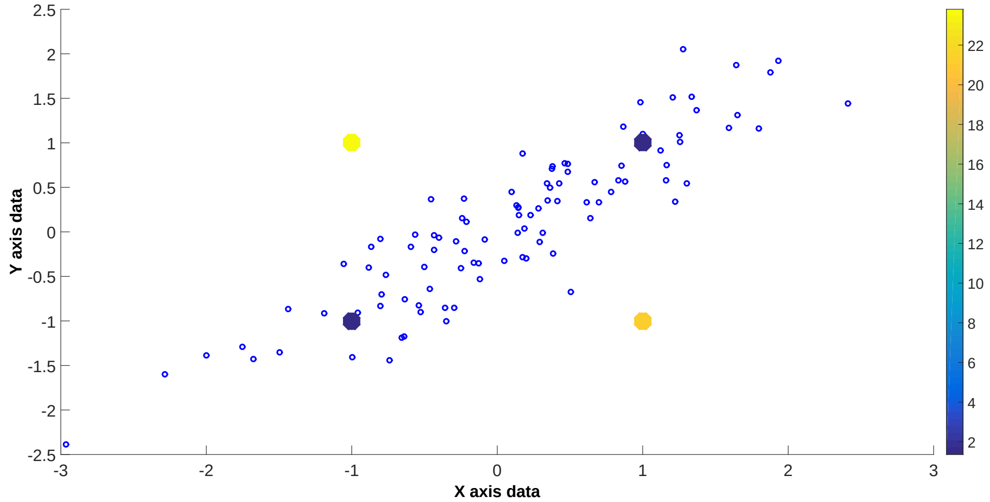

Figure 4.9: A conceptual representation of the Mahalanobis distance

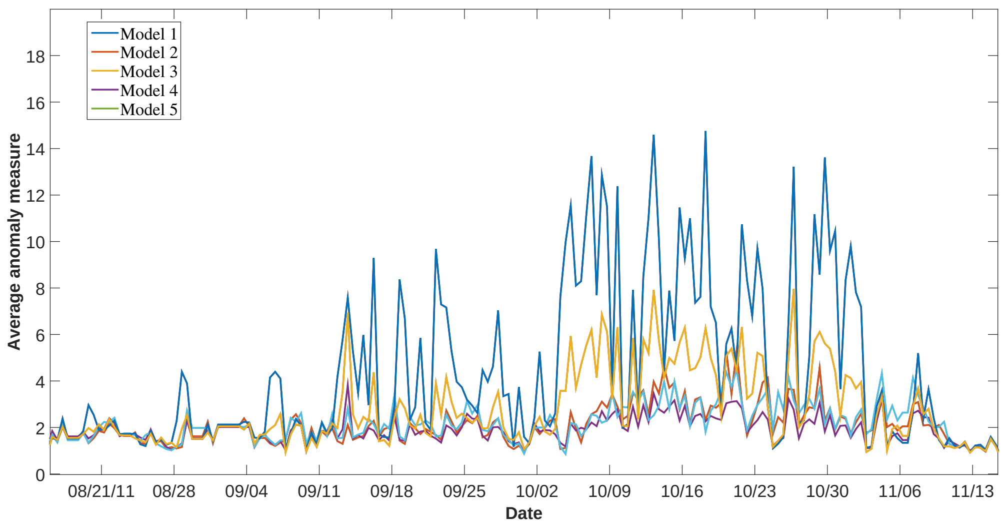

Figure 4.10: Outputs of five ANN models trained with the same data

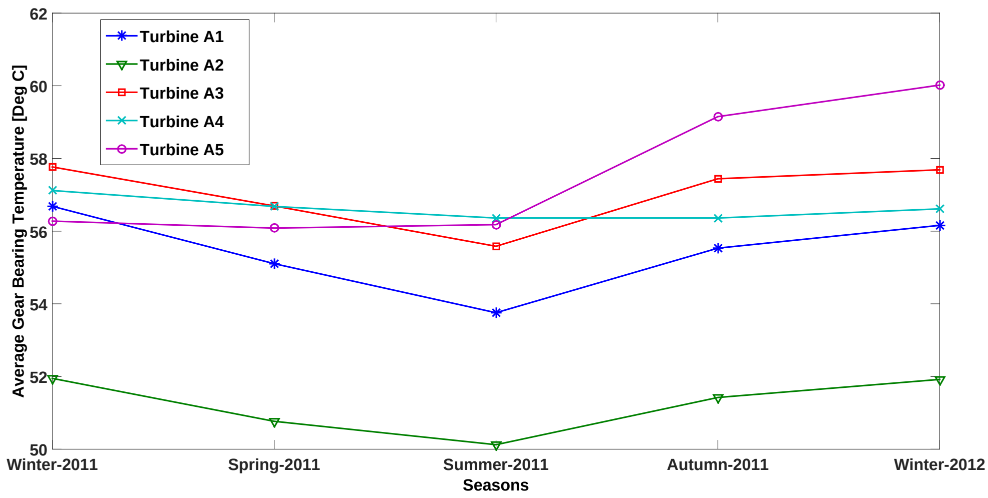

Figure 4.11: Seasonal average gearbox bearing temperatures for five wind turbines in a wind farm

In order to avoid the effect of this randomness in the modeling process, and to increase the confidence in the final output, several ANN models are trained using randomly initialized weights for each training instance. Out of all the models a small subset of the best performing models is selected, and the final output is averaged over these. The training of a large number of ANN models is a computationally expensive process, which might take upwards of one hour depending on the amount of training data and the specifications of the computer. However, their application for condition monitoring is fast.

4.7 The selection of training data

The ANN model needs to be trained with the help of data that is representative of the environment or system being modeled. Conventionally, the training data is selected manually to represent the behavior of a system; see for example, [6]. However, with a large number of wind turbines, a manual selection of training data might become a time consuming task. Moreover, as shown in Figure 4.11, the behavior of wind turbines subjected to similar operating conditions differ considerably, which necessitates that the ANN models are trained with data from each individual wind turbine. In order to overcome these issues, an "Automated training data selection approach" was proposed in [43], and later extended for updating the training data after a component replacement in Paper I. The approach is outlined in Figure 4.12.

The process of training the ANN models begins by deciding the initial time period in which there have been no recorded failures in the wind turbines. This could, for example, be the first year of the wind turbine operation. The relevant data for the ANN model is extracted from the SCADA system and the general filter, presented in Section 4.5, is applied to the data set in order to remove the out-of-range measurement values. Following the initial filtering a behavior profile for the wind turbine is created, which is used for the final training data selection.

The automated training data selection approach is centered around understanding the operating characteristic (*behavior profile*) of the wind turbine. The behavior profile of a wind turbine can be understood as the seasonal variations in the parameter being monitored. This season specific behavior of the wind turbine, presented in Figure 4.11, is used for the final

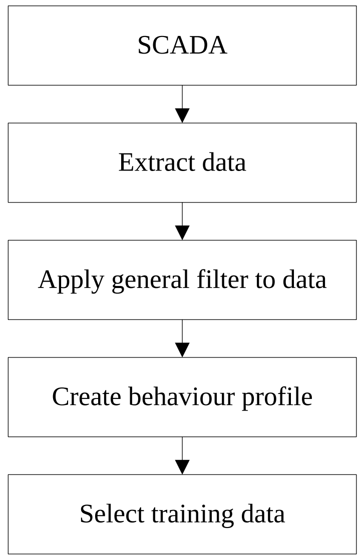

Figure 4.12: Outline of the automated training data selection procedure

selection of the training data set. The training data set can be considered to be sufficient when it contains all the normal operating conditions for the wind turbine. In order to ensure that maximum normal operating conditions are included in the training data set, the diversity measure

$$\mathrm{DM} := \underset{i,j \in \{1,2,\ldots,n\}}{\arg\max} \; |\tau_{\mathrm{av}_i} - \tau_{\mathrm{av}_j}| \tag{4.3}$$

is utilized. The diversity measure indicates which two seasons should be considered for the selection of the training data set, n is the number of seasons, and τ_{av_i} is the average value of the operating parameter that is intended to be modeled using ANN for season i. For example, referring to Turbine A1 in Figure 4.11, the value of DM will be maximum when the Winter-2011 and Summer-2011 months are compared. Hence, the training data set will be picked up from these two months. The next step in the selection of the training data set is the addition of more operating points with an aim to include the maximum range of operating points that the wind turbine has been subjected to. The addition of these extra data points is performed using the control parameter ε according to

$$\left[\sum_{i=1}^{\mathcal{M}} (A_i^{\max} - B_i^{\max}) + \sum_{i=1}^{\mathcal{M}} (B_i^{\min} - A_i^{\min})\right] + N \leq \varepsilon, \tag{4.4}$$

where $A^{\max}$ is an $\mathcal{M}$- vector of maximum values of input parameters in data set containing data from one year, and $\mathcal{M}$ is the total number of input parameters. Analogously, $B^{\max}$ is the vector of maximum values of input parameters in the training data set. $A^{\min}$ and $B^{\min}$ are analogously defined. The value N is the number of sample points in the training data set, and ε is a control parameter, which limits the number of sample points to a maximum value. The value of $\varepsilon > 0$ can be selected to be in range of 8500 to 9000 in order to ensure that the training data set contains 10-min average SCADA data from at least two months.

A training data set with redundant sample points does not have any benefit in improving the performance of the ANN model using batch training ([34]). Moreover, with too many

Table 4.3: Input and output parameters

Output parameters	Input parameters
Gearbox bearing temperature [°C]	Power production [kW]
	Rotor RPM
	Nacelle temperature [°C]
Gearbox lubrication oil temperature [°C]	Ambient temperature [°C]
	Missing data input [-]

sample points in the training data set, the training of the ANN model might take longer, and there is a risk of over-fitting the model. Hence, it can be beneficial to reduce the number of training points, as long as all the operating points for the wind turbine are covered so that the accuracy of ANN model is not compromised. Furthermore, the approach can be used to re-train the ANN models, automatically, after the component being monitored is replaced following a maintenance action. This approach to update the ANN model is presented together with a case study in Paper I.

4.8 Case studies

In order to validate the proposed ANN based CMS, the method was applied to data from wind turbines with a component failure. Application results for two wind turbines, referred to as Turbine-A and Turbine-B are presented in this section; more case studies can be found in Appendix A. Both turbines are 2 MW onshore wind turbines located in the central part of Sweden. The input and output parameters for the ANN model were selected based on the approach for parameter selection presented in Section 4.4. The NARX ANN model with 20 neurons in the hidden layer, with a delay of one ten-minute time unit, was selected as the ANN configuration for the modeling. The parameters selected for the modeling are listed in Table 4.3. The training of the ANN models has been carried out with data from one year of operations during which time there were no recorded failures in the wind turbines. The output from the anomaly detection stage, i.e, the Mahalanobis distance (MHD) value, has been averaged over the 100 best ANN models selected from a total of 300 trained models.

The 10-min average SCADA data is used for monitoring purposes. Hence, in 24 hours there are a maximum of 144 measurements. The results for the anomaly detection are presented as an average of 12-hour periods, resulting in two MHD values per day. In order to increase the confidence in the prediction and in line with the missing data filtering approach, it is ensured that at least 3 hours of data is available for an output from the anomaly detection to be considered. In cases where sufficient data is not available, the previous valid output is copied and an indication of missing data is presented in the output.

4.8.1 Case study for Turbine-A

The ANN models for Turbine-A were trained on data from the year 2011 and applied for anomaly detection during the year 2012. The output from the application to anomaly detection is presented in Figure 4.13. The output is presented for both the gearbox bearing and the gearbox lubrication oil models. The first alarm was seen from the gearbox bearing model on December 6, 2012, while there were no alarms from the gearbox lubrication oil model. From the maintenance records it was realized that the gearbox was replaced in February

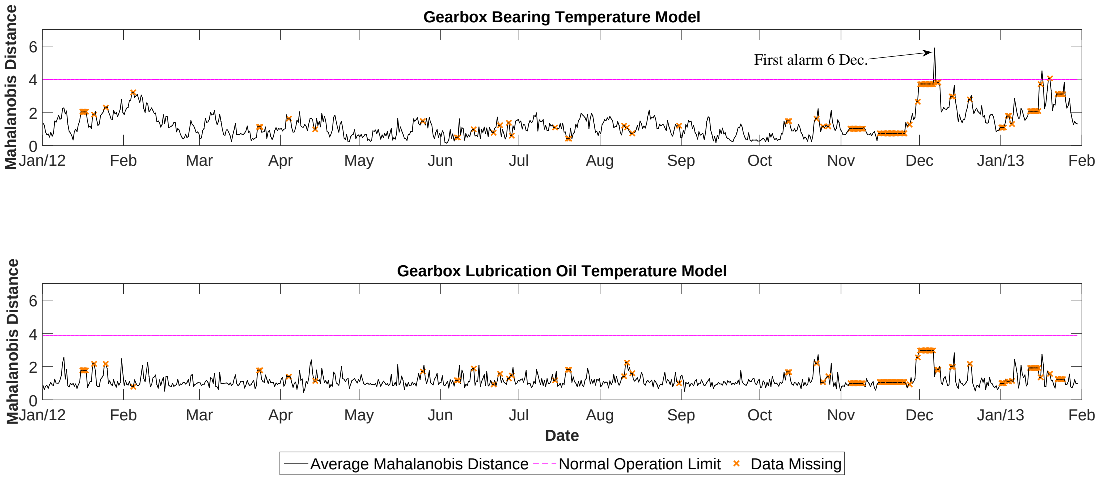

Figure 4.13: Anomaly detection output for Turbine-A

2013. Furthermore, the vibration monitoring system reported an alarm on November 23, 2012, and an inspection was carried out on November 28, which revealed a damage in the monitored bearing. The output of the anomaly detection also shows a steep rise in the MHD value after the inspection date. It can be concluded that the ANN based CMS system is almost at par with the vibration based CMS in this case. However, the frequent interruptions in the availability of the SCADA data in the month of November, 2012, resulted in a delay in the alarm.

The ANN models lack a physical understanding of the system being modeled, and hence it is necessary to ensure that the anomaly detected by the ANN model is not a result of incorrect inputs to the model. The four inputs to the ANN models for the gearbox bearing temperature and the gearbox lubrication oil temperature are presented in Figure 4.14 for the month of December 2012, when the anomaly was detected. The SCADA recorded value for the output parameters for the same period are presented in Figure 4.15. The upper limit and the lower limit for the data in Figure 4.15 and Figure 4.14 correspond to the maximum and minimum values of the data used in the training set, which are decided after application of the data filters presented in Section 4.5. It can be observed that the input and output parameters for the month of December have been within the limits of the data provided to the ANN model during the training process. Hence, it can be concluded that the anomaly detected using the models is, in fact, a result of the component having an abnormal operation.

4.8.2 Case study for Turbine-B

The ANN models for Turbine-B were trained on data from the year 2010 and applied for anomaly detection during the year 2011. The output from the application to anomaly detection is presented in Figure 4.16. The first alarm was seen in the gearbox lubrication oil model on September 13, 2011, and in the gearbox bearing model on October 7, 2011. Unlike the case for Turbine-A, in this case, there was no alarm from the vibration based CMS. The gearbox was replaced on November 19, 2011 after it got stuck and the wind turbine could not be restarted.

The input and the output parameters to the ANN models were found to be within the

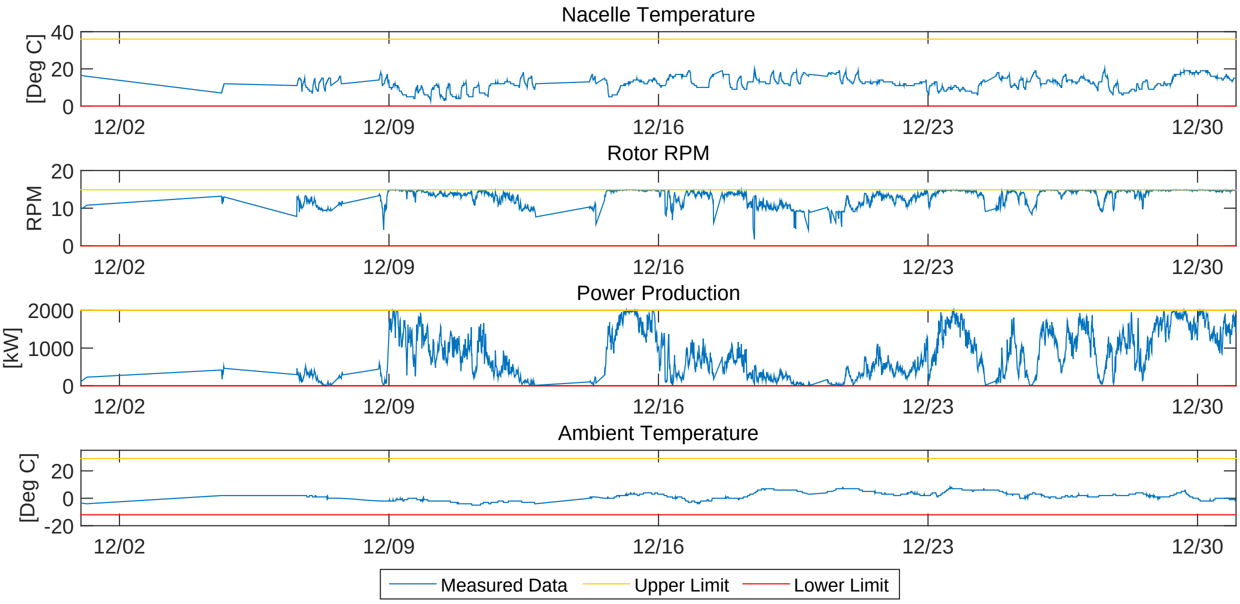

Figure 4.14: Inputs to the ANN model for Turbine-A

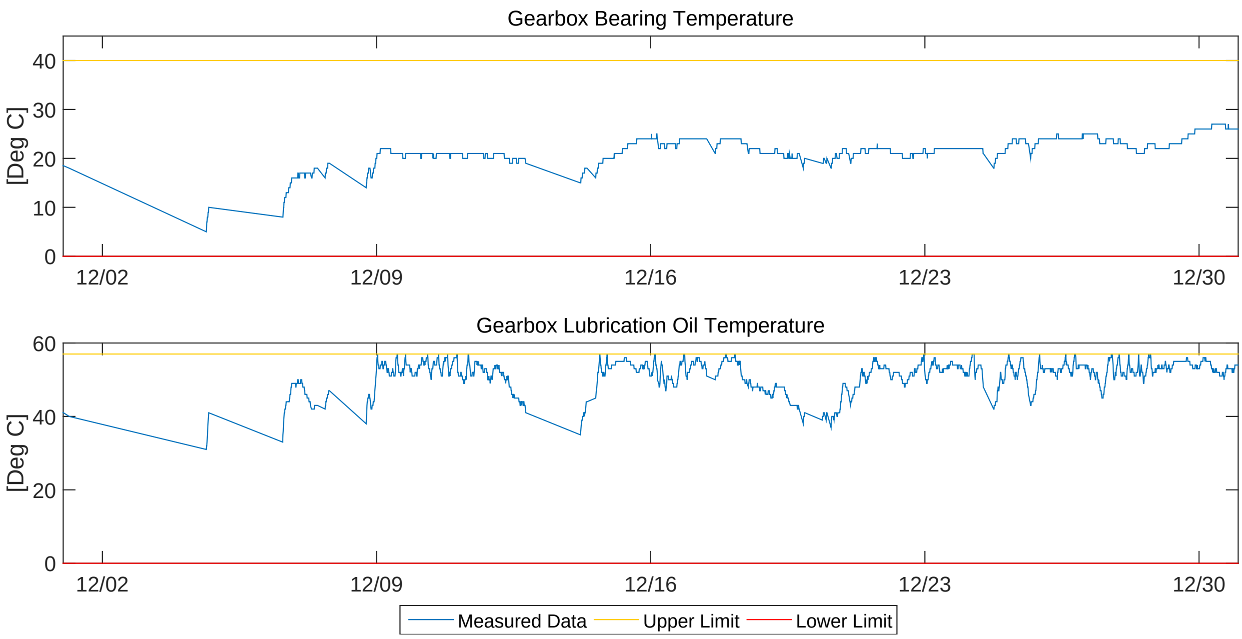

Figure 4.15: Output parameters recorded in SCADA for Turbine-A

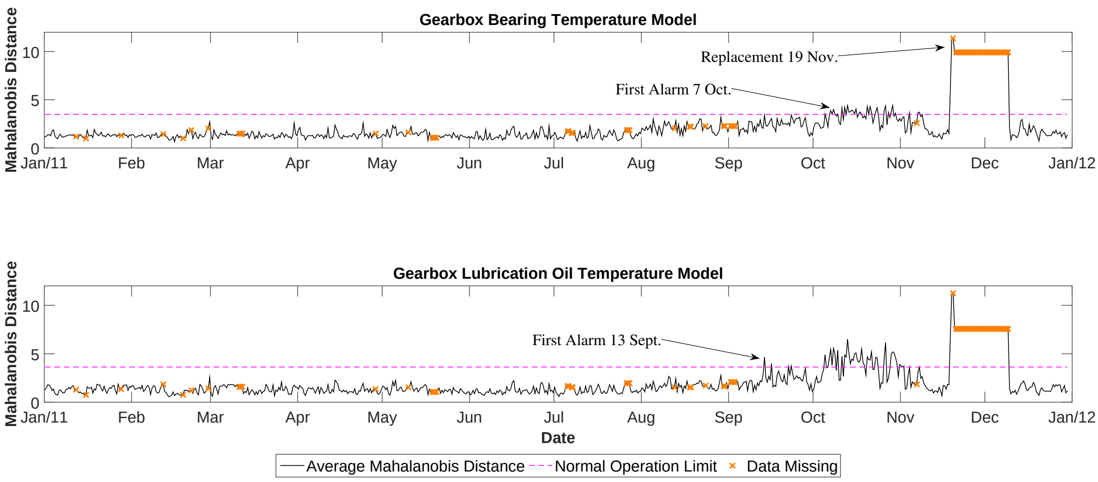

Figure 4.16: Anomaly detection output for Turbine-B

limit of the training data. The input and output parameters for the months of September and October 2011 are presented in Figures 4.17 and 4.18, respectively. It can be observed that the ANN based CMS method is capable of detecting faults even when there is no visible change in the behavior of neither the gearbox bearing nor the lubrication oil temperatures.

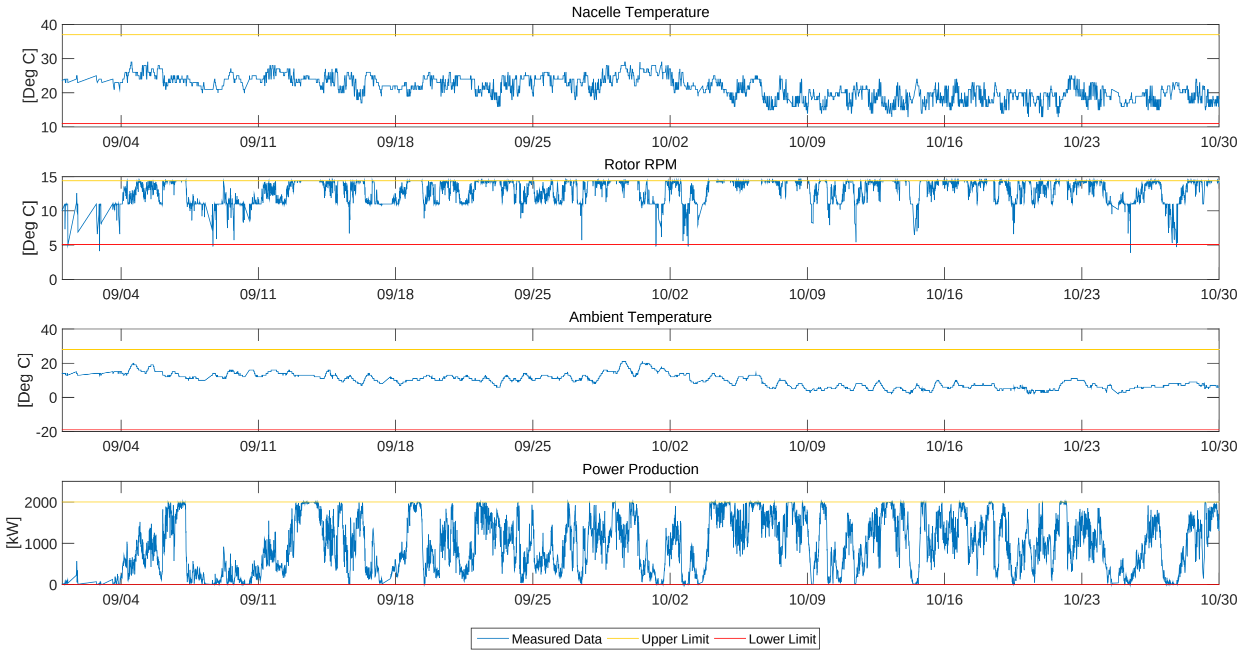

Figure 4.17: Inputs to the ANN model

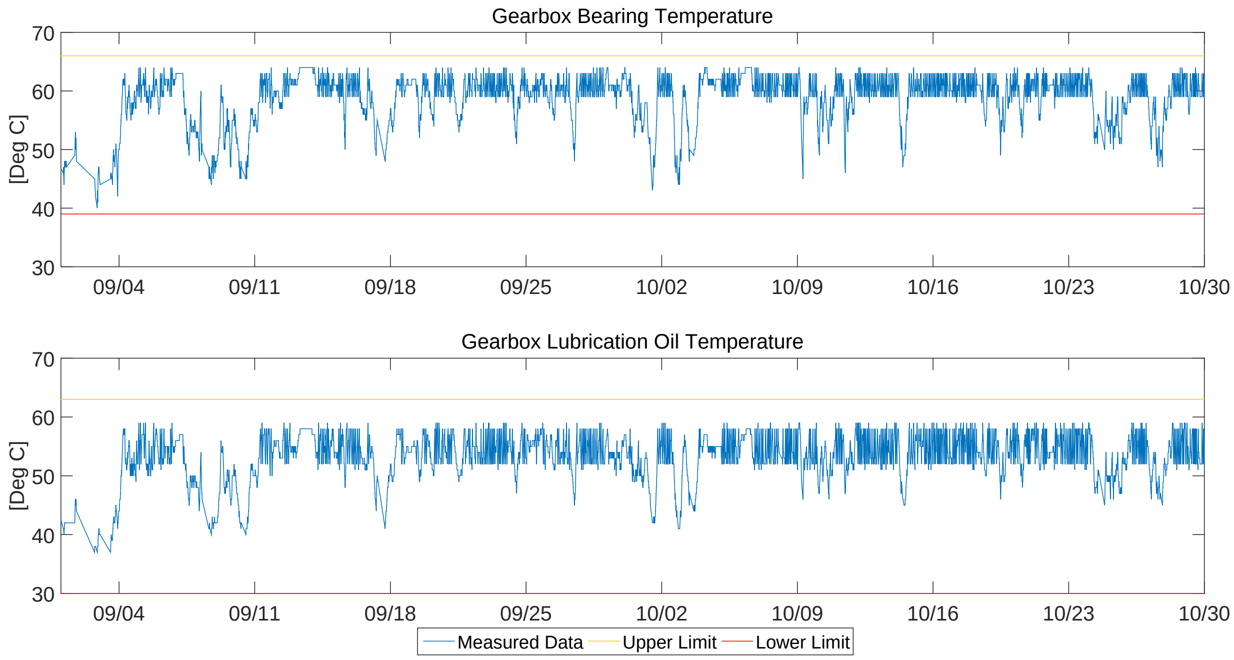

Figure 4.18: Output parameters recorded in SCADA

4.9 Limitation of ANN based CMS

The success of the ANN based CMS is largely dependent on the range of measurements available in the SCADA system. In order for the method to be able to detect abnormal operating conditions in the monitored component, the failure mode in the component should manifest itself such that the monitored parameter is affected. In the case studies presented above, the temperatures in the bearing and the lubrication oil were affected as a result of a deterioration in the gearbox, which was picked up by the ANN based CMS method. However, failures in intermediate shaft gears might not have a significant affect on the low speed and high speed bearing temperatures. In such cases the ANN based CMS might fail to raise an alarm. This has been demonstrated through a case study in Paper III. The proposed ANN based CMS method is intended to be complementary to other installed monitoring systems, like the vibration based CMS, and consequently it will aid in improving the overall efficiency of condition monitoring in the wind turbines.

Chapter 5

Maintenance optimization

This chapter presents a mathematical model for maintenance optimization. Furthermore, case studies are presented to demonstrate the applicability of the model within the SEMS framework. The material in this chapter is most strongly connected to Paper IV.

5.1 The mathematical optimization model

A mathematical optimization model, called Preventive Maintenance Scheduling Problem with Interval Costs (PMSPIC), was introduced in [69], and its application for ABPM scheduling for wind farms applications was demonstrated. In this thesis, the PMSPIC model has been developed further to enable CBPM scheduling.

Consider a wind farm with $\mathcal{M}$ wind turbines, each turbine having a set $\mathcal{N} := \{1, \ldots, n\}$ of defined components that can be maintained at discrete time steps $\mathcal{T} := \{1, \ldots, T\}$, where T denotes the planning horizon. A preventive maintenance activity includes the replacement of a component, and it is considered that all the components have obtained PM at time instance 1 and will get PM at time $T + 1$. As time instance 1 is the beginning of the planning period, it can be safely assumed that the component is in an as good as new condition, and at $T + 1$ the component life has been consumed and the component is being decommissioned. In the PMSPIC model, if PM of component $i \in \mathcal{N}$ is scheduled at the times $s \in \mathcal{T} \cup \{1\}$ and $t \in \{s+1, \ldots, T+1\}$, but not during the time steps $\{s+1, \ldots, t-1\}$, then the maintenance interval denoted by (s, t), generates the interval cost C^i_{st}. The decision variables are defined over the set $\mathcal{I} := \{(s, t) \mid s \in \mathcal{T} \cup \{1\}, t \in \{s + 1, \ldots, T + 1\}\}$, and the mathematical maintenance optimization model is shown in Model (5.1), below:

$$
\begin{aligned}
\text{minimize} \quad & \sum_{t\in\mathcal{T}}\sum_{m\in\mathcal{M}} dz_t^m + \sum_{m\in\mathcal{M}}\sum_{i\in\mathcal{N}}\sum_{(s,t)\in I} C_{st}^i x_{st}^{mi}, && && (5.1\text{a})\\
\text{subject to} \quad & \sum_{s=1}^{t-1} x_{st}^{mi} \le z_t^m, && i\in\mathcal{N},\ m\in\mathcal{M},\ t\in\mathcal{T}, && (5.1\text{b})\\
& \sum_{s=1}^{t-1} x_{st}^{mi} = \sum_{s=t+1}^{T+1} x_{ts}^{mi}, && i\in\mathcal{N},\ m\in\mathcal{M},\ t\in\mathcal{T}, && (5.1\text{c})\\
& \sum_{s=1}^{T+1} x_{1s}^{mi} = 1, && i\in\mathcal{N},\ m\in\mathcal{M}, && (5.1\text{d})\\
& x_{st}^{mi} \in \{0,1\}, && i\in\mathcal{N},\ m\in\mathcal{M},\ (s,t)\in\mathcal{I}, && (5.1\text{e})\\
& z_t^m \in \{0,1\}, && m\in\mathcal{M},\ t\in\mathcal{T}. && (5.1\text{f})
\end{aligned}
$$

The objective (5.1a) is to minimize the sum of all set-up and interval costs, where the variable x_{st}^{mi}, $i \in \mathcal{N}$, $m \in \mathcal{M}$, $(s,t) \in \mathcal{I}$, is the decision variable which takes the value 1 only if a maintenance is scheduled in component $i \in \mathcal{N}$ of turbine $m \in \mathcal{M}$ at times s and t. The variable z_t^m, $m \in \mathcal{M}$, $t \in \mathcal{T}$, is the variable which takes the value 1 only if a maintenance is scheduled in the wind turbine $m \in \mathcal{M}$ at time $t \in \mathcal{T}$. The parameter d represents the set up cost incurred each time a wind turbine is visited for a maintenance activity.

Constraint (5.1b) ensures that if a maintenance interval for component i in wind turbine m ends at time t, then maintenance occurs at time t. For each wind turbine m and component i, the constraints (5.1c) ensure that the same number of maintenance intervals end and start at time t. The constraints (5.1d) ensure that a maintenance interval of component i starts at time $t = 1$. The set of constraints (5.1e) and (5.1f), ensure that the decision variables x_{st}^{mi} and z_t^m are binary. Finally, the interval cost C_{st}^i is defined as the sum of the preventive maintenance cost C_i^{PM} and the deterioration cost $M_i(t-s)$ in the time interval (s,t), as

$$C_{st}^i := C_i^{\mathrm{PM}} + M_i(t-s), \quad i \in \mathcal{N},\ (s,t) \in \mathcal{I}. \tag{5.2}$$

The deterioration cost can be calculated as the risk of having to do a corrective maintenance after failure in the component. However, in practical situations, if the failure occurs close to a scheduled preventive maintenance activity, some cost savings can be achieved by moving the preventive maintenance to an earlier date and performing a corrective maintenance at that date. The deterioration cost is modeled considering this rescheduling cost, as

$$M_i(t) := \mathbb{E}\left[\sum_{j=1}^{K} \mathbb{I}_{(F_j \le t)} G(F_j, t)\right] \mathrm{Rn}_i(t), \quad i \in \mathcal{N},\ t \in \mathcal{T}, \tag{5.3}$$

where $K \gg 10000$ is a large number used for simulation of survival times for component i. (The indicator function $\mathbb{I}$ takes the value 1 when the survival time F_j is less than or equal to t, otherwise the value is zero.) The survival time F_j for component i is a random variable derived from the probability distribution function for failures of component i. The value $\mathrm{Rn}_i(t)$ denotes the number of renewals for component i in time interval $(1,t)$ and is calculated based on the renewal function, which is estimated using the recursive procedure shown in Section 2.2.8. The cost function is defined for all s, as

$$G(s,t) = \left(C_i^{\mathrm{CM}} + d\right) - \left(\frac{s}{t}\right)^{\lambda} \left(C_i^{\mathrm{PM}} + d\right), \quad i \in \mathcal{N},\ (s,t) \in \mathcal{I}. \tag{5.4}$$

The cost function is formulated in a manner that allows consideration of a re-scheduling cost when the failure occurs close to a scheduled maintenance activity. The parameter λ, which is used to decide the effect of this re-scheduling on the cost is considered to have a fixed value of 3, based on the suggestion in [69].

5.2 Modifications for CBPM

The function of a CMS is to provide an indication of a deterioration in the component being monitored. However, to achieve an effective CBPM schedule, a condition-based failure rate model is necessary. To this effect, researchers have developed models which provide failure probabilities for components based on condition monitoring signals; for example see [31,32,49,70–72]. In line with the SEMS framework, an indication of a possible failure in the monitored component from the condition monitoring system will initiate an inspection, which will be followed by an update in the maintenance schedule, if necessary. The PMSPIC model has been modified to consider the possibility of CBPM scheduling. In order to account for a different failure rate after an indication from the CMS, the failure rate model for the effected component is updated according to

$$f(t) := \begin{cases} \text{Condition based failure rate model}, & \text{if} \quad T_{\mathrm{CMS}} \leq t \leq T_{\mathrm{Repl}}, \\ \text{Age based failure rate model}, & \text{if} \quad T_{\mathrm{Repl}} < t \leq T, \end{cases} \tag{5.5}$$

where T_{CMS} is the time instant when information about a deterioration is received from the CMS, and T_{Repl} is the time instant for the next scheduled replacement for the component based on the age-based preventive maintenance schedule. In order to update the maintenance decision based on the new information, the constraints (5.1d) are replaced by constraints (5.6), which ensure that exactly one replacement of the damaged component is scheduled in the time interval $[T_{\mathrm{CMS}}, T_{\mathrm{Repl}}]$, and no replacements are scheduled in the time interval $[1, T_{\mathrm{CMS}}]$:

$$\sum_{t=1}^{T+1} x_{1t}^{mi} = 1,\ i \in \mathcal{N} \setminus \{\mathrm{DC}\},\ m \in \mathcal{M}, \tag{5.6a}$$

$$\sum_{t=T_{CMS+1}}^{T_{Repl}} x_{T_{CMS},t}^{mi} = 1,\ i \in \{\mathrm{DC}\},\ m \in \{\mathrm{FWT}\}, \tag{5.6b}$$

$$\sum_{t=1}^{T_{CMS}-1} x_{t,T_{CMS}}^{mi} = 0,\ i \in \{\mathrm{DC}\},\ m \in \{\mathrm{FWT}\}, \tag{5.6c}$$

where $\mathrm{FWT} \subset \mathcal{M}$ is the set of wind turbines with one or more damaged components, and $\mathrm{DC} \subset \mathcal{N}$ is the set of damaged components in the wind turbines $m \in \mathrm{FWT}$.

5.3 ABPM scheduling with PMSPIC

The ABPM schedule provides the expected number of replacements during the life for the components, based on historical failure times recorded. The ABPM schedule can be beneficial, as it provides an opportunity to make financial plans for the entire life of the component.

Table 5.1: Input Data

Component	Failure Replacement Cost [1000 \$]	Preventive Replacement Cost [1000 \$]	Weibull Shape Parameter β	Weibull Scale Parameter α [Months]
Rotor	162	36.75	3	100
Main Bearing	110	23.75	2	125
Gearbox	202	46.75	3	80
Generator	150	33.75	2	110

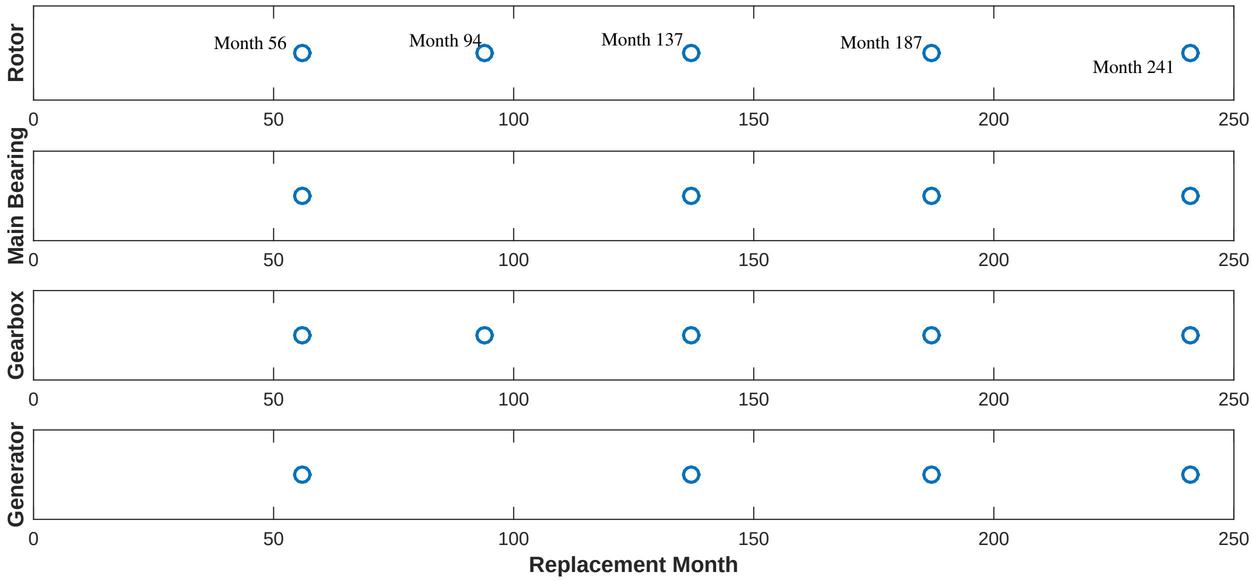

Figure 5.1: An optimal ABPM schedule from the PMSPIC model

In this section the PMSPIC model is applied with the data presented in Table 5.1 to provide an ABPM schedule. The wind turbine is considered to have four critical components, which are intended to be included in the preventive maintenance regime. The components are considered to have Weibull distributed failure times with the shape and scale parameter values presented in Table 5.1 (taken from [49]).

The life of the wind turbine is considered to be $T = 240$ months (20 years) and the ABPM schedule from the PMSPIC model is presented in Figure 5.1. The deterioration cost $M_i(t)$ is simulated based on the Weibull failure rate models with data from Table 5.1. The ABPM schedule from the PMSPIC model has been compared to a schedule obtained from a frequently applied constant interval maintenance optimization model in Paper IV. The results show that the PMSPIC model provides an economically better schedule even with one replacement less in the generator and the main bearing during the wind turbine life. Furthermore, the modifications to the PMSPIC model allow a CBPM optimization, which is demonstrated in Section 5.4.

5.4 CBPM scheduling with PMSPIC

The application of PMSPIC for CBPM scheduling, with Gamma distributed failure times for a hypothetical case of gearbox failure, is presented in Paper IV. In this section, the application of the proportional hazards model (PHM) presented in Section 2.2 is described. The application of PHM for condition based maintenance has been presented in [32,33,46]. In [32] the CBPM scheduling has been achieved through a control limit policy, where the threshold value of the CMS signal for initiating a PM is optimized. This approach however requires that the signals from CMS are recorded continuously, which might be difficult with a large population of wind turbines. Furthermore, the control limit policy does not provide an expected number of replacements during the life of the turbine, and hence does not allow for an initial financial plan. These shortcomings can be overcome by the use of the extended PMSPIC model, defined by (5.1), (5.5), (5.6), and applied with the SEMS maintenance management framework.

The application of PHM for CBPM planning with the PMSPIC model is non-trivial. Hence, the procedure to apply PHM is demonstrated with a hypothetical case study. Consider that the condition based failure rate can be modeled by a Weibull baseline hazard rate with an exponential link function, similar to the ones suggested in [32]. The PHM model, h, is shown in (5.7), where β is the shape parameter, α is the scale parameter of the baseline Weibull hazard rate, and $\mathrm{e}^{(\gamma\cdot z(t))}$ is the link function with a vector of constants γ and a vector of time dependent covariates $z(t)$:

$$h(t;z(t)) := \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1}\mathrm{e}^{(\gamma\cdot z(t))}. \tag{5.7}$$

The historical failure times along with the historical measured covariate data is utilized to establish the relationship between the hazard rate $h(\cdot)$ and the behavior of the covariate $z(\cdot)$. Traditional methods like the maximum likelihood estimation (MLE), described in Section 2.2.7, can be applied to estimate the coefficient γ, which establishes the relationship between the hazard rate at time t and the measured covariate quantity at time t. Furthermore, in order to predict the future hazard rate of component given its relationship with a certain measured covariate quantity, it is also necessary to model the expected future behavior of the covariate $z(t)$. The procedure to predict the behavior of a covariate is presented in the appendix of [73], where a range of covariates were investigated for industrial pumps.

In order to utilize the PHM with the PMSPIC model (5.1), the survival times need to be simulated from the the PHM model. The survival times for a PHM with constant covariate value and Weibull baseline hazard can be generated using (5.8), as shown in [55], where U represents a uniform distribution between $[0,1]$, and T is the total time horizon for planning (240 months):

$$S[t;z(t)] := \left(\frac{-\log(U)}{\alpha^{\beta}\mathrm{e}^{\gamma z(t)}}\right)^{\frac{1}{\beta}} T. \tag{5.8}$$

A method to estimate the residual life of components from the output of the ANN normal behavior model, and its application to maintenance scheduling was presented in [74], in which the risk indicators were calculated as the accumulated error between the ANN model estimated and measured parameter values. This approach can be applied with the ANN based CMS method, presented in this thesis, to create a covariate, which can be applied with the PHM model for updating the maintenance schedule for the damaged component. However, recorded covariate behavior data from similar failure modes of the component under consideration is required to create a robust estimate of the covariate as well as to estimate the value of coefficient γ in the PHM model. Such recorded historical covariate behavior data and failure statistics were not available in this project. Hence, in order to demonstrate the application of PHM with the modified PMSPIC model, a hypothetical but realistic case is considered with data from one wind turbine, and the cumulative MHD measure is utilized as a covariate.

The MHD method of anomaly detection provides a possibility to quantify the deviations in the current operating conditions from the normal operation conditions represented by the training data set utilized to train the ANN model. Hence, the cumulative MHD measure can, potentially, provide the extent of damage in the monitored component and can be used to track the deterioration in the component being monitored. The cumulative Mahalanobis distance measure is calculated as

$$\mathcal{Z}_{t_o} = \int_1^{t_o} (\mathrm{MHD}(t) - \mathrm{Threshold})\, \mathbb{I}_{(\mathrm{MHD(t)>Threshold})}\, dt, \tag{5.9}$$

where $\mathrm{MHD}(t)$ is the MHD value at time instant t, and Threshold is the normal operation limit value decided based on the method presented in Section 4.6. The indicator function $\mathbb{I}_{(\mathrm{MHD}(t)>\mathrm{Threshold})}$ takes a value 1 when the MHD is greater than the threshold value, otherwise it is 0. Following the indication from the ANN based CMS, the cumulative MHD signal can be constructed based on the output from the monitoring system, as shown in Figure 5.2.

The output presented in Figure 5.2, which is derived using (5.9), has been divided into three sections, showing normal operation, behavior just after an indication of anomaly, and a higher deterioration condition. The case studies presented in [73] show, that in some cases, the covariate behavior can be represented by a time dependent affine function. Hence, in line with the observations in [73], the covariate $z(t)$ is modeled as a time dependent affine quantity with a coefficient A and with an offset value $\mathcal{Z}_{t_o}$, which is defined as

$$z(t) = At + \mathcal{Z}_{t_o}, \tag{5.10}$$

where the value of the offset $\mathcal{Z}_{t_o}$, is calculated at discrete time instances t_o using the Equation (5.9). In this case, the discrete time instance t_o is considered as one month and the value of the offset is updated every month after the ANN based CMS has provided the first alarm. Consequently, the maintenance decisions will be updated every month based on the latest information about the condition of the component.

The survival times for the PHM model are simulated for each discrete time instant t using (5.8), considering that the covariate $z(t)$ has a finite and constant value at t, calculated using (5.10) and (5.9). The survival times are used to calculate the interval costs using (5.2) and (5.3). The complete PHM model can be represented as

$$h(t) := \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{(\beta-1)} \mathrm{e}^{\gamma(At+\mathcal{Z}_{t_o})}. \tag{5.11}$$

Consider that at time instant $t = 20$ months (the 13$^{\text{th}}$ of September), the ANN based CMS method gives an alarm. At this point the historical covariate behavior data is used to create a model to represent its expected future behavior. Consequently, the expected future behavior of the covariate is utilized with the PHM model to predict the hazard rate for the damaged component. The parameters in (5.10) are calculated based on data from segment 1, in Figure 5.2, at time instance $t_o = 20$ months. Consequently, the model is updated at time instances $t_o = 21$ and $t_o = 22$ months, to account for a change in the rate of deterioration,

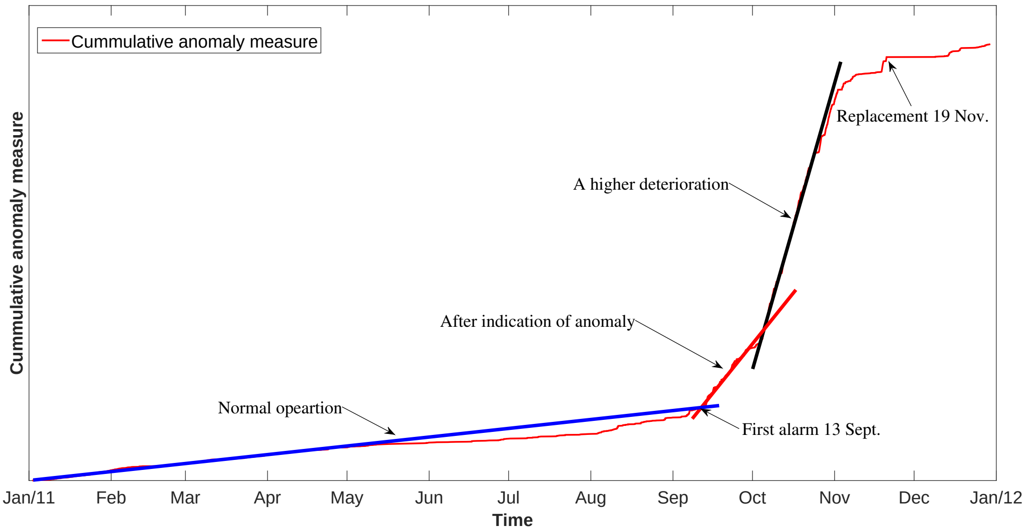

Figure 5.2: The cumulative frequency of threshold violation from ANN model over the period of one year for Turbine-B presented in Section 4.8.2

Table 5.2: Parameters for the proportional hazards model presented in Equation (5.11)

Scenario	Segment	Coefficient [γ]	Coefficient [A]	Offset [$\mathcal{Z}_{t_o}$]
Low deterioration	Segment 1	1	0.2	0.1
Medium deterioration	Segment 2	1	0.6	0.5
High deterioration	Segment 3	1	1	1

represented by segments 2 and 3 respectively. Table 5.2 presents the hypothetical values of the constants used to model the covariate behavior for the three segments.

The maintenance schedule computed using the age-based failure rate models is updated with failure rates based on the PHM at time instances $t = 20$ months, with a normal operation model, at $t = 21$ months with a medium deterioration model, and at $t = 22$ months with a high deterioration model. The maintenance schedule at each time step is updated and is presented in Figure 5.3.

The CBPM schedule presented in Figure 5.3 can then be utilized to determine the next immediate decision about preventive replacement activities. It can be noticed that the optimal decision of the next replacement is provided considering the effect of an early replacement of the damaged component, in this case the gearbox, on all the critical components in the wind turbine system over the life of the wind turbine. However, the updated preventive replacement schedule of the undamaged components is indicative and will be updated, in the same manner as demonstrated for the gearbox, based on an indication of deterioration from their respective condition monitoring systems, in line with the SEMS framework. Moreover, the indicative schedule of all the components over the life of the wind turbine provides an outline of the effect of following a certain maintenance schedule, given the assumption that all future replacements after the early replacement of the damaged component will follow the ABPM maintenance schedule utilizing the failure rate models presented in Table 5.1.

The modified PMSPIC model also accounts for the possibility of opportunistic maintenance scheduling. A case study to demonstrate the effect of such an opportunistic maintenance schedule, when the indication of an impending failure from the CMS is obtained close to the scheduled preventive maintenance activity, is illustrated in Paper IV.

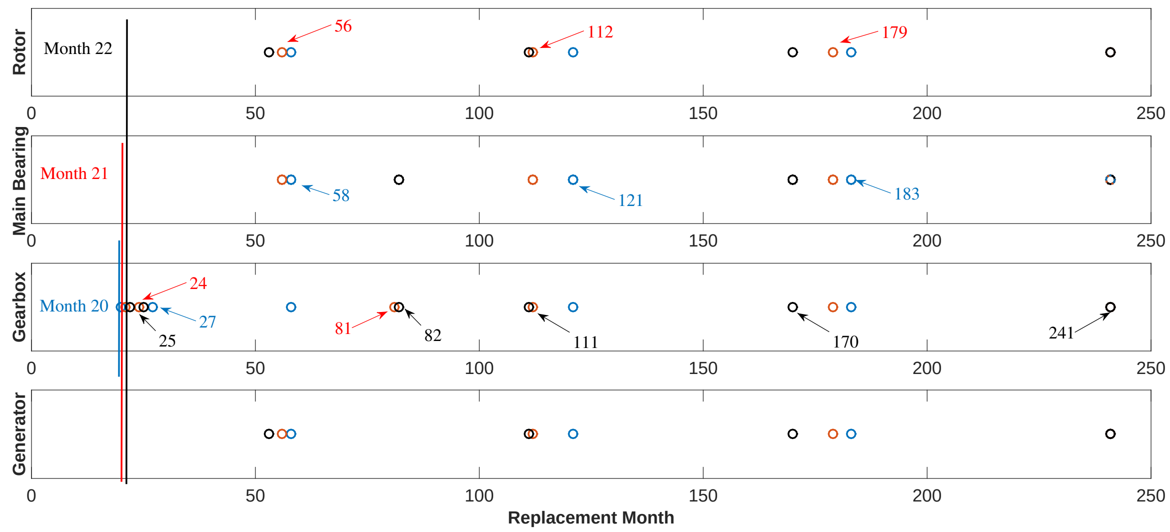

Figure 5.3: Maintenance schedule updated with PHM at three different instances in time, the colors used represent the three segments presented in Figure 5.2. The color blue represents the maintenance decisions corresponding to deterioration rate model Segment 1, red corresponds to Segment 2, and black corresponds to Segment 3. The circles represent the suggested month of replacement.

5.5 Discussion

The hypothetical case studies presented above shows the possibility of utilizing the ANN based CMS method for condition based preventive maintenance applications. However, due to lack of data it was not possible to create a PHM model with real values. Data from more than one wind turbine failures is desirable to create statistically relevant failure rate models. Furthermore, the modified PMSPIC model can be further improved to provide more realistic short term decisions by including weather constraints, constraints on requirement of lead time for procurement, etc. However, the results from the case studies illustrate the possibility to update the maintenance decisions in real time as and when a new information about component deterioration is available from the CMS. Consequently, it can be inferred that a systematic application of the presented mathematical model with guidelines provided in the SEMS framework will aid in improvement of the wind turbine asset management.

Chapter 6

Closure

This chapter summarizes the main results from the thesis and discusses future work.

6.1 Conclusions

A maintenance management framework called Self Evolving Maintenance Scheduler (SEMS) was presented in this thesis. The SEMS framework provides guidelines for the use of the O&M data from various sources to improve the maintenance activities in critical wind turbine components. The two main parts of the SEMS framework are summarized below.

6.1.1 Condition monitoring

The ANN based CMS presented in this thesis is capable of monitoring not only the mechanical but also the electrical components in the wind turbine, given that suitable measurements are available from the SCADA system. Various drawbacks and issues with the application of ANN models to condition monitoring applications were discussed, and suitable mitigation techniques to overcome these drawbacks and improve the confidence in the ANN based CMS process were presented. In addition to this, an algorithm for selecting the training data set was presented, which can be used to update the ANN models after the monitored component has been replaced. Three approaches for filtering of training data were presented with a discussion about their effect on the performance of ANN models. Finally, an anomaly detection method utilizing the Mahalanobis distance measurement was presented, which enables an early detection of anomalies even with small deviations in the operating characteristics of the damaged components.

The case study results presented in the thesis demonstrate that the proposed ANN based CMS method can detect failures in the gearbox components about three months before the eventual replacement is required, providing ample opportunity for condition based preventive maintenance (CBPM) planning.

6.1.2 Mathematical model for maintenance optimization

A mathematical model for maintenance optimization referred to as Preventive Maintenance Scheduling Problem with Interval Costs (PMSPIC), was discussed in the thesis, and was compared to a frequently used simple mathematical model for maintenance optimization and shown to provide better results. The PMSPIC model was modified for application with the SEMS framework. The modified PMSPIC model is capable of providing an optimal age based preventive maintenance schedule (ABPM), which is then upgraded to an optimal condition based preventive maintenance (CBPM) schedule when any new information about the deterioration in a component is available. The application of the mathematical model with the SEMS framework was presented, for a hypothetical but realistic scenario.

The main advantages of the CBPM schedule from the modified PMSPIC model are the following:

- the maintenance schedule for the damaged component is optimized considering the effect of its replacements on the entire life of the wind turbine, and
- the maintenance schedule also considers opportunistic replacements of other critical components in the wind turbine and the effect of such replacements on the wind turbine life.

6.2 Future work

The future development of the concepts presented in this thesis can be divided into two areas of application: the condition monitoring and the maintenance optimization. A few ideas for future work in each area are presented in the following sections.

6.2.1 Condition monitoring

The ANN based CMS presented in the thesis has been developed in an academic environment and is suitable when the number of wind turbines is not very large. However, to make the proposed method applicable for larger systems, it has to be developed within a computationally efficient platform such as C#, Python, etc., and a data interface has to be developed which is capable of extracting data directly from the SCADA servers with minimum disruptions in communication. Furthermore, the method presented uses data from only one wind turbine for the purpose of condition monitoring. The confidence in the final output can be improved by considering the output from neighboring wind turbines during the condition monitoring process. In addition to this, the system uses 10-min average data, which is available in normal SCADA systems. However, using data with higher frequency— like 1-min average data— might improve the condition monitoring. An investigation into the effect of increasing the frequency of recorded SCADA data on the condition monitoring output could be a useful future work.

It was shown in the thesis that the output from the ANN based CMS can be used to create signals, which can track the failure in the component. However, due to lack of data of similar failures in the components, further investigation was not possible. With the availability of data from more wind turbines, and particularly, with more failure data, a robust Residual Life Estimation (RLE) model can be created using, for example, a Bayesian approach ([47]). Such RLE models can be very useful for CBPM scheduling.

6.2.2 Mathematical optimization model

The cost data used in the PMSPIC model, presented in this thesis, has been extracted from available literature. An interesting future work could focus on creating accurate cost models for maintenance activities as well as models for risk of failures. Such models will require data from past experiences as well as information about the cost of spare parts, cost of loss of revenue, among other things. Furthermore, the short-term decisions from the PMSPIC model can be improved by including weather constraints, and seasonal constraints in the model. As maintenance activities cannot be carried out on wind turbines under certain weather conditions, such constraints may play an important role in the final decisions. Such an extension to the model will be particularly important for offshore applications.

Bibliography

[1] "World energy outlook 2015," International Energy Agency, Tech. Rep., 2015. [Online]. Available: http://www.iea.org/Textbase/npsum/WEO2015SUM.pdf

[2] P. Takoutsing, R. Wamkeue, M. Ouhrouche, F. Slaoui-Hasnaoui, T. Tameghe, and G. Ekemb, "Wind turbine condition monitoring: State-of-the-Art review, new trends, and future challenges," *Energies*, vol. 7, no. 4, pp. 2595–2630, Apr 2014.

[3] "Wind turbine gearbox condition monitoring round robin study – Vibration analysis," National Renewable Energy Laboratory, Tech. Rep., 2012. [Online]. Available: http://www.nrel.gov/docs/fy12osti/54530.pdf

[4] Z. Hameed, Y. Hong, Y. Cho, S. Ahn, and C. Song, "Condition monitoring and fault detection of wind turbines and related algorithms: A review," *Renewable and Sustainable Energy Reviews*, vol. 13, no. 1, pp. 1–39, Jan 2009.

[5] M. C. Garcia, M. A. Sanz-Bobi, and J. del Pico, "SIMAP: Intelligent System for Predictive Maintenance," *Computers in Industry*, vol. 57, no. 6, pp. 552–568, 2006.

[6] A. Zaher, S. McArthur, D. Infield, and Y. Patel, "Online wind turbine fault detection through automated SCADA data analysis," *Wind Energy*, vol. 12, no. 6, pp. 574–593, 2009.

[7] A. Kusiak and A. Verma, "Analyzing bearing faults in wind turbines: A data-mining approach," *Renewable Energy*, vol. 48, pp. 110–116, Dec 2012.

[8] M. Schlechtingen, I. F. Santos, and S. Achiche, "Wind turbine condition monitoring based on SCADA data using normal behavior models. Part 1: System description," *Applied Soft Computing*, vol. 13, no. 1, pp. 259–270, 2013.

[9] L. Tarassenko, "7 - design, training and testing of the prototype," in *Guide to Neural Computing Applications*, L. Tarassenko, Ed. New York: Butterworth-Heinemann, 1998, pp. 77–97.

[10] N. Baydar and A. Ball, "Detection of gear deterioration under varying load conditions by using the instantaneous power spectrum," *Mechanical Systems and Signal Processing*, vol. 14, no. 6, pp. 907–921, nov 2000.

[11] J. Xiang, S. Watson, and Y. Liu, "Smart monitoring of wind turbines using neural networks," in *Sustainability in Energy and Buildings - Proceedings of the International Conference in Sustainability in Energy and Buildings, SEB'09*, 2009, pp. 1–8.

[12] O. Bennouna, N. Héraud, H. Camblong, M. Rodriguez, and M. A. Kahyeh, "Diagnosis and fault signature analysis of a wind turbine at a variable speed," *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, vol. 223, no. 1, pp. 41–50, mar 2009.

[13] X. Wang, V. Makis, and M. Yang, "A wavelet approach to fault diagnosis of a gearbox under varying load conditions," *Journal of Sound and Vibration*, vol. 329, no. 9, pp. 1570–1585, apr 2010.

[14] K. Kim, G. Parthasarathy, O. Uluyol, W. Foslien, S. Sheng, and P. Fleming, "Use of SCADA data for failure detection in wind turbines," in *ASME 2011 5th International Conference on Energy Sustainability.* ASME, 2011, pp. 2071–2079.

[15] S. Gill, B. Stephen, and S. Galloway, "Wind turbine condition assessment through power curve copula modeling," *IEEE Transactions on Sustainable Energy*, vol. 3, no. 1, pp. 94–101, jan 2012.

[16] Y. Qiu, Y. Feng, P. Tavner, P. Richardson, G. Erdos, and B. Chen, "Wind turbine SCADA alarm analysis for improving reliability," *Wind Energy*, vol. 15, no. 8, pp. 951–966, Nov 2012.

[17] W. Yang, R. Court, and J. Jiang, "Wind turbine condition monitoring by the approach of SCADA data analysis," *Renewable Energy*, vol. 53, pp. 365–376, may 2013.

[18] Y. Feng, Y. Qiu, C. J. Crabtree, H. Long, and P. J. Tavner, "Monitoring wind turbine gearboxes," *Wind Energy*, vol. 16, no. 5, pp. 728–740, Jul 2013.

[19] H. Guo, S. Watson, P. Tavner, and J. Xiang, "Reliability analysis for wind turbines with incomplete failure data collected from after the date of initial installation," *Reliability Engineering & System Safety*, vol. 94, no. 6, pp. 1057–1063, Jun 2009.

[20] P. J. Tavner, J. Xiang, and F. Spinato, "Reliability analysis for wind turbines," *Wind Energy*, vol. 10, no. 1, pp. 1–18, Jan 2007.

[21] J. Ribrant and L. M. Bertling, "Survey of failures in wind power systems with focus on Swedish wind power plants during 1997-2005," *IEEE Transactions on Energy Conversion*, vol. 22, no. 1, pp. 167–173, Mar 2007.

[22] F. Spinato, P. Tavner, G. van Bussel, and E. Koutoulakos, "Reliability of wind turbine subassemblies," *IET Renewable Power Generation*, vol. 3, no. 4, pp. 387–401, 2009.

[23] "Project final report," ReliaWind Project, Tech. Rep., Mar. 2011. [Online]. Available: http://cordis.europa.eu/result/rcn/55560_en.html

[24] J. Andrawus, J. Watson, and M. Kishk, "Modelling system failures to optimise wind turbine maintenance," *Wind Engineering*, vol. 31, no. 6, pp. 503–522, Dec 2007.

[25] F. Besnard, M. Patriksson, A.-B. Strömberg, A. Wojciechowski, K. Fischer, and L. Bertling, "A stochastic model for opportunistic maintenance planning of offshore wind farms," in *2011 Trondheim PowerTech.* IEEE, Jun 2011, pp. 1–8.

[26] F. Besnard, K. Fischer, and L. Bertling Tjernberg, "A model for the optimization of the maintenance support organization for offshore wind farms," *IEEE Transactions on Sustainable Energy*, vol. 4, no. 2, pp. 443–450, 2013.

[27] Z. Hameed and J. Vatn, "Role of grouping in the development of an overall maintenance optimization framework for offshore wind turbines," *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, vol. 226, no. 6, pp. 584–601, 2012.

[28] M. Shafiee, M. Patriksson, and A.-B. Strömberg, "An optimal number-dependent preventive maintenance strategy for offshore wind turbine blades considering logistics," *Advances in Operations Research*, vol. 2013, pp. 1–12, 2013.

[29] F. Besnard and L. Bertling, "An approach for condition-based maintenance optimization applied to wind turbine blades," *IEEE Transactions on Sustainable Energy*, vol. 1, no. 2, pp. 77–83, 2010.

[30] J. D. Sørensen, "Framework for risk-based planning of operation and maintenance for offshore wind turbines," *Wind Energy*, vol. 12, no. 5, pp. 493–506, 2009.

[31] Z. Tian, T. Jin, B. Wu, and F. Ding, "Condition based maintenance optimization for wind power generation systems under continuous monitoring," *Renewable Energy*, vol. 36, no. 5, pp. 1502–1509, 2011.

[32] P. J. Vlok, J. L. Coetzee, D. Banjevic, A. K. S. Jardine, and V. Makis, "Optimal component replacement decisions using vibration monitoring and the proportional-hazards model," *Journal of the Operational Research Society*, vol. 53, no. 2, pp. 193–202, Jan 2002.

[33] Z. Tian and H. Liao, "Condition based maintenance optimization for multi-component systems using proportional hazards model," *Reliability Engineering & System Safety*, vol. 96, no. 5, pp. 581–589, 2011.

[34] H. Simon, *Neural Networks and Learning Machines*, 3rd ed. Upper Saddle River: Pearson Education, 2009.

[35] D. Brezak, T. Bacek, D. Majetic, J. Kasac, and B. Novakovic, "A comparison of feed-forward and recurrent neural networks in time series forecasting," in *2012 IEEE Conference on Computational Intelligence for Financial Engineering & Economics (CIFEr)*. IEEE, Mar 2012, pp. 1–6.

[36] M. Salmasi, H. Mahdavi-Nasab, and H. Pourghassem, "Comparison of feed-forward and recurrent neural networks in active cancellation of sound noise," in *2011 International Conference on Multimedia and Signal Processing*, vol. 2. IEEE, May 2011, pp. 25–29.

[37] M. Sundermeyer, I. Oparin, J.-L. Gauvain, B. Freiberg, R. Schluter, and H. Ney, "Comparison of feedforward and recurrent neural network language models," in *2013 IEEE International Conference on Acoustics, Speech and Signal Processing*. IEEE, May 2013, pp. 8430–8434.

[38] K. Levenberg, "A method for the soultion of certain non-linear problems in least squares," *Quaterly Journal of Applied Mathematics*, vol. II, no. 2, pp. 164–168, 1944.

[39] D. W. Marquardt, "An algorithm for least-squares estimation of nonlinear parameters," *Journal of the Society for Industrial and Applied Mathematics*, vol. 11, no. 2, pp. 431–441, 1963.

[40] M. Patriksson, N. Andrèasson, A. Evgrafov, E. Gustavsson, and M. Önnheim, *Introduction to Continuous Optimization.* Studentlitteratur, Lund, 2013.

[41] J. Nocedal and S. J. Wright, *Numerical Optimization*, 2nd ed. New York: Springer, 2006.

[42] M. T. Hagan and M. B. Menhaj, "Training feedforward networks with the Marquardt algorithm." *IEEE transactions on neural networks / a publication of the IEEE Neural Networks Council*, vol. 5, no. 6, pp. 989–93, Jan 1994.

[43] P. Bangalore and L. B. Tjernberg, "An approach for self evolving neural network based algorithm for fault prognosis in wind turbine," in *2013 IEEE Grenoble Conference.* IEEE, Jun 2013, pp. 1–6.

[44] S. Urolagin, K.-V. Prema, K.-V. Reddy, and N.-V. Subba, *Generalization Capability of Artificial Neural Network Incorporated with Pruning Method.* Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 171–178.

[45] M. Rausand and A. Hoyland, *System Reliability Theory: Models, Statistical Methods, and Applications*, 2nd ed. Wiley, 2004.

[46] A. K. Jardine and A. H. Tsang, *Maintenance, Replacement, and Reliability: Theory and Applications*, 1st ed. CRC Press, 2006.

[47] W. Q. Meeker and L. A. Escobar, *Statistical Methods for Reliability Data.* New York, USA: Wiley, 1998.

[48] J. van Noortwijk, "A survey of the application of gamma processes in maintenance," *Reliability Engineering & System Safety*, vol. 94, no. 1, pp. 2–21, 2009.

[49] Z. Tian, "An artificial neural network method for remaining useful life prediction of equipment subject to condition monitoring," *Journal of Intelligent Manufacturing*, vol. 23, no. 2, pp. 227–237, 2009.

[50] T. E. Tallian, "A data-fitted rolling bearing life prediction model Part I: Mathematical mode," *Tribology Transactions*, vol. 39, no. 2, pp. 249–258, 1996.

[51] R. Barlow and L. Hunter, "Optimum preventive maintenance policies," *Operations Research*, vol. 8, no. 1, pp. 90–100, 1960.

[52] F. Ding and Z. Tian, "Opportunistic maintenance optimization for wind turbine systems considering imperfect maintenance actions," *International Journal of Reliability, Quality and Safety Engineering*, vol. 18, no. 05, pp. 463–481, 2011.

[53] N. L. Johnson and S. Kotz, *Distributions in statistics: Continuous univariate distributions. 2.* New York: John Wiley, 1970.

[54] R. Bender, T. Augustin, and M. Blettner, "Generating survival times to simulate Cox proportional hazards models," *Statistics In Medicine*, vol. 25, no. 11, pp. 1978–9, 2006.

[55] L. M. Leemis, L.-H. Shih, and K. Reynertson, "Variate generation for accelerated life and proportional hazards models with time dependent covariates," *Statistics & Probability Letters*, vol. 10, no. 4, pp. 335–339, Sep 1990.

[56] *Maintenance Terminology - Svensk Standard SS-EN 13360*, SIS Förlag AB, Stockholm, Sweden Std., 2005.

[57] F. Besnard, "On maintenance optimization for offshore wind farms," PhD Thesis, Chalmers University of Technology, Gothenburg, Sweden, 2013.

[58] John Moubray, *Reliability-centered Maintenance*, 2nd ed. Industrial Press, 1997.

[59] L. Bertling, R. Allan, and R. Eriksson, "A Reliability-Centered Asset Maintenance method for assessing the impact of maintenance in power distribution systems," *IEEE Transactions on Power Systems*, vol. 20, no. 1, pp. 75–82, Feb 2005.

[60] K. Fischer, F. Besnard, and L. Bertling, "Reliability-centered maintenance for wind turbines based on statistical analysis and practical experience," *IEEE Transactions on Energy Conversion*, vol. 27, no. 1, pp. 184–195, 2012.

[61] L. Pettersson, J.-O. Andersson, C. Orbert, and S. Skagerman, "RAMS - Database for Wind Turbines," Elforsk, Tech. Rep., 2010. [Online]. Available: http://www.elforsk.se/Rapporter/?rid=10{_}67{_}

[62] D. Karlsson, "Wind turbine performance monitoring using artificial neural networks with a multi-dimensional data filtering approach," Masters' Thesis, Chalmers University of Technology, Gothenburg, Sweden, 2015.

[63] Y. Yan, J. Li, and D. Gao, "Condition parameter modeling for anomaly detection in wind turbines," *Energies*, vol. 7, no. 5, pp. 3104–3120, May 2014.

[64] S. Letzgus, "SCADA-data analysis for condition monitoring of wind turbines," Masters' Thesis, Chalmers University of Technology, Gothenburg, Sweden, 2015.

[65] A. Kusiak and A. Verma, "Monitoring Wind Farms With Performance Curves," *IEEE Transactions on Sustainable Energy*, vol. 4, no. 1, pp. 192–199, Jan 2013.

[66] J. H. Ward, "Hierarchical Grouping to Optimize an Objective Function," *Journal of the American Statistical Association*, vol. 58, no. 301, pp. 236–244, Mar 1963.

[67] G. Niu, S. Singh, S. W. Holland, and M. Pecht, "Health monitoring of electronic products based on Mahalanobis distance and Weibull decision metrics," in *Microelectronics Reliability*, vol. 51, no. 2, 2011, pp. 279–284.

[68] Y. Wang, Q. Miao, E. W. M. Ma, K.-L. Tsui, and M. G. Pecht, "Online anomaly detection for hard disk drives based on Mahalanobis distance," *IEEE Transactions on Reliability*, vol. 62, no. 1, pp. 136–145, Mar 2013.

[69] E. Gustavsson, M. Patriksson, A.-B. Strömberg, A. Wojciechowski, and M. Önnheim, "Preventive maintenance scheduling of multi-component systems with interval costs," *Computers & Industrial Engineering*, vol. 76, pp. 390–400, Oct 2014.

[70] N. Gebraeel and A. Elwany, "Residual life predictions in the absence of prior degradation knowledge," *IEEE Transactions on Reliability*, vol. 58, no. 1, pp. 106–117, 2009.

[71] N. Z. Gebraeel and M. A. Lawley, "A neural network degradation model for computing and updating residual life distributions," *IEEE Transactions on Automation Science and Engineering*, vol. 5, no. 1, pp. 154–163, 2008.

[72] N. Z. Gebraeel, M. A. Lawley, R. Li, and J. K. Ryan, "Residual-life distributions from component degradation signals: A Bayesian approach," *IIE Transactions*, vol. 37, no. 6, pp. 543–557, 2005.

[73] P. J. Vlok, "Dynamic residual Life estimation of industrial equipment based on failure intensity proportions," PhD Thesis, University of Pretoria, Pretoria, South Africa, 2001.

[74] R. De Andrade Vieira and M. Sanz-Bobi, "Failure risk indicators for a maintenance model based on observable life of industrial components with an application to wind turbines," *IEEE Transactions on Reliability*, vol. 62, no. 3, pp. 569–582, 2013.

Appendix A

Case studies

In addition to the various case studies presented in the thesis and the appended publications, the ANN based CMS was validated with applications to wind turbines with different ratings and technologies. The purpose of the validation was to realize the advantages and disadvantages of the proposed method. The Appendix presents the case study results of the application of ANN based CMS method to the wind turbines listed in Table A.1.

A.1 Direct Drive Wind Turbine

The process of creating ANN based condition monitoring starts with an analysis of the extent of data available in the wind turbine SCADA system. The direct drive wind turbine recorded measurements from various components in the wind turbine systems, as shown in Figure A.1. The approach presented in Section 4.4 to decide the input and output parameters for the ANN based CMS was applied to the wind turbine. It was realized that the best solution, given the measurements available from the SCADA system, for detecting failures in the generator bearing and turbine blade failure, would be to use an ANN model which predicts the generated power from the wind turbine. Table A.2 presents the inputs parameters selected for predicting the average power produced from the wind turbines.

The turbulence measure is not directly available from the SCADA system, but is calculated as the difference between the 10-min maximum wind speed and 10-min minimum wind speed. The results of application of the ANN based CMS to the data available from the direct drive wind turbines are presented in the following subsections.

Table A.1: Details of wind turbines

Turbine ID	Turbine Rating [kW]	Technology	Damaged Component
Turbine 1	1500	Direct Drive	Generator bearing
Turbine 2	1500	Direct Drive	Generator bearing
Turbine 3	1500	Direct Drive	Turbine blade
Turbine 4	1500	Direct Drive	Turbine blade
Turbine 5	1500	Indirect Drive	Gearbox bearing in secondary planet wheel
Turbine 6	1500	Indirect Drive	Gearbox first stage ring gear
Turbine 7	1500	Indirect Drive	Gearbox planet bearing

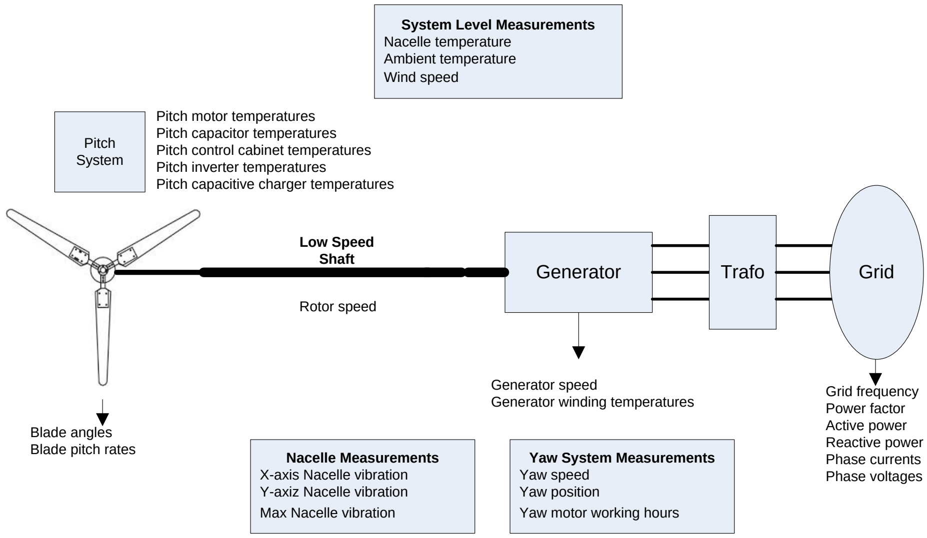

Figure A.1: Schematic representation of data from Direct Drive wind turbine.

Table A.2: Input and output parameters

Output Parameter	Input Parameters
Average Power Production [kW]	Average Wind Speed [m/s] Turbulence Measure [m/s] Nacelle Position Ambient Temperature [°C]

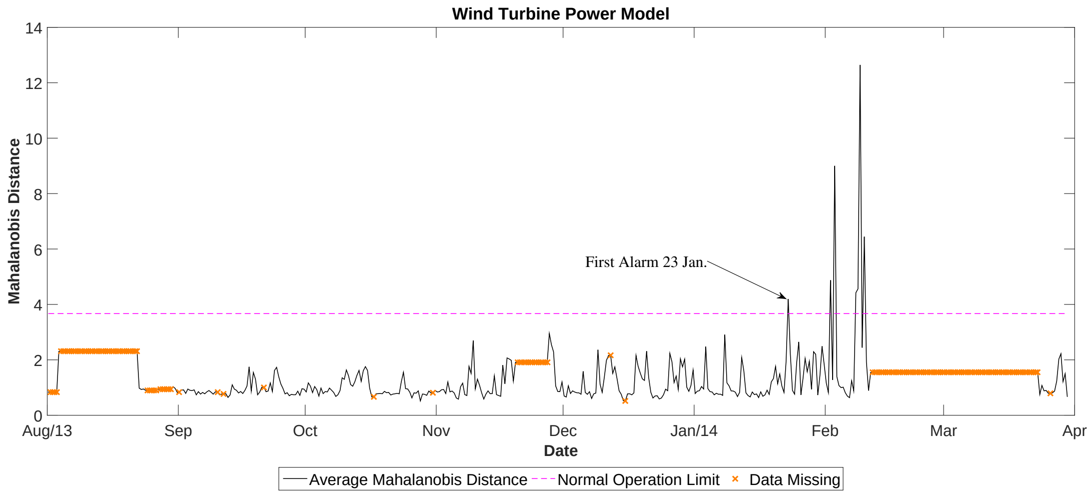

Figure A.2: Application of ANN based CMS to Turbine 1

A.1.1 Turbine 1

The best parameter to model for detecting a generator bearing failure would be the generator bearing temperature. However, the generator bearing temperature was not available in the wind turbine SCADA system, and hence an indirect monitoring approach using the wind power production as the modeled parameter had to be applied. The recorded SCADA measurement was available from January 1, 2013, and a failure in the generator bearing was detected during routine visual inspection on February 11, 2014. The bearing was replaced on March 22, 2014. The ANN models have been trained with data from January 1, 2013 to June 30, 2013. The results of the ANN based CMS is presented in Figure A.2. The first alarm from the ANN based CMS system was seen on January 23, 2014, which is two months before the final replacement and 19 days before the failure was detected by visual inspection.

A.1.2 Turbine 2

The recorded SCADA measurement was available from January 1, 2013. A failure in the generator bearing was detected on February 12, 2014. The bearing was replaced on March 15, 2014. The ANN models have been trained with data from January 1, 2013, to June 30, 2013. The results of the ANN based CMS is presented in Figure A.3. The first alarm from the ANN based CMS system was seen on January 22, 2014, which is two months before the final replacement and 21 days before the failure was detected by visual inspection.

The case study results for Turbine 1 and Turbine 2 show that there is a possibility to detect a deterioration in the generator bearing using the model for wind power production, if the generator bearing temperature is not available. However, as the power production in the wind turbine could be affected by issues in several components in the wind turbine, it would be difficult to pinpoint the problem based only on the output from ANN based CMS.

A.1.3 Turbine 3

A blade failure was observed in Turbine 3 on January 19, 2014, and the replacement was made on February 20, 2014. The wind power production model has been utilized for ANN based CMS, as no other signals, which could directly represent a deterioration in the blade,

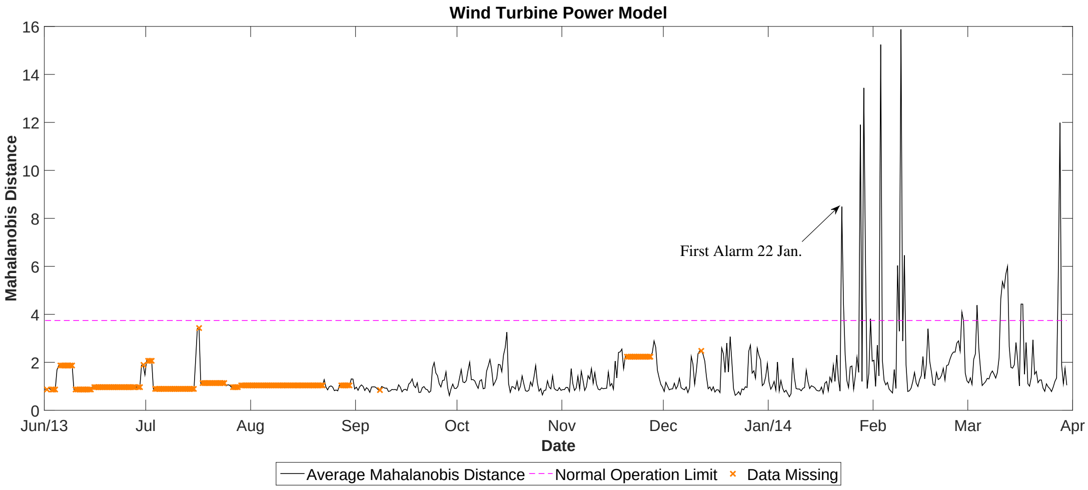

Figure A.3: Application of ANN based CMS to Turbine 2

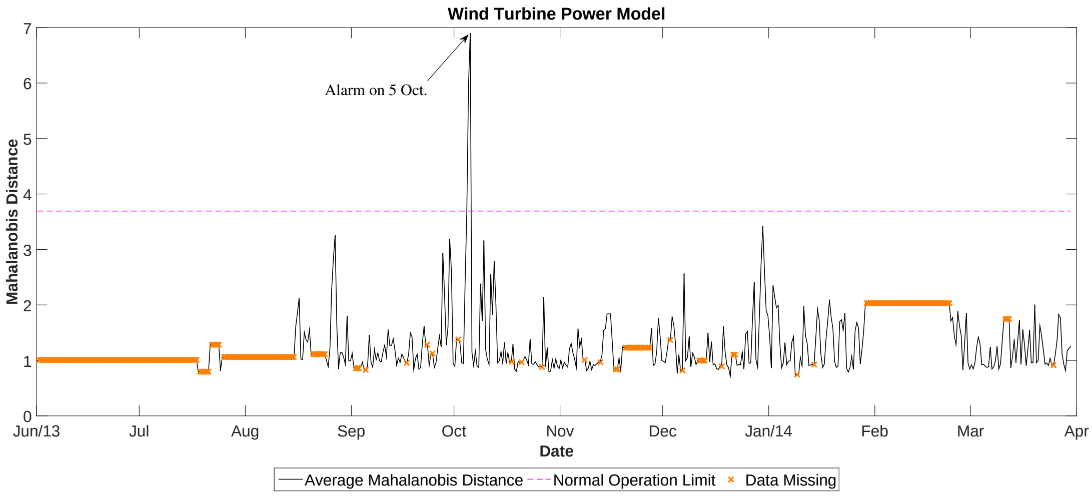

Figure A.4: Application of ANN based CMS to Turbine 3

were available. The ANN model has been trained for a period from November 18, 2012, to May 31, 2013, and the output from the condition monitoring system is presented in Figure A.4.

An alarm from the ANN based CMS system was seen on October 5, 2013. In order to establish the reason for the alarm from the condition monitoring method, a detailed analysis of the data was performed. The plot of power produced by the wind turbine for the month of September, 2013 and the period between 4–6 October, 2013 is presented in Figure A.5. It can be observed that the reason for the alarm from the system is a clear under production from the wind turbine.

The under production could typically be a result of a curtailment in the wind turbine. However, following a consultation with the owner it was realized that during the period under consideration there was no curtailment in the wind turbine. It can be ensured that the wind turbine was under normal operation by creating a model to estimate the generator Rotations Per Minute (RPM). The generator RPM model was created using the same inputs as presented in Table A.2. The result of application of the ANN based condition monitoring

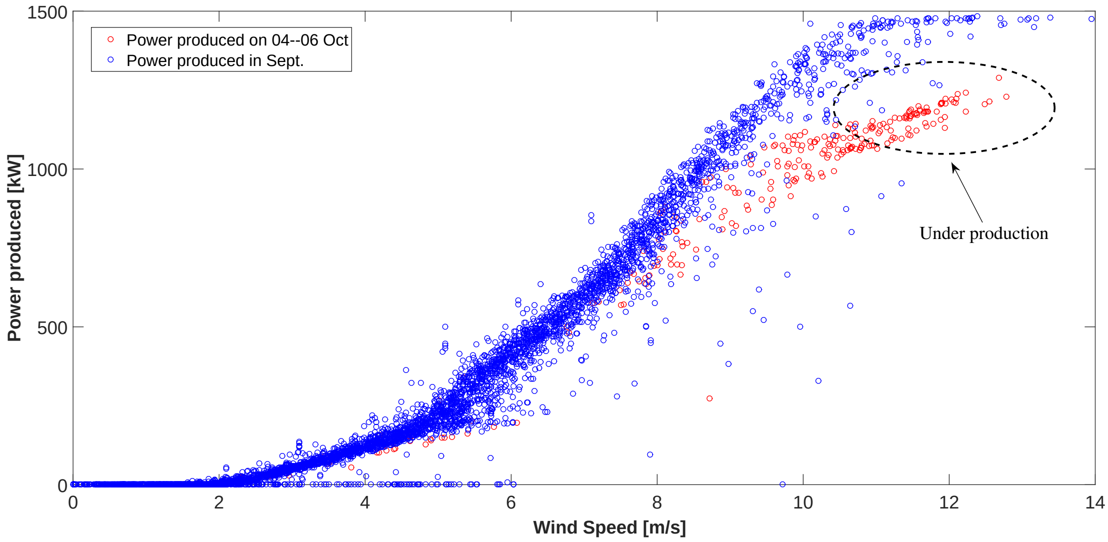

Figure A.5: Power production from the wind turbine

to the generator RPM is presented in Figure A.6. It can be observed that there are no alarms from the generator RPM model, suggesting that there was no curtailment of power during the period when there was an alarm in the wind turbine power model.

It cannot be concluded that this particular alarm from the ANN based CMS is due to a deterioration in the wind turbine blades, as the alarm did not persist for a longer duration. However, this case study illustrates the possibility of application of the ANN based normal behavior models for wind turbine performance monitoring, which can also be supported with the applications to several case studies presented in [62].

A.1.4 Turbine 4

A blade failure in Turbine 4 was observed on May 27, 2014, and the replacement was made on June 5, 2014. The ANN model for wind power production was trained with data from November 18, 2012, to October 31, 2013, and the output is presented in Figure A.7. The ANN based CMS for wind turbine power production is not able to detect the failure in the blades for Turbine 4. This could be due to small effect of the blade failure on the wind turbine power production. However, in this particular case the extent of data available was limited to only seven months. Hence, the issue of non-detection of failure could be related to the short comings in the ANN model due to lack of training data.

A.2 In-direct Drive Wind Turbines

The extent of SCADA data available for the in-direct drive wind turbines is presented in Figure A.8. The ANN based CMS for gearbox in wind Turbines 5, 6, and 7 have been achieved using the ANN models with input and output parameters as presented in Table 4.3. The case study results for the three turbines are presented in the following subsections.

A.2.1 Turbine 5

The gearbox failure in Turbine 5 originated in the bearing of the secondary planet wheel and the replacement was carried out on May 6, 2014 and the failure was detected only a

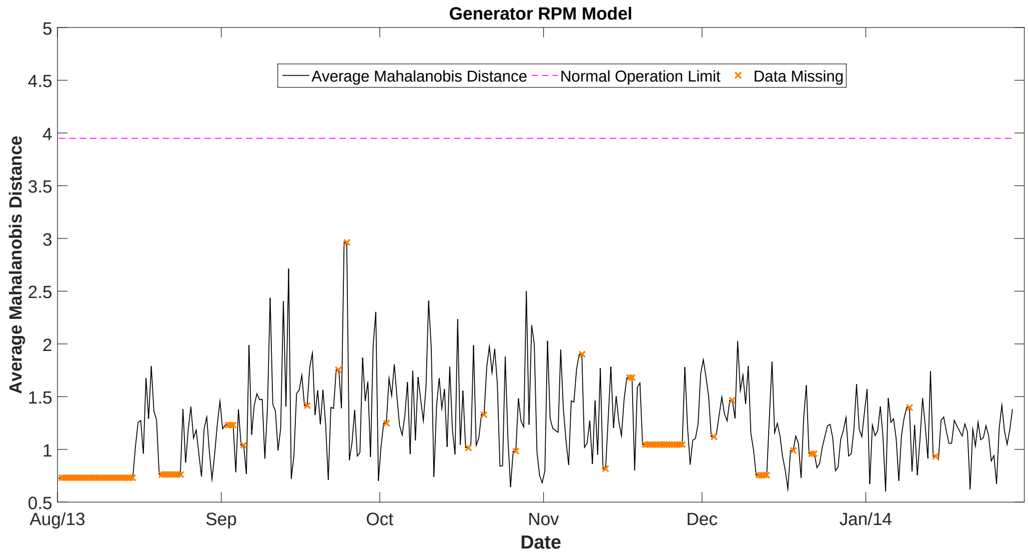

Figure A.6: Application of ANN based CMS to Turbine 3 (Generator RPM model)

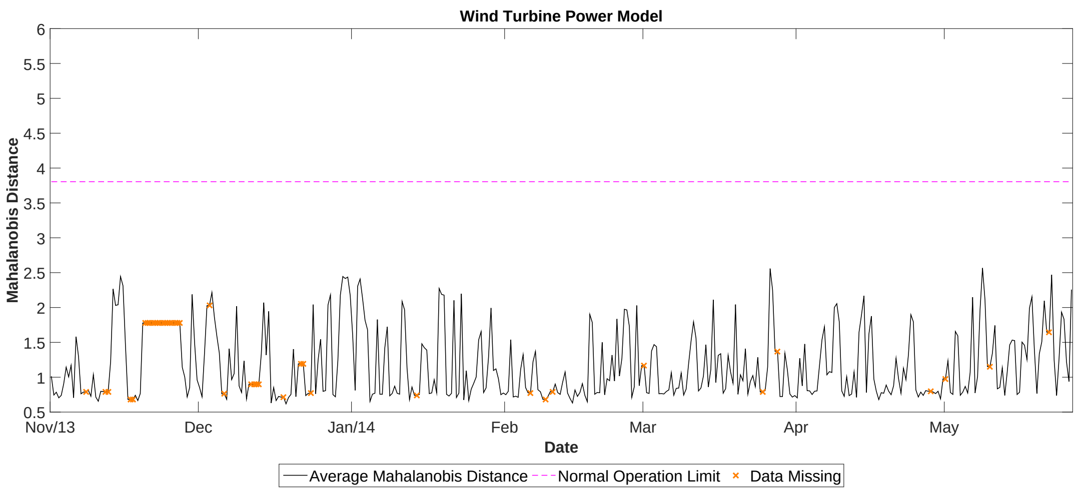

Figure A.7: Application of ANN based CMS to Turbine 4

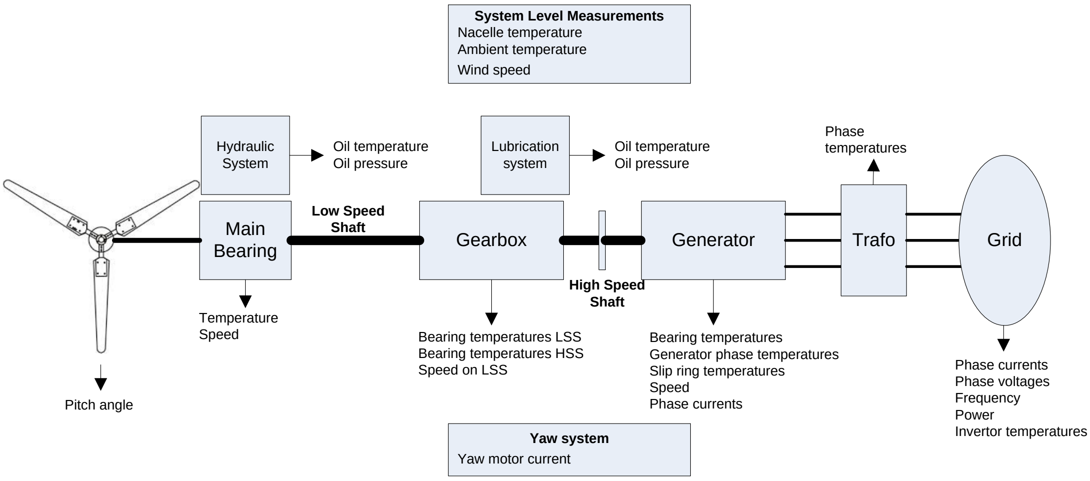

Figure A.8: Schematic representation of data from In-direct Drive wind turbine

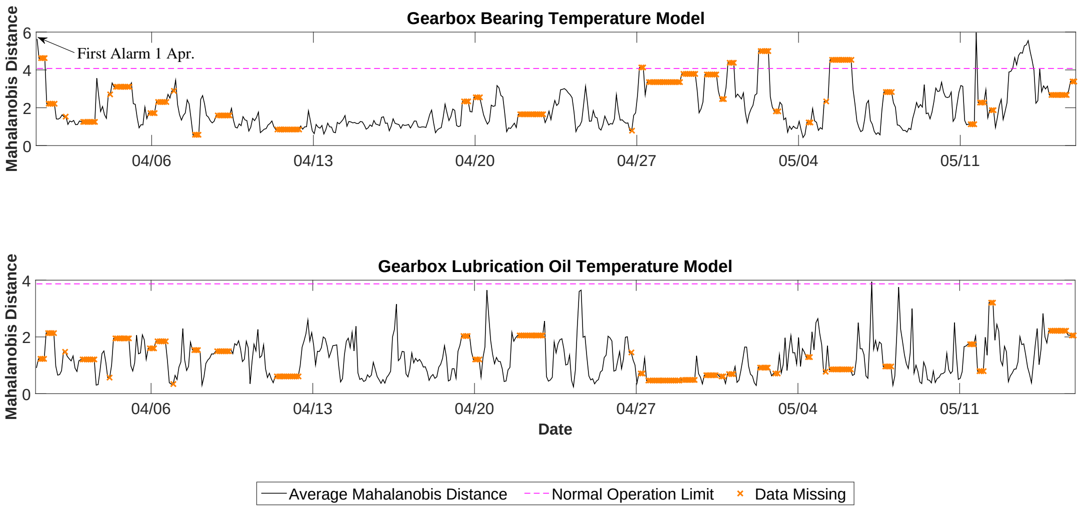

Figure A.9: Application of ANN based CMS to Turbine 5

week before the replacement was made. The ANN models were trained with data from February 16, 2014, to March 31, 2014. The short training period was necessitated due to the unavailability of data from an earlier date. The output from the ANN based CMS is presented in Figure A.9

The first alarm from the gearbox bearing model can be seen on April 1, 2014, which is almost 40 days before the failure was detected. Furthermore, in the later part of April there are a few more alarms, which might indicate a higher level of deterioration. Moreover, the gearbox lubrication oil temperature model does not show any alarms, which indicates towards a failure originating in the gearbox bearings. In addition to the 10-min. average data available from SCADA, 10-sec. average data was also available for this wind turbine for a period of one week before the failure date. The ANN models trained on 10-min. average data were applied to the 10-sec. average data and the results for the application are shown in Figure A.10.

The output showed a constant alarm state from the ANN based CMS for both the gearbox bearing and lubrication oil temperature models. In order to understand the reason behind

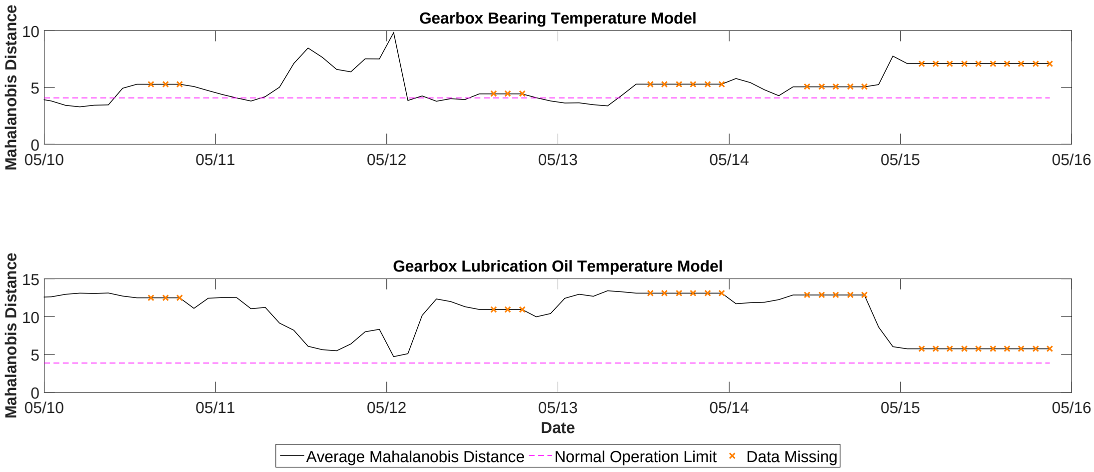

Figure A.10: Application of ANN based CMS to data with 10-sec. average values for Turbine 5

this behavior, the 10-sec. average values recorded in the SCADA system were compared to 10-min. average values, and the probability distribution of these data sets is presented in Figure A.11. The comparison showed that both the gearbox bearing and lubrication oil temperatures showed higher measurement values close to the replacement date. The ANN based CMS indicated an anomaly based on the higher than expected values of the bearing temperatures. The result is interesting, as it shows that a higher frequency of the data could lead to better condition monitoring.

A.2.2 Turbine 6

The SCADA data for Turbine 6 was available for a short duration, like the case was for Turbine 5. A replacement in the first stage gear of the gearbox was carried out on April 28, 2015 following a detection of failure through inspection a week before the replacement. The ANN models for the condition monitoring were trained with data from January 28, 2015, to March 9, 2015, and the result of the condition monitoring with 10-min. average data is presented in Figure A.12.

The first alarm was observed on March 11, in both the gearbox bearing and lubrication oil temperature models, which is in line with expectations, as the fault originated in the gears of the gearbox. Similar to Turbine 5, 10-sec. data for a week before replacement was available for Turbine 6 and the application of ANN based CMS on the 10-sec. data is presented in Figure A.13. A comparison of the 10-min. and 10-sec. average data is presented in Figure A.14.

The comparison of the temperature values from the 10-sec. and 10-min. data set revealed that the gearbox bearing and lubrication oil temperatures were, in fact, lower than normal during the period close to the failure. It is difficult to pinpoint the reason for such a behavior without further analysis, but referring to Figure A.14, it can be said with certainty that all temperature values seen in the 10-sec. data set for Turbine 6 are within the range of the data that the ANN model was trained with. Hence, the anomaly detected by the ANN based CMS is not due to incorrect input values.

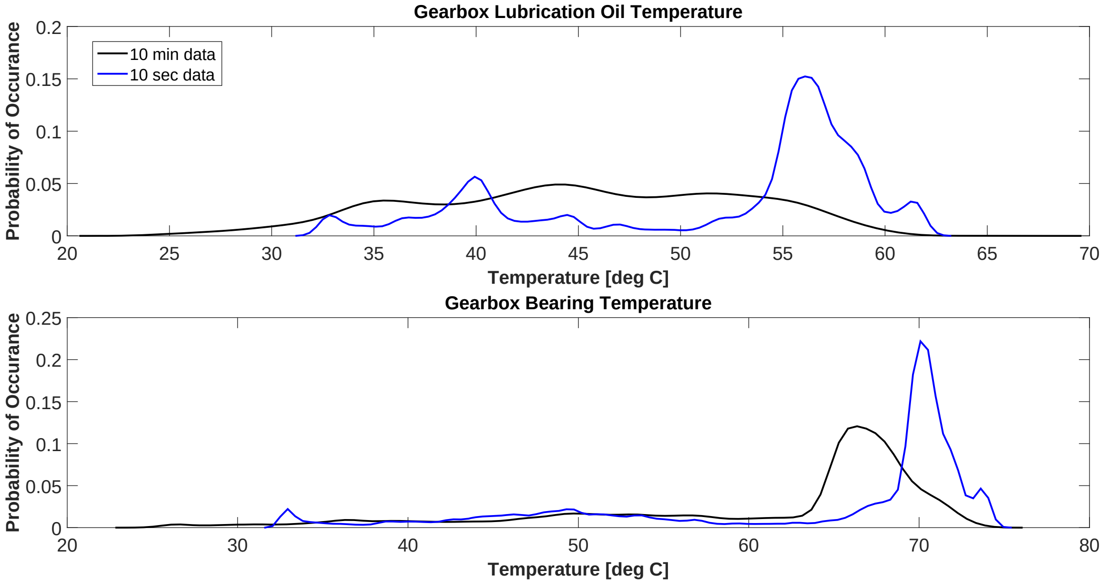

Figure A.11: Comparison of 10-min. and 10-sec. average data for Turbine 5

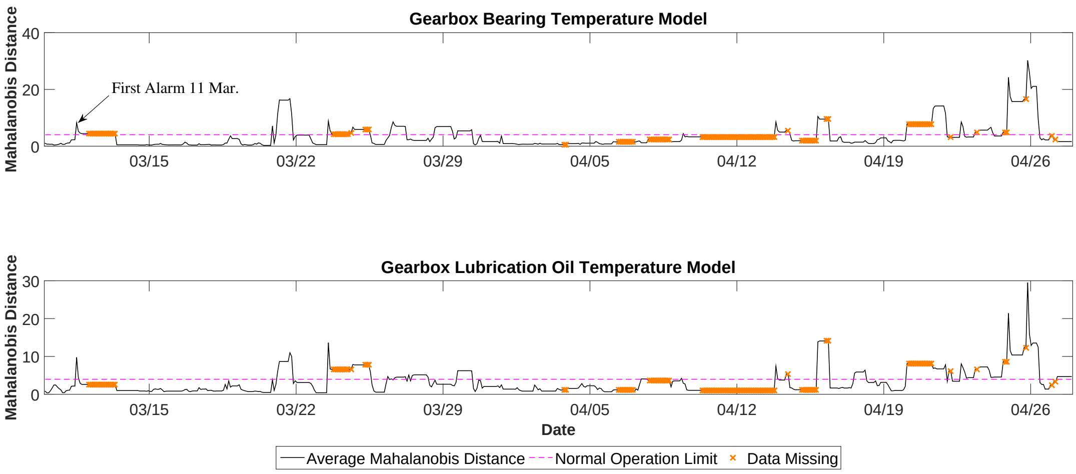

Figure A.12: Application of ANN based CMS to Turbine 6

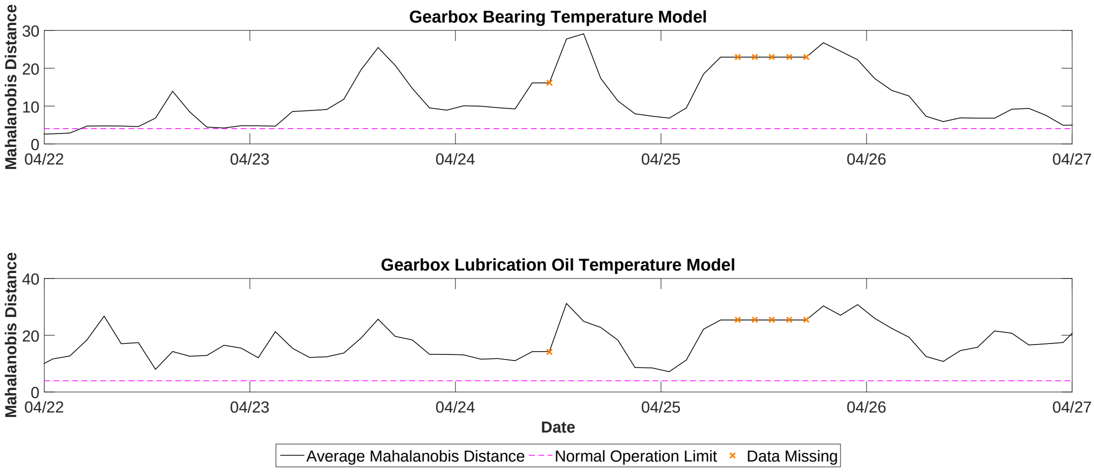

Figure A.13: Application of ANN based CMS to data with 10-sec. average values for Turbine 6

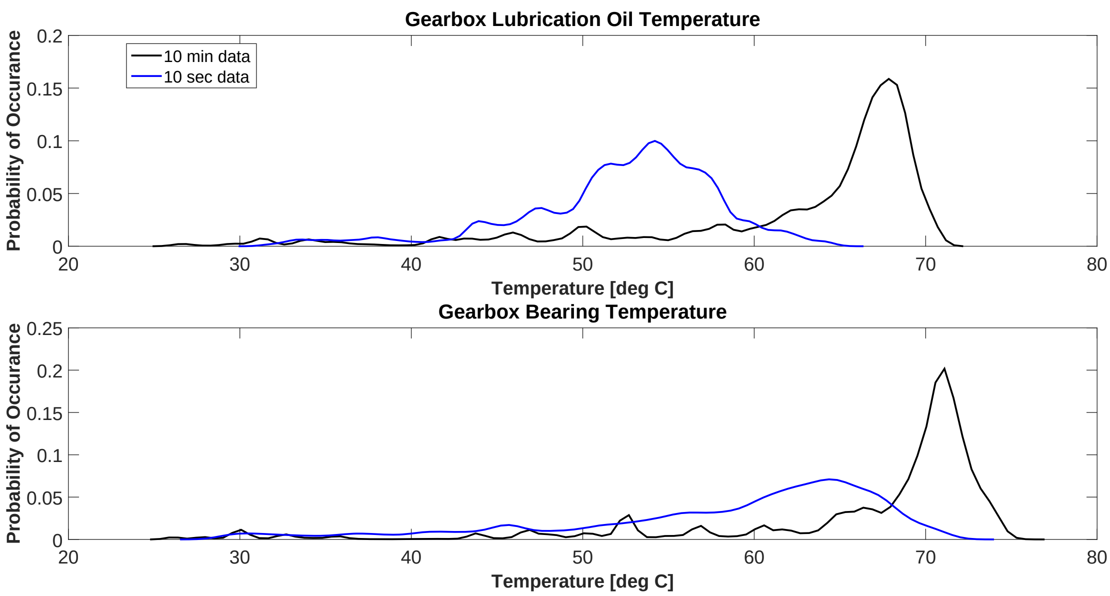

Figure A.14: Comparison of 10-min. and 10-sec. average data for Turbine 6

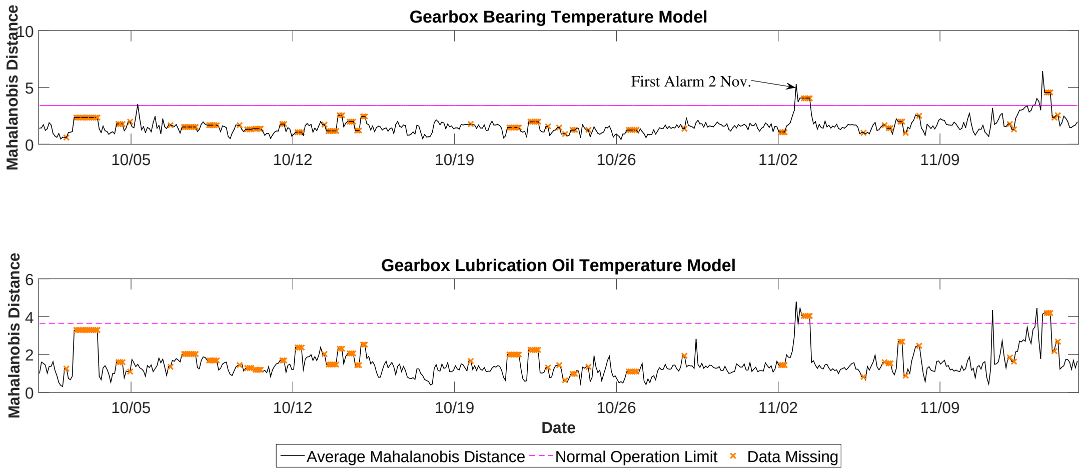

Figure A.15: Application of ANN based CMS to Turbine 7

A.2.3 Turbine 7

The failure in the gearbox of Turbine 7 originated in the planet bearing, and the gearbox replacement was done on November 15, 2015, however information about the actual detection date was not available for this wind turbine. The ANN models were trained with data from August 15, 2015, to September 30, 2015, and the result of the application is shown in Figure A.15.

The first alarm in the gearbox bearing temperature model was seen on November 2, which is very close to the replacement date. The reason for detection of failure so close to the actual replacement date, could be the small amount of training samples available, or the fact that the fault itself did not have any significant effect on the gearbox bearing or lubrication oil temperatures. The ANN models were applied to the 10-sec. average data, for a period of one week before the replacement. The result is presented in Figure A.16, and the comparison of the 10-min. and 10-sec. average values is presented in Figure A.17.

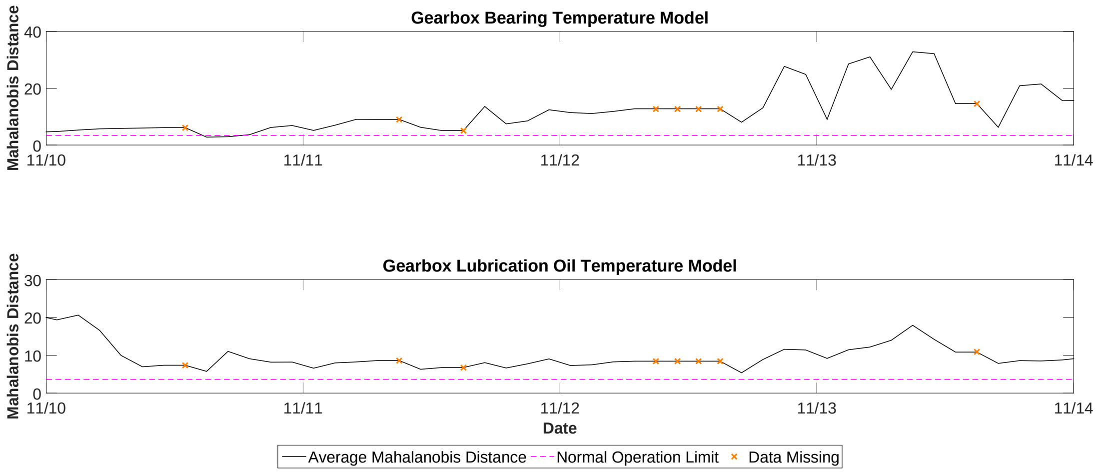

Figure A.16: Application of ANN based CMS to data with 10-sec. average values for Turbine 7

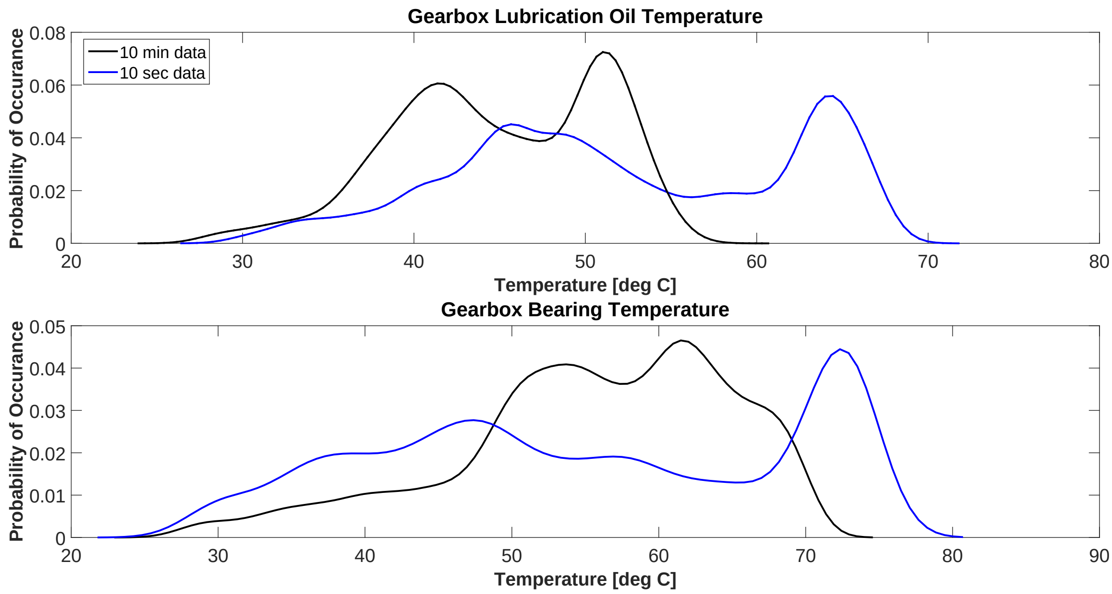

Figure A.17: Comparison of 10-min and 10-sec. average data for Turbine 7

The results of the application to 10-sec. average data are similar to those for Turbine 5, where the ANN based CMS was in a constant state of alarm. Furthermore, it can be seen that the 10-sec. data set displays much higher temperatures compared to the 10-min average values. This points to a fact that there is a loss of information in the 10-min. average data due to the averaging.

A.3 Discussion

The ANN based condition monitoring method was successful in detecting a fault in the generator bearing of the direct drive wind turbine, as well as in the gearbox bearings of the in-direct drive wind turbines. The application of the ANN model predicting the power production for fault detection shows the possibility of using the method for wind turbine performance analysis also. It can be concluded that the ANN based CMS method can be applied to different types and ratings of wind turbines, given that sufficient SCADA data is available.

The proposed condition monitoring method was unsuccessful in detecting faults in the wind turbine blades in the two case studies presented. Furthermore, it was not possible to detect a failure in the gearbox planetary bearing in sufficient time before replacement. These case studies represent the shortcomings of the proposed ANN based CMS. The method is capable of detecting only those failure modes, which have a direct effect on the modeled parameter. It could be interesting for the owner/operator of the wind turbine to decide on the extent of SCADA measurement that will be available from the SCADA system during the contract stage. Conscious efforts by the stakeholders in the wind industry could lead to a standardization of the SCADA signals, which can play a significant role in the improvement of wind turbine condition monitoring in the future.

In addition to the effect of extent of SCADA data on the CMS method, the case studies presented with 10-sec. average data show that there is a considerable amount of information missing in the 10-min. average data. This leads to a question, whether higher frequency measurement data from SCADA will lead to better condition monitoring. However, higher frequency of data will require more storage, leading to higher costs and hence this question needs to be investigated further.

Appendix B

Input/Output configuration for ANN models

The approach for selection of ANN model input and output parameters utilizing the domain knowledge was discussed in Section 4.4. This approach can be applied to decide the input/output configuration of ANN models which can then be applied for condition monitoring of various wind turbine components. In order to decide the extent of ANN models that can be created, it is necessary to carefully analyze the list of signals available in the wind turbine SCADA system. Based on one such analysis for a typical indirect drive onshore wind turbine, rated 2 MW, an indicative list of ANN models that can be created is presented in Table B.1. The input parameters are divided into sets and the list of corresponding input parameters for each set is presented in Table B.2.

The actual list of ANN models that can be created, and consequently the components that can be monitored with the ANN based CMS will depend on the extent of measurement signals available in the SCADA system. Currently, the list of measurement signals available from the SCADA system depends on the wind turbine manufacturer, and hence, it is suggested this list be decided at the contractual stage to take full advantage of the ANN based CMS.

Table B.1: List of ANN models for a typical in-direct drive wind turbine

Input parameter set	Output parameter
Set 1	Gearbox high speed bearing A temperature [°C] Gearbox high speed bearing B temperature [°C] Gearbox high speed bearing C temperature [°C] Gearbox planet bearing non-drive end temperature [°C] Gearbox planet bearing drive end temperature [°C] Gearbox lubrication oil temperature [°C] Spinner temperature [°C]
Set 2	Generator front end bearing temperature [°C] Generator rear end bearing [°C] Generator slip ring temperature [°C] Rotor inverter temperature [°C] Generator phase temperatures [°C]
Set 3	Grid inverter average temperature [°C] Transformer phase temperature [°C]
Set 4	Hydraulic oil temperature [°C]

Table B.2: List of input parameter sets with corresponding input parameters

Input parameter set	Input parameter
Set 1	Power production [kW] Rotor RPM Nacelle temperature [°C] Ambient temperature [°C] Missing data input [-]
Set 2	Power production [kW] Generator RPM Nacelle pemperature [°C] Ambient pemperature [°C] Missing data Input [-]
Set 3	Reactive power [kvar] Frequency [Hertz] Nacelle temperature [°C] Ambient temperature [°C] Missing data input [-]
Set 4	Hydraulic oil pressure [bar] Power production [kW] Nacelle temperature [°C] Ambient temperature [°C] Missing data input [-]