THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

Load and Risk Based Maintenance Management of Wind Turbines

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Abstract

The cost of maintenance is a considerable part of the total life cycle cost in wind turbines, especially for offshore applications. Research has shown that some critical components account for most of the downtime in the wind turbines. An improvement of maintenance practices and focused condition based maintenance for critical components can improve the reliability of the wind turbines; at the same time appropriate maintenance management can reduce maintenance costs.

This thesis presents the conceptual application of the reliability centered asset management (RCAM) approach, which was defined for electrical distribution systems by Bertling in 2005, to wind turbine application. Following the RCAM approach failure statistics extracted from the maintenance records of 28 onshore wind turbines, rated 2MW, are presented. It is realized from the statistics that gearbox is a critical component for the system and the gearbox bearings are major cause of failures in gearboxes.

A maintenance management framework called self evolving maintenance scheduler (SEMS) is proposed in the thesis. The SEMS framework considers the indication of deterioration from various condition monitoring systems to formulate an optimal maintenance strategy for the damaged component. In addition to SEMS, an artificial neural network (ANN) based condition monitoring approach using the data stored in the supervisory control and data acquisition (SCADA) system is proposed. The proposed approach uses a statistical distance measurement called Mahalanobis distance to identify any abnormal operation of monitored component. A self evolving feature to keep the ANN model up-to-date with the changing operating conditions is also proposed.

The proposed ANN based condition monitoring approach is applied for gearbox bearing monitoring to two cases with real SCADA data, from two wind turbines of the same manufacturer, rated 2 MW, and situated in the south of Sweden. The results show that the proposed approach is capable of detecting damage in the gearbox bearings in good time before a complete failure. The application of the proposed condition monitoring approach with the SEMS maintenance management framework has a potential to reduce the maintenance cost for critical components close to end of life.

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

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Abbreviations

ANN	Artificial Neural Network
CBM	Condition Based Maintenance
CM	Corrective Maintenance
CMS	Condition Monitoring System
DM	Diversity Measure
HSS	High Speed Shaft
LCC	Life Cycle Cost
LMA	Levenberg Marquardt Algorithm
MD	Mahalanobis Distance
NARX	Non-linear Autoregressive network with exogenous input
O&M	Operation and Maintenance
PCB	Planet Carrier Bearing
PM	Preventive/Planned Maintenance
RCAM	Reliability-Centered Asset Maintenance
RCM	Reliability-Centered Maintenance
RMSE	Root Mean Squared Error
SCADA	Supervisory Control And Data Acquisition
SEMS	Self Evolving Maintenance Scheduler
SM	Scheduled Maintenance
WT	Wind Turbine
WT28	Database containing SCADA and maintenance data for 28 onshore wind turbines

Contents

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 Optimisation, Structure and Foundation, Maintenance and Reliability as well as Cold Climate.

This project is part of Theme group 5.

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

Chapter 1

Introduction

1.1 Background

Wind power penetration into electric power system has increased significantly in the recent years [1]. With renewable energy getting more impetus, the amount of wind power in power systems is set to grow in future. The European Union's 20-20-20 targets aim at raising the share of EU energy consumption from renewable energy to 20% by year 2020. By the end of 2012, 7.8% of EU's gross power production was from wind power and 11,159 MW wind power was installed across Europe in year 2013 [2].

Even with this high number of installations of wind turbines, the EU countries are lagging the targeted figures in terms of wind power production. The installation of new wind turbines in 2013 dropped by 8% compared to 2012 [2]. High maintenance cost and long downtimes have proved to be obstacles in the development of wind power industry. For onshore wind turbines the operation and maintenance cost could be as high as 20-30% of the total levelized life cycle cost [3]. The operation and maintenance costs are more prominent for the offshore wind turbine applications, where wind turbine accessibility is difficult. In order to make wind power competitive in the market it is important to reduce the operation and maintenance costs and at the same time improve availability.

In recent years, maintenance management of wind turbines has received increased attention. One of the most commonly adopted methods to reduce the maintenance cost for wind turbines is shifting from unscheduled corrective maintenance to scheduled preventive maintenance strategies [4-6]. To be proactive in maintenance, information about an impending failure is valuable. Condition monitoring of critical components has been applied in wind turbines, which can be beneficial in reducing the overall lifecycle cost of wind turbines [7]. However, proper application of the information from the condition monitoring system (CMS) to improve the maintenance activities with an aim to improve the availability and reduce costs still lacks application.

1.2 Related Research Projects

This research work has been performed within the Swedish Wind Power Technology Centre (SWPTC) and the Wind Power Asset Management (WindAM) research group at Chalmers University of Technology. 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 Centre is funded by the Swedish Energy Agency, Chalmers University of Technology, industry and academic partners. This research project has been carried out in partnership with Göteborg Energi, Triventus and SKF.

Within the framework of SWPTC various projects in the field of wind power are being undertaken. Two projects are focusing on developing methods to detect faults in critical components in wind turbines. The project titled "Models of electrical drives for wind turbines" is focusing on developing analytical models to detect inter-turn faults within permanent magnet synchronous generators used in direct drive wind turbines. The project titled "Wind turbine drive train dynamics, system simulation and accelerated testing" deals with modeling of wind turbine drive train components including shaft, gearbox bearings and couplings to develop a methodology to detect faults in the drive train.

The WindAM group was initiated by Prof. Lina Bertling Tjernberg at Chalmers University of Technology in 2009. The WindAM group was a result of RCAM group which was created at KTH in 2002. The WindAM group focused on developing the application of the reliability centred asset management (RCAM) approach [8] for wind turbine maintenance management. Dr. Katharina Fischer completed a project at the WindAM research group that focused on development of mathematical model to predict failure in generator bearings based on vibration signals from the condition monitoring system [6]. Also, within WindAM group, Dr. Francois Besnard presented an optimization model for maintenance support organization for offshore wind turbines in his PhD thesis [9].

1.3 Project Objectives

Wind turbine Supervisory Control and Data Acquisition (SCADA) system stores large amounts of data about operating conditions of the wind turbine. The main objective of this research project is to propose an approach to use the data stored in the SCADA system to estimate the health of critical components. Furthermore, the project aims at developing a maintenance management framework, which can be utilized for optimal maintenance strategy selection, based on information of damage in critical components.

1.3.1 Main Contributions

The main contributions of the research work are listed below:

a) An Artificial Neural Network (ANN) based condition monitoring approach is presented to analyze the data stored in SCADA system for early detection of faults in the gearbox bearings
b) A self evolving approach for training and updating the ANN model is presented
c) A maintenance management framework called Self Evolving Maintenance Scheduler (SEMS) has been proposed, which aids in the maintenance planning based on information about deterioration in critical components from condition monitoring system

1.4 List of Papers

The following list of papers has been published / submitted within the research project:

I. P. Bangalore, L. Bertling Tjernberg, "An Approach for Self Evolving Neural Network Based Algorithm for Fault Prognosis in Wind Turbine", in Proceedings of IEEE PowerTech conference, Grenoble, June 2013.
II. P. Bangalore, L. Bertling Tjernberg, "Self Evolving Neural Network Based Algorithm for Fault Prognosis in Wind Turbines: A Case Study", Submitted to Probabilistic Methods Applied to Power Systems (PMAPS) conference, Durham, 2014.
III. P. Bangalore, L. Bertling Tjernberg, "An Artificial Neural Network Approach for Early Fault detection of Gearbox Bearings", Submitted to The IEEE Transactions on Smart Grid, special issue on "Asset Management in Smart Grid".

1.4.1 Organization of the Thesis Report

Chapter 1: Gives an introduction to the research project with the project objective and main contributions

Chapter 2: Introduces the concept of maintenance management and RCAM applied to wind turbines and presents the proposed SEMS maintenance management framework

Chapter 3: Gives a theoretical background to ANN

Chapter 4: Presents the ANN based condition monitoring approach. The application results for monitoring wind turbine gearbox bearings are presented

Chapter 5: Describes the preliminary mathematical model, which will be developed as a part of future work and presents the project conclusion

Chapter 2

Maintenance Management in Wind Turbines

This chapter provides an introduction to the concept of maintenance management used in this thesis and gives a review of different maintenance approaches used for wind turbines. RCAM approach is discussed. A brief analysis of maintenance records for the population of wind turbine under consideration is presented. Finally, the SEMS maintenance management framework is presented.

2.1 Maintenance Management

An activity carried out with an aim to restore or maintain a machine or system to a state in which it can perform its intended function is termed as maintenance. Figure 2-1 presents the common classification of maintenance strategies.

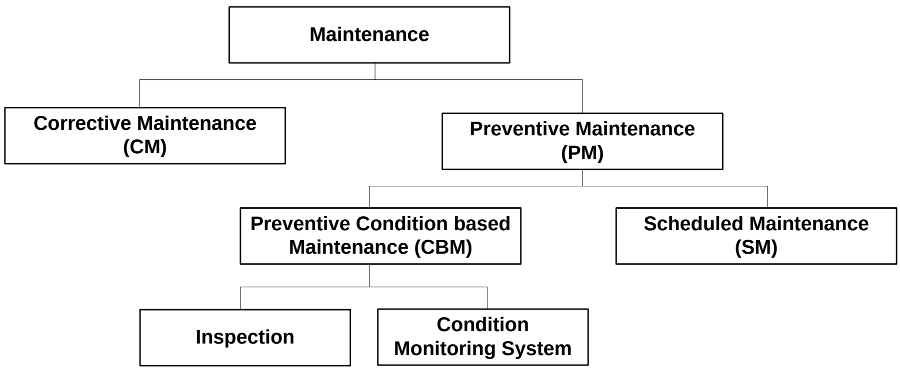


Figure 2-1 *The types of maintenance strategies [10]*

A corrective maintenance (CM) activity is performed following a failure event and a preventive maintenance (PM) activity is performed prior to a failure event. PM activities can be planned in two different ways. PM activity following a predefined schedule, e.g. once a year, is termed as scheduled maintenance (SM). PM activity planned based on sensor information, e.g. from condition monitoring systems (CMS), is termed as condition based maintenance (CBM).

Failure is the termination of the ability to perform the required function and, fault is defined as a situation, which exists after a failure [11].

Maintenance management is the strategy building process which aims to reduce the life cycle cost (LCC) of the asset by optimizing the balance between PM and CM activities. Life cycle cost (LCC), which is the total discounted cost of investment and operational expenditures over the life time for a system can be calculated using a simplified model presented in Eq. 2-1 [7].

$$LCC = C_{inv} + C_{CM} + C_{PM} + C_{PL} + C_{Rem} \qquad \textit{Eq. 2-1}$$

C_{inv} is the cost of investment, C_{CM} is the total cost of corrective maintenance, C_{PM} is the total cost of preventive maintenance, C_{PL} is the lost revenue due to downtime because of maintenance and failures and C_{Rem} is the remainder value at the end of life for a wind turbine. The net present value of LCC can be estimated using the interest and inflation rates.

SM can, typically, be applied to systems, which experience age related failures and an accurate probability density function of failures can be established. CBM, which encompasses both visual inspections and online condition monitoring system, is beneficial for components which show degradation before an eventual failure. However, in some cases SM and CBM based strategies are more expensive than a maintenance strategy with only CM, due to higher frequency of maintenance activities in the former. However, this increase in cost is off-set by increased reliability of the system. Through the process of maintenance management the cost-benefit ratio for different maintenance strategies can be realized so that the best maintenance strategy can be adopted in order to reduce the LCC.

2.2 Maintenance Strategies applied to Wind Turbines

Maintenance management of wind turbines has gained importance with the increase in the amount of wind energy in the electric power systems and the need to make wind power more competitive. Various maintenance strategies have been developed and discussed by researchers, which focus on optimizing the cost of maintenance for individual wind turbine or for a wind farm.

A thorough understanding of reliability of wind turbines is highly desirable to formulate an optimal maintenance management strategy. However, wind power installations for the most parts 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. This difficulty is also augmented by the fact that wind turbine failure statistics are not freely available. In absence of data which is required for accurate reliability predictions, the only source is publications, which present data about failures in wind turbines. In [12] the statistics of failure for Swedish wind turbines between years 1997-2005 were published. This was one of the first publications on wind turbine failure statistics; the industry does not typically publish similar data. In [13], publicly available databases from Germany and Denmark were presented with results of reliability analysis on a subassembly level.

Models and methods used for reliability calculations are important tools. Different methods have been proposed for reliability analysis of wind turbines in the literature. A reliability analysis method based on failure statistics collected from publicly available data has been presented in [14]. The method focuses of reliability analysis for incomplete data sets. Funded under European Unions' framework seven, 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 application has been outlined [15], which gives guidelines for performing reliability evaluation of wind turbines for a given data set.

Considering that the reliability of wind turbines can be estimated with acceptable accuracy, a schedule based maintenance planning can be initiated. In [5] a model for maintenance support organization for offshore wind farms based on predicted reliability of future wind turbines, has been presented. The model considers different aspects like placement of maintenance crew, choice of transfer vessels and number of technicians to give an optimal strategy for long term benefit to wind farms owners. A risk-based decision making method, which combines the traditional risk analysis with the probability of failure approach towards maintenance management has been presented in [16].

A strategy where an opportunity to perform maintenance; typically corrective maintenance on one wind turbine, is utilized to perform other maintenance activities; typically preventive maintenance, is termed as opportunistic maintenance strategy. Opportunistic maintenance becomes increasing attractive for offshore wind farms, where accessibility of wind turbines is expensive. An optimization framework using opportunistic structure was presented in [17]. The information about CM activities was utilized to plan PM activities. It was shown that a saving of 43% can be achieved in the cost of PM using the opportunistic approach. Generally, it is assumed that any PM activity will bring the state of the component back to as-good-as new condition. Such a PM activity is termed as '*perfect maintenance*'. However, perfect maintenance is not always possible, hence, giving the term '*imperfect maintenance*'. The imperfect maintenance actions are considered along with opportunistic approach for optimizing the maintenance of a wind farm in [18].

Similar to the opportunistic structure, different maintenance actions can be grouped together to reduce the initial set up cost of maintenance. Such a grouping strategy using the component age in addition to the component deterioration information for maintenance optimization in wind turbines has been described in [19]. The strategy to replace components which are close to replacement age when another damaged component is being replaced is suggested for offshore wind turbines.

With advent of sensor technology and subsequently introduction of condition monitoring systems, advance condition assessment of component has been made possible. A review of development in different condition monitoring techniques applied to wind turbines is provided in [20]. In addition to the traditional vibration based condition monitoring, new techniques like acoustic monitoring and analysis of temperature, current and power measurements has also been applied to wind turbine systems.

CBM strategies have the potential to reduce the overall maintenance cost for wind turbines [7]. Methods have been developed to integrate the use of component health assessment through both, inspection and continuous condition monitoring to maintenance planning and optimization for wind turbine applications. An approach for CBM for wind turbine blades using CMS information has been presented in [21]. Different condition monitoring strategies have been compared from a LCC perspective and the optimum strategy for blade monitoring is suggested. In [22], a number-dependent preventive maintenance (NDPM) strategy has been applied for optimizing maintenance of blades in offshore wind turbines. The problem is formulated to find an optimal number N of observable damages in wind turbine blades, which can be allowed before initiating either a PM or CM. The optimization model considers the cost of PM, CM, logistics cost and the cost for production losses. An ANN based CBM strategy has been presented in [23]. Historical failure and suspension data from the CMS is used to train an ANN to predict the failure probability of a component. Based on the predicted failure probability, CBM is initiated. A software package called GESTIONE used for maintenance optimization is introduced in [24]. The software uses Bayesian networks, ANN and failure mode effect and cause analysis (FMECA) to optimize maintenance in offshore wind farms. In [25], a risk-based maintenance optimization using Bayesian theory is introduced. Observable indicators of deterioration are used to make a risk-based maintenance optimization. A partially observed markov decision process is used to model degradation process for critical components in wind turbines. The stochastic nature of the wind turbine operating conditions is considered in modeling the degradation process and for maintenance optimization. A similarity-based interpolation (SMI) approach is used for failure prognosis based CBM optimization in [26]. Historical data is used with SMI approach to estimate the remaining useful life of the component based on which a CBM strategy is decided. A hybrid approach using reliability centered maintenance (RCM) and life cycle cost analysis (LCA) was applied to wind turbine along with CMS to formulate a CBM strategy, which was compared with TBM in [27]. Further the concept of delay time maintenance model (DTMM) is applied to wind turbine maintenance optimization in [4]. The delay time is the time between detection of component damage and the eventual failure. The DTMM is used to find the optimum inspection intervals, considering perfect inspections.

The recent trend in wind turbine maintenance management is towards CBM methods coupled with tradition maintenance optimization strategies like opportunistic maintenance, especially for offshore applications. Hence, in line with recent trends, a CBM approach along with more traditional maintenance optimization is proposed in this thesis.

2.3 Reliability Centered Asset Management

The Reliability Centered Maintenance (RCM) approach developed for the civil aviation industry in 1960s has been successfully applied to various fields for maintenance management. RCM proposes to focus the maintenance efforts on those components of a system, which are critical in terms of reliability of the entire system. However, RCM is a qualitative approach which lacks applicability in terms of quantitative maintenance optimization [8]. To overcome this short coming of RCM approach, it was extended by including the quantitative optimization to relate the reliability of a component with the preventive maintenance activities in the Reliability Centered Asset Management (RCAM) approach [8]. The application of RCAM for wind turbines was demonstrated in [6]. The RCAM approach is divided in to three steps:

1. System reliability analysis
2. Component reliability modeling
3. System reliability cost/benefit analysis for different maintenance strategies

RCAM approach is presented in Figure 2-2. RCAM starts by defining a reliability model and the required input data for reliability analysis of a system. The critical components in the system are identified based on the effect of each component on the overall reliability of the system. In the second stage a failure mode effect analysis (FMEA) is done for the identified critical components. FMEA reveals the different ways in which the component can fail. If the level of detail in the data permits, a failure rate is established for each failure cause. Preventive maintenance activities can avoid or postpone specific failure causes, the effect of such PM activities on the failure rate is mathematically modeled for each critical component. A PM strategy is formulated to reduce the failure rate through focused PM. In the final stage a PM strategies are defined in detail and the cost benefit of each strategy is assessed vis-à-vis the reliability improvement. Finally, the optimal maintenance strategy is selected. The following Sections present the application of different stages of the RCAM approach to a population of wind turbine being considering in this research project.

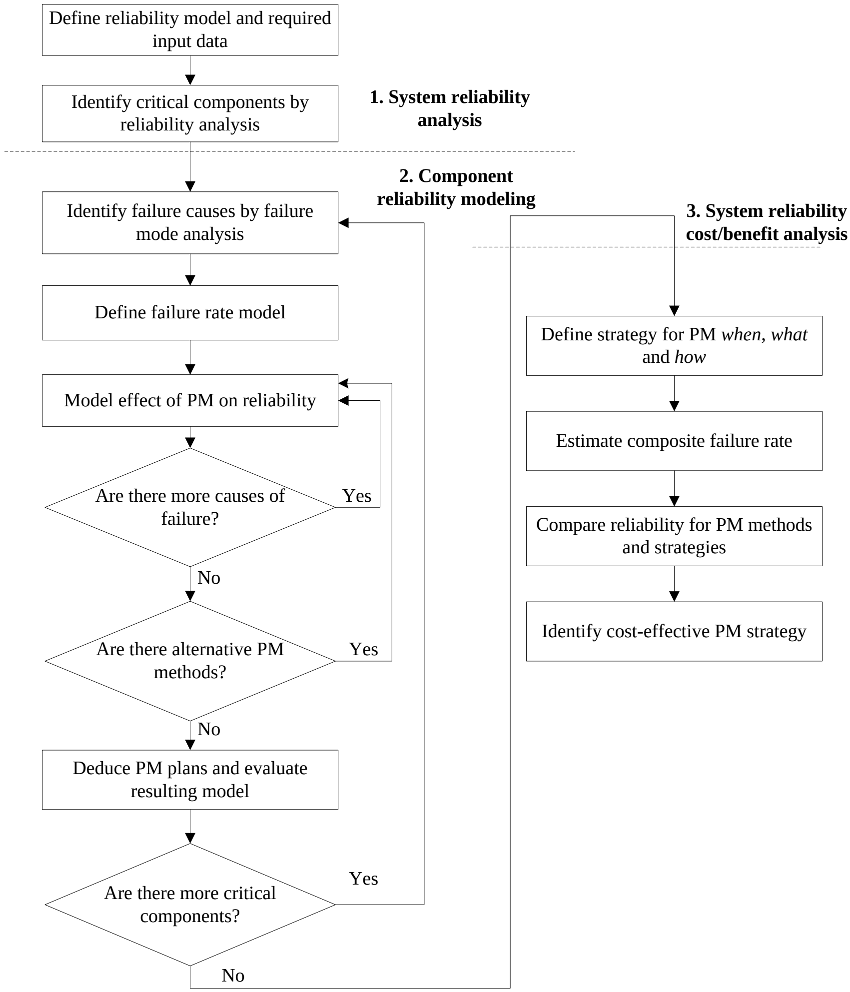


Figure 2-2 *The RCAM approach for maintenance management (Amended from [8, 28])*

2.4 Wind Turbine Data

In this thesis work, data for 28 onshore wind turbines of the same manufacturer rated 2 MW have been selected. The age of the wind turbines range from 1 year to 3 years and the wind turbines are located at different geographical locations mainly in the south and central parts of Sweden. The database which contains the maintenance reports and SCADA data for these wind turbines is from here on referred to as '*WT28 database*'.

Stage 1 of RCAM analysis focuses on a system level reliability analysis. In order to achieve a system level understanding of critical components, an analysis was carried out based on the maintenance work orders for the population of wind turbines under consideration, which has an accumulated history of 73 wind turbine years. A total of 728 maintenance work orders were analyzed and the faults or failures leading to the maintenance were grouped in different categories based on the subsystem responsible for the fault. The average downtime due to a subsystem per year per wind turbine was calculated using Eq. 2-2

$$t_{dwt} = \frac{\sum_{i=1}^{I} \sum_{j=1}^{n} \mathrm{d_{ij}}}{\sum_{i}^{I} N_i T_i} \qquad \textit{Eq. 2-2}$$

where, $t_{dwt}$is the total downtime, $\mathrm{d_{ij}}$ is the downtime caused by subsystem j with $j=1...n$ subsystems in the time interval i with $i=1...I$ total time intervals. N_i is the total number of wind turbines reporting in the time interval i and T_i is the length of the time interval i. Figure 2-3 shows the distribution of total downtime over different subsystems.

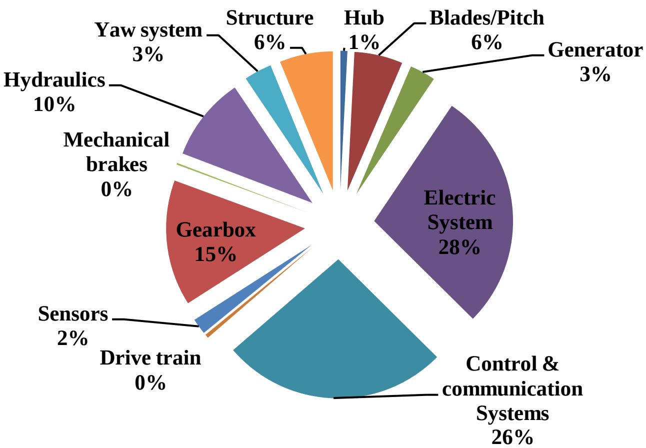


Figure 2-3 *The distribution of downtime over subsystem for 28, 2 MW onshore wind turbines under consideration [WT28 Database]*

The statistics presented in Figure 2-3 contains only the unscheduled maintenance activities and consists of both replacement and repair of minor and major components. It can be observed that the most critical components were control & communication system, electrical system and gearbox. In addition to this, Figure 2-4 shows the average downtime caused by faults and the fault rate for different subsystems.

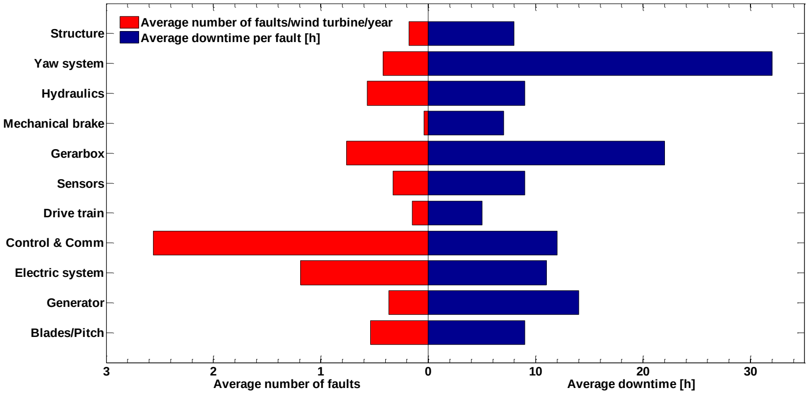


Figure 2-4 *The average downtime per fault for different subsystems in the wind turbine [WT 28 Database]*

The wind turbine population, in consideration, is scattered over different geographical area with a maximum five wind turbines located in the same area. Hence, communication in these wind turbines is based on wireless communication technology, which has shown high fault rate. However, for wind farms with higher number of wind turbines wired communication is preferred eliminating these high number of faults in the communication function. Moreover, preventive maintenance activities cannot directly aid in reducing the number of faults in the communication system.

The second most common fault has been observed in the electrical system consisting of relays, circuit breakers and the converter system. These faults occurred due to various reasons ranging from lightning strikes to grid disturbances and the remedial action was mainly replacement of small components or in most cases a restart of the wind turbine.

The third most common cause of failure and the third biggest contributor to the overall downtime was the gearbox. The gearbox is a mechanical component and it is possible to improve reliability by preventive maintenance actions.

The number of wind turbines is small and hence it was necessary to verify the statistical outlay of distribution of downtime due to different subsystems with other populations of wind turbines, analyzed in literature.

In [12], failures in wind turbines in Sweden between years 1997 to 2005 are reported. The study revealed that gearbox; control system and the electrical system cause the maximum number of failures and result to major portion of downtime for wind turbines. An investigation of publicly available databases from Germany and Denmark indicated that gearbox, generator and rotor blades are critical equipment resulting to majority of downtime in the wind turbines [14]. A similar reliability analysis for more recent wind turbines was carried out as a part of Reliawind project. The results show that about 60% of failures in wind turbines can be attributed to pitch system, electrical system including generator and the gearbox [13]. The studies agree with the results from analysis of maintenance records in this thesis, that the gearbox is a critical component in wind turbines causing long downtimes. Hence, in this thesis the focus has been given to early detection of deterioration and subsequent maintenance planning for gearbox.

Stage-2 of the RCAM approach focuses on component level reliability. Once the critical component is decided further analysis is done to understand the different failure modes for the critical component. Hence, a preliminary failure mode analysis was done for the gearbox based on data from literature survey.

2.4.1 The Gearbox

The gearbox used in the wind turbines considered in this thesis is a planetary gearbox combined with two-stage parallel shaft gearbox. This is a common configuration used in the wind industry due to its large ratio and power capacity. The gearbox has a flexible mounting and is connected to the generator shaft using composite coupling. The brake disc is mounted on the high speed shaft (HSS) of the gearbox coupled to the composite coupling. Several parameters of the gearbox such as bearing temperature, lubrication oil temperature and lubrication oil pressure are monitored and recorded in SCADA system.

Figure 2-5 shows a schematic diagram of a three stage planetary gearbox with different bearings. Five different bearings are labeled; PCB-A (Planet carrier bearing- Rotor End), PCB-B (Planet carrier bearing- Non-rotor End), HSS-A/B/C (High speed shaft bearings A, B and C). 10-min average temperature measurement for these five bearings is available in SCADA system. This information is used in Chapter 4, where an ANN based approach for early fault detection in the gearbox bearings is presented in detail.

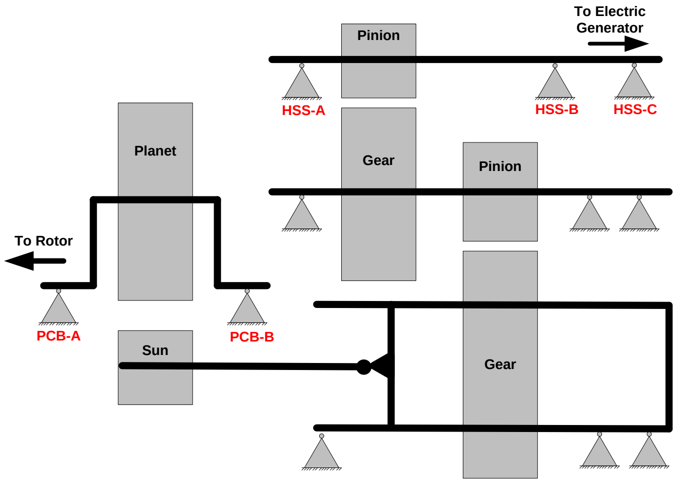


Figure 2-5 *A schematic representation of three stage planetary wind turbine gearbox (Amended from [29])*

An analysis of database containing 289 gearbox damage records conducted by National Renewable Energy Laboratory (NREL) [30], shows that 70% of gearbox failures are caused by failure in the bearings and 26% failures are caused by failure of gears. Figure 2-6 shows the damage distribution in a wind turbine gearbox.

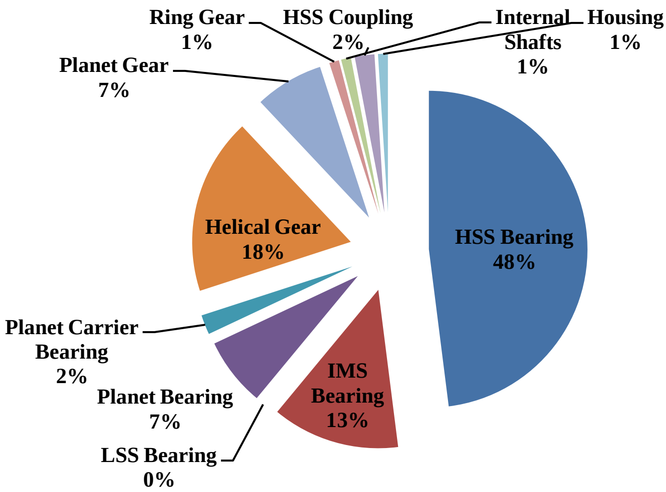


Figure 2-6 *The distribution of damage in wind turbine gearbox (Amended from [30])*

In view of the result from this analyses and in line with the RCAM approach it was concluded that by focusing on the gearbox and particularly on the gearbox bearings, there is a possibility to optimize the maintenance and thereby an opportunity to improve the reliability of a wind turbine.

2.5 Self Evolving Maintenance Scheduler (SEMS)

Stage-3 of RCAM describes the formulation of an optimal maintenance strategy to improve the reliability of the critical components. In this thesis, a maintenance management framework called Self Evolving Maintenance Scheduler (SEMS) is proposed. The SEMS framework can be used for maintenance optimization of wind turbine assets with a focus on maximum possible utilization of the remaining useful life of identified critical components with visible signs of damage. The visible signs of damage could be indications from the vibration based condition monitoring system, a visual inspection or signals from other condition monitoring systems.

The SEMS framework considers a short window of time, which exists between an indication of impending failure from CMS and the eventual failure of the component. Figure 2-7 shows the schematic representation of the SEMS framework for maintenance management of wind turbines.

According to the SEMS framework any alarm from the vibration based CMS or the ANN based condition monitoring approach, will give intimation to the maintenance personnel to perform an on-site inspection of the specific component. The main outcome of this inspection is to judge the extent of damage to the component. The maintenance planning is initiated after the information from the inspection is available. The maintenance planning considers remaining useful life of the damaged component, forecast of power from the wind turbine and the forecasted weather windows suitable for maintenance. The maintenance decision can be optimized by considering various factors like opportunistic maintenance and minimization of the loss of production due to downtime. The SEMS framework relates the indication of impending failure from CMS to the maintenance activity, which could be scheduled replacement of the damaged component.

A feedback loop is shown in Figure 2-7. Through this feedback, information is given to the ANN model about a maintenance activity done on the component being monitored. This feedback enables the system to up-date the ANN model to keep in tune with changing operating conditions in the wind turbine due to replacement of components, hence, giving a self evolving feature to the framework. The ANN based condition monitoring approach is discussed in detail in Chapter 4. Preliminary mathematical formulation for the SEMS framework has been discussed in Section 5.2.1.

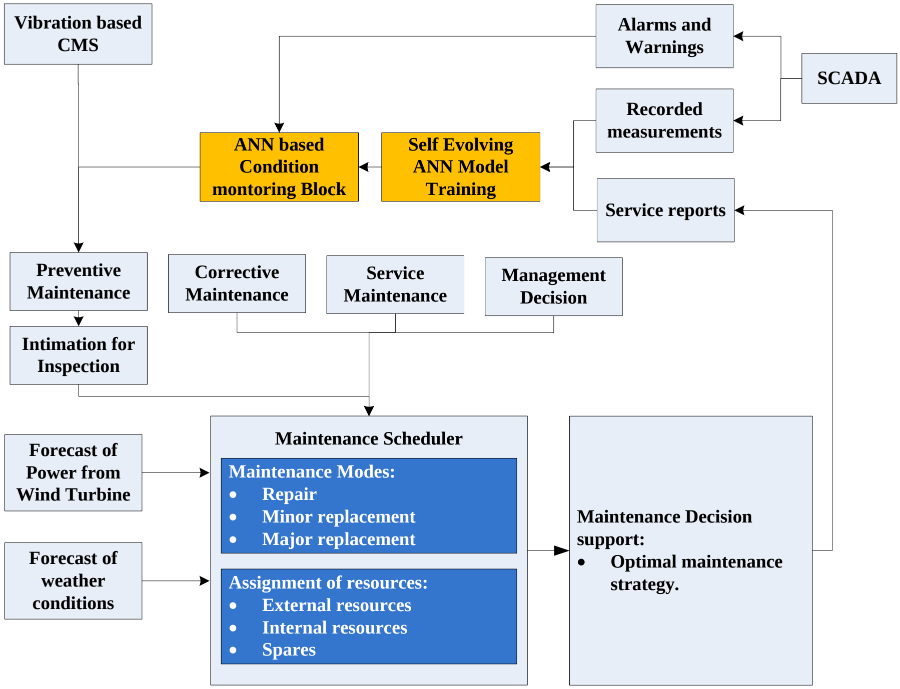


Figure 2-7 *The proposed Self Evolving Maintenance Scheduler (SEMS) approach*

The highlighted blocks: 'Self Evolving ANN Model Training' and 'ANN based Condition monitoring Block' are explained in detail in Chapter 4.

A summary of the proposed SEMS maintenance framework is provided as follows:

1. An inspection is done following an indication of deterioration in the component from the condition monitoring system. The time horizon for decision making is decided based on the results of inspection. The time horizon is considered as the estimated maximum remaining useful life of the component. However, the component can be replaced earlier if it is found to be an optimal solution.

2. A spare is ordered once it is realized that a major component, like wind turbine gearbox, is damaged. The cost of such a spare is considered in addition to a lead time for the spare to be received. During the lead time, replacement of the component cannot be done. After the spare is received, if the replacement is not done immediately an inventory cost is considered for the time, which the spare is to be stored in the warehouse.

3. As maintenance for wind turbines are weather dependent, weather windows suitable for maintenance are considered. Loss of power due to downtime during maintenance activities is considered in the SEMS framework.

4. In line with the RCAM approach, the effect of PM on the failure rate of the component is modeled. It is considered that any PM on the damaged component has the potential to marginally extend the remaining useful life of the component. This gives the maintenance personnel an incentive to perform maintenance even though the component is known to be damaged.

Chapter 3

Introduction to Artificial Neural Networks

In this thesis work the book by Simon Haykin "Neural Network and Learning Machines" has been used. This chapter provides a brief theoretical background to artificial neural networks (ANN). The chapter begins with basic definitions, and an introduction to the different types of ANN structures. Different training methods used for training ANN models are described. Finally, a review of different methods using ANN applied to wind turbine condition monitoring is provided.

3.1 Terminology

The terminology used for artificial neural networks in this thesis is presented here:

- *Artificial Neural Network (ANN)*: Computational models which use neurons connected in specific structure to estimate a non-linear relationship between the input and output
- *Environment or System*: A group of inputs and corresponding outputs which is intended to be modeled using ANN
- *Neuron*: A fundamental building block of ANN
- *Synaptic Weights*: Strength of connection of input in each neuron
- *Activation Function*: A mathematical model which decides the output of each neuron
- *ANN Learning*: The procedure of teaching the ANN to emulate the relationship between inputs and outputs
- *Training data set*: A representative set of data extracted from the environment or system, which is being modeled
- *Multilayer Perceptron*: A specific structure of ANN where there are more than one layers of neurons arranged in a specific manner connecting the inputs to the outputs

3.2 Theory

The brain functions in different ways that lets us interact with our immediate surroundings. For example; vision is one of the functions of brain, wherein an image, input from the retina of the eye, is processed which lets us perceive, understand and interact with the object being visualized. All this processing takes a matter of milliseconds.

The human brain 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 produce the desired results. These connections are established early in the life through a learning procedure, commonly referred to as '*experience*'.

The artificial neural network (ANN) intends to mimic the structure of 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 process and the retention of the knowledge with the inter-neuron connections called synaptic weights [31].

3.2.1 Model of a Neuron

A neuron is the fundamental building block of an ANN. Function of the neuron is to generate an output based on the input. The output of the such neuron is generally in the interval [0,1] or [-1,1] depending on the activation function.

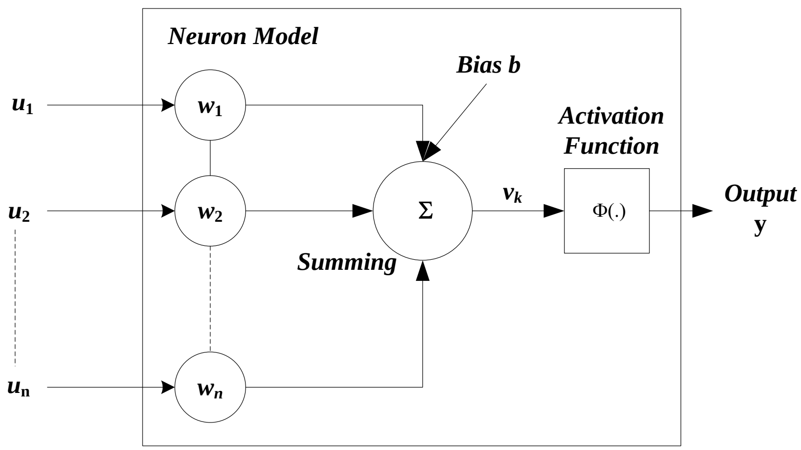


Figure 3-1 *A model of neuron*

Figure 3-1 shows the model of a neuron, where u_1, u_2 … u_n are the inputs and w_1, w_2…. w_n are the respective synaptic weights. $\Phi\,(.)$ is the activation function, which decides the final output y from the neuron. A bias b is used which either increases or decreases the input to the activation function depending on whether it is positive or negative.

The mathematical representation of a neuron depicted in Figure 3-1, can be achieved as follows:

$$v = \sum_{j=1}^{n} w_j u_j \qquad \textit{Eq. 3-1}$$

$$y = \Phi\,(v + b) \qquad \textit{Eq. 3-2}$$

3.2.2 Activation Functions

The output of the neuron depends on the activation function $\Phi\,(.)$. In this section two types of activation functions, which are commonly used in neural networks are described.

Threshold Function:

The threshold type of activation function is defined in Eq. 3-3 and presented in Figure 3-2.

$$\Phi\,(v) = \begin{cases} 1 & if\ v \geq 0 \\ 0 & if\ v < 0 \end{cases} \qquad \textit{Eq. 3-3}$$

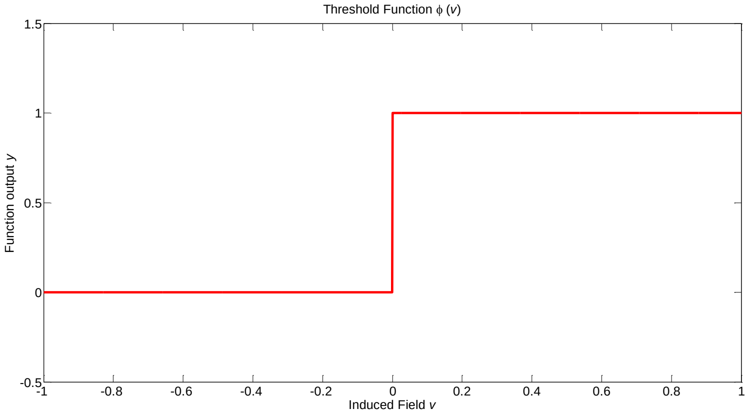


Figure 3-2 *The threshold function*

The threshold function can have output either 1 or 0 depending on the induced field. Threshold functions are often used in the output layer of ANN where binary classification of the input might be required.

Sigmoid Function:

Sigmoid function is a non-linear activation function defined by Eq. 3-4 and shown in Figure 3-3.

$$\Phi\,(v) = \frac{1}{1 + e^{-av}} \qquad \textit{Eq. 3-4}$$

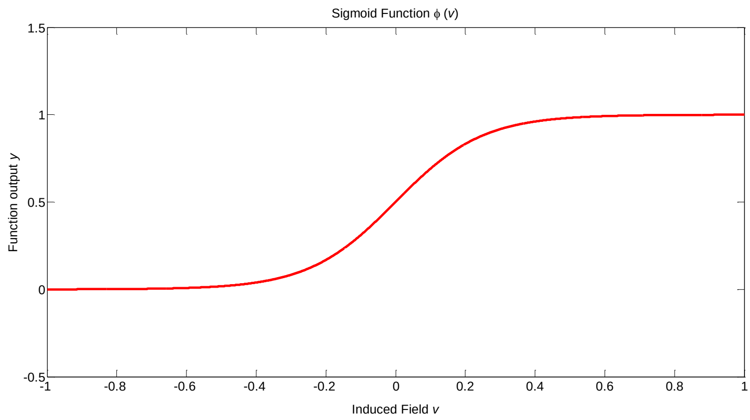


Figure 3-3 *The sigmoid function*

Sigmoid function is one of the most common activation functions used in neural networks. The slope of the sigmoid function can be varied by the slope parameter '*a*', as *a* tends to infinity the sigmoid function becomes 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.

3.2.3 Neural Network Architectures

The input-output relation for a neural network is strictly dependent on the network structure. Different neural network architectures can be realized by the manner in which neurons are connected to each other. In this section three main types of network structures are discussed.

Single-Layer Feed-forward Network:

As the name suggests, a set of inputs and outputs is connected directly through a single layer of neurons. The single layer networks do not have any feedback loops connected from the output to the input and, hence, represent a feed-forward structure. Figure 3-4 shows the structure of a single layer feed-forward neural network.

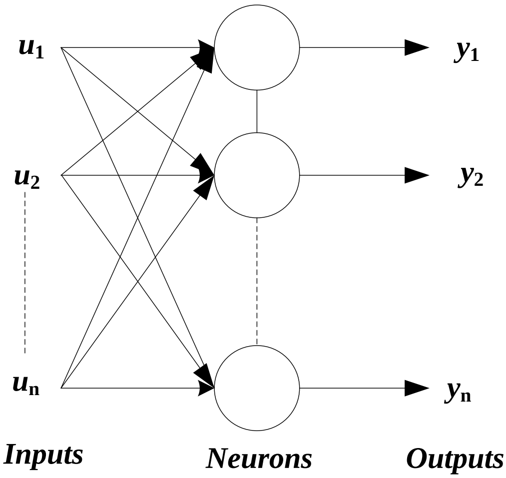


Figure 3-4 *A Single Layer Feed-forward neural network*

Multilayer Feed-forward Network:

As compared to the single layer feed-forward network, the multilayer structure has additional layers of neurons called hidden layers. These layers are named '*hidden*' because of the fact that they cannot be seen either from input or output layer. This structure is also called 'M*ultilayer Perceptron*'. A schematic representation of a sample multilayer perceptron is shown in Figure 3-5.

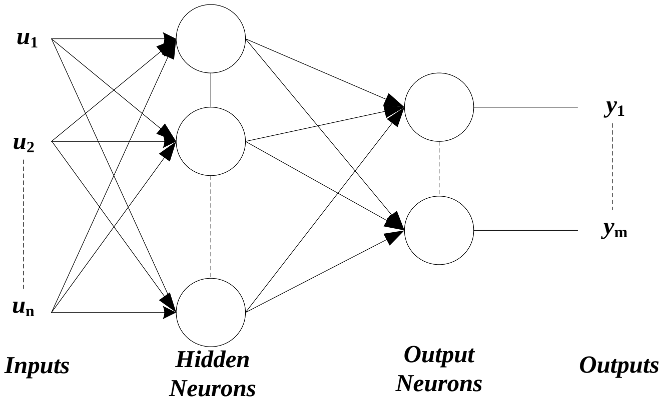


Figure 3-5 *A multilayer feed-forward network*

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 number of hidden layers; however, two hidden layers are, generally sufficient to model real world non-linear relationships with accuracy.

Multilayer Recurrent Network:

In contrast to the feed-forward neural networks, the recurrent neural networks are characterized by at least one feedback loop. Figure 3-6 shows a schematic representation of a recurrent neural network.

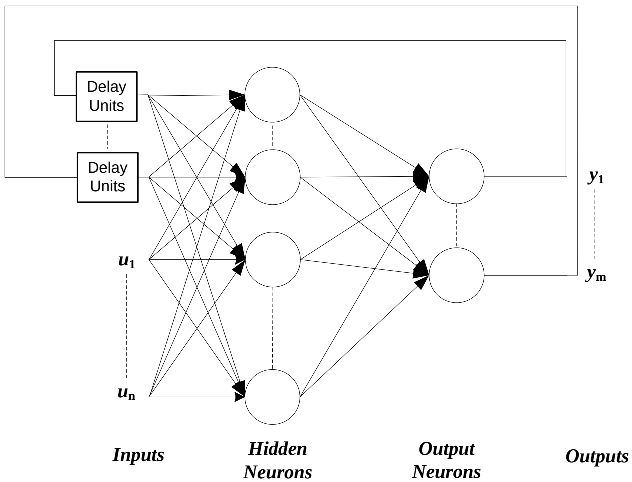


Figure 3-6 *A recurrent neural network structure*

It can be seen from Figure 3-6 that 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 [32-34].

3.3 Learning Methods

For a given neural network the information about the relationship between the inputs and outputs is stored in the synaptic weights '*w*' 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 '*training data set*' and the network learns the relationship between inputs and outputs in this training data set. The learning methods can be classified as shown in Figure 3-7.

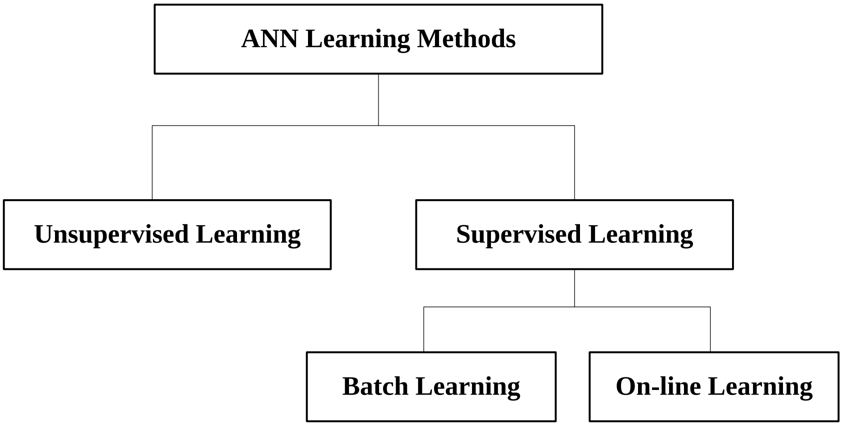


Figure 3-7 *A classification of ANN learning methods*

3.3.1 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 as supervised learning. Supervised learning is represented schematically in Figure 3-8.

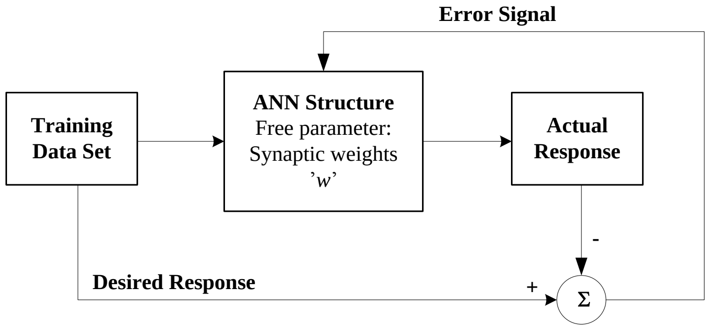


Figure 3-8 A schematic representation of supervised learning method for ANN

A data set consisting of samples of input vectors and the desired outputs corresponding to each input vector 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 has no information about the environment or system being considered; i.e. the values of the free parameters in the ANN, the synaptic weights '*w*' are undecided. The intention of the teacher is transfer the knowledge in the training data set to the ANN; i.e. decide the values of the synaptic weights. As shown in Figure 3-8, the knowledge transfer is achieved through the influence of the error signal and the training samples. The error signal is defined as the difference between output achieved by ANN and the desired response, which is stored in the training data set. The learning approach when applied to a multilayer perceptron is also called '*back propagation*' learning, as the synaptic weights are adjusted twice, once in the forward direction based on the samples in the training data set and then in the backward direction based on the error signal.

The knowledge transfer or '*training*' of the ANN is continued till a pre-defined performance parameter is minimized. A performance parameter can be considered to be, for example, the sum of mean squared error, over the training data set, defined as a function of synaptic weights. The training of an ANN is an iterative process with an aim to make the ANN replicate the behavior of the environment or the system with as much accuracy as is possible. The training essentially reduces to a minimization problem, wherein the objective is to minimize the performance parameter with the synaptic weights as variables. Standard minimization algorithms like gradient descent can be used for ANN training. However, more advanced minimization algorithms have been used for training ANN and one such advanced learning algorithm is discussed in Section 3.3.3.

The supervised learning method is able to map the input-output relation with good accuracy given adequate number of samples in the training data set. Supervised learning is divided in to two classes of training methods; batch learning and online learning.

Batch Learning:

In batch supervised learning method all the samples of the training data set are presented to the ANN at the same time. The synaptic weights are decided based on N samples in the training data set. The process of presenting all the samples is called one epoch. The final synaptic weights are decided based on an epoch-by-epoch approach, where the samples in the training data set are randomly shuffled and presented again to the ANN in every epoch. The performance of the randomly initialized ANN is then minimized using a minimization algorithm. The learning curve is constructed by averaging the performance of such randomly initialized ANN over a large enough number of epochs. The training stops when the learning curve does not show any improvement.

The two advantages of batch learning method are ensured convergence to a local minimum and parallelization of learning process. The parallelization of learning makes the learning faster. However, the disadvantage of batch learning method is the fact that the global minimum might not be achieved thereby the best possible performance is not guaranteed. The storage requirements for batch learning are also higher compared to the online learning method [31].

Online Learning:

Contrary to the batch learning method, in online learning the synaptic weights are adjusted based on a sample by sample approach. An epoch is achieved when all N samples in the training data set are presented to the ANN. Similar to the batch learning method, randomly initialized ANN are trained for different epochs where the samples in the training data set are randomly shuffled. The learning curve is then plotted as the average performance function for each epoch.

Online learning has the advantage of being more responsive to the redundancies in the training data set; i.e. if the training samples are repeated, online learning method takes advantage of this fact as the samples are presented to the ANN one-by-one. The online learning is comparatively simpler to implement and provides a better solution for large scale pattern recognition problems. However, as parallelization of the process is not possible, it is slower than batch learning method [31].

The supervised training of ANN can be summarized in following steps:

1. decide the ANN architecture (refer Section 3.2.3)
2. decide the training data set such that the samples represent the environment or the system being modeled
3. decide which performance parameter should be used
4. decide the training method (supervised batch learning or on-line learning)
5. train the ANN

3.3.2 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 the method unsupervised learning. This method of learning is used mainly when it is not possible or is difficult to construct a training data set, which represents the environment or the system being modeled. Unsupervised learning is hence achieved through unlabelled samples of inputs and outputs, which are available easily for any environment or system.

3.3.3 Levenberg-Marquardt Learning Algorithm

The synaptic weights ‘w’ are updated for a given structure of ANN based on the training algorithm adopted. In this sub-section, the Lavenberg-Marquardt training algorithm (LMA) is presented. LMA is one of the most common algorithms used for training ANN. It has the combined advantage of Gradient descent method, which is ensured convergence and the Newton method, which is fast to converge. LMA gives better performance in terms of accuracy for neural networks with less than 100 neurons [35]. Hence, in this thesis, the LMA has been used for training of ANN as the number of neurons required for modeling is less than 100.

The input/output relationship for an ANN can be represented by Eq. 3-5:

$$y = F(u_1, u_2, \dots \dots, u_m) \qquad \textit{Eq. 3-5}$$

F is the non-linear approximation function that the network models, to emulate the relationship between the inputs u and output y. The suffix m in Eq. 3-5 represents the total number of input parameters u, which are used to model one output parameter y.

Consider $\{u(i), d(i)\}^{N}{}_{i=1}$ is training data set with N sample points and $F(u(i);w)$ is the non-linear function emulated by ANN, where w is the weight vector. The network training is achieved by minimizing the cost function presented in Eq. 3-6

$$\Im(w) = \frac{1}{2N}\sum_{i=1}^{N}\left[d(i) - F(u(i);w)\right]^2 \qquad \textit{Eq. 3-6}$$

According to LMA the weight vector is updated as per Eq. 3-7

$$\Delta w = \left[H + \lambda I\right]^{-1} g \qquad \textit{Eq. 3-7}$$

H is the Hessian matrix approximated as per Eq. 3-8, and g is the gradient vector defined as per Eq. 3-9. I is an identity matrix with dimensions same as H and λ is a scalar parameter used to switch between Newton's method and Gradient decent method.

$$H = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{\partial F(x(i);w)}{\partial w}\right]\left[\frac{\partial F(x(i);w)}{\partial w}\right]^T \qquad \textit{Eq. 3-8}$$

$$g = \frac{\partial \Im(w)}{\partial w} \qquad \textit{Eq. 3-9}$$

If the value of λ is zero, Eq. 3-8 reduces to Newton's method and if λ is large enough to over-power H, the method is similar to Gradient descent method. The aim of the method is to move to Newton's method, which is fast near minimum value and hence value of λ is reduced at each consecutive step as long as the performance function of the network defined by Eq. 3-6 is reduced. The value of λ is increased, if the performance function increases for a consecutive step. The value is increased or decreased by a factor of 10 and the initial value of λ is considered to be 1.

3.4 Application of ANN to Wind Turbines

The SCADA system is an integral part of wind turbines, which records various temperature and current signals from the wind turbine and stores the 10-min average value of these measurements on a server. The recorded SCADA measurements can be extracted at any point of time and can be used to estimate the health of components in the wind turbines.

The ANN method has been successfully applied for condition monitoring applications for wind turbines, using data stored in SCADA system. A software tool named SIMAP, which uses ANN and fuzzy expert system for fault diagnosis and maintenance optimization for wind turbines was presented in [36]. The work introduced a method to build a normal behavior model based on signals from SCADA. An anomaly detection technique was used on the component being monitored to determine deviation from normal behavior by comparing the real time signal with the output from the normal behavior model. A similar ANN based strategy for fault prognosis in wind turbines was proposed in [37]. ANN based model for prediction of the gearbox bearing temperature and generator bearing temperature was developed and used for incipient fault detection in wind turbines. In [38], the authors have used principal component analysis (PCA) for non linear domain using Auto associative artificial neural networks (AANN) on SCADA signals and alarms to develop an algorithm for fault prediction. A neural network based model for monitoring the generator bearing was presented in [39]. In [40] feed forward neural network has been used to predict the gearbox condition. A data mining approach used to find the parameters which affect the generator bearing temperature the most was presented in [41]. As an output of the data mining various parameters were found to be important for modeling the generator bearing temperature accurately. Further a neural network based method was used to model the generator bearing temperature based on the selected parameters. To analyze the results a moving average window method was presented, which was used to filter out noise from the output. In [42], the authors have presented a technique using SCADA data and basic laws of physics to derive relationship between efficiency and temperatures in the gearbox. Based on proposed method a case study is presented for gearbox fault detection. The authors also suggest that integration of SCADA based and vibration condition monitoring would improve the fault prognosis considerably.

In addition to the ANN based methods some techniques have also been developed to use the indicative information from the SCADA alarms. A methodology to prioritize SCADA alarms using time-sequencing and probability method was presented in [43]. The authors mention an urgent need to standardize the alarm handling in wind power industry and stress the importance of SCADA alarms in fault detection in wind turbines.

The SCADA data has proved to be a gold mine of information, which can be accessed to extract valuable estimates about the health of wind turbine components. In addition to the data stored in the SCADA, the alarms and warnings generated by SCADA are good indicators towards the maintenance requirements in wind turbines. Hence, in this thesis, an approach using ANN is developed which utilizes the measurement information stored in SCADA as well as SCADA alarms and warning analysis together, for condition monitoring of gearbox bearings in wind turbines. The proposed approach is explained in detail in Chapter 4.

Chapter 4

ANN Based CMS Using SCADA

This chapter provides an introduction to the wind turbine SCADA system. Furthermore, the ANN based condition monitoring approach using SCADA data has been introduced. The self evolving approach for training the ANN models is discussed. The classification of SCADA alarms and warnings has been presented and finally case study results are presented to validate the ANN based approach. The proposed ANN based condition monitoring approach is compared with similar approaches found in literature.

4.1 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.

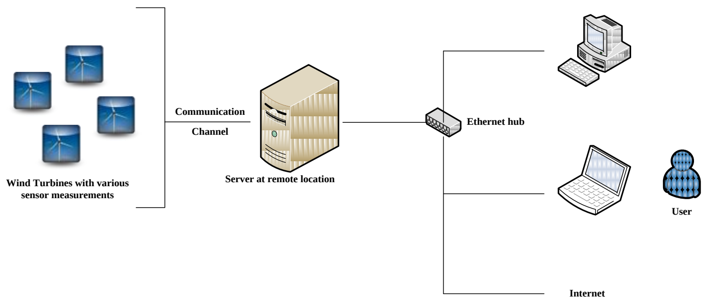


Figure 4-1 *A schematic representation of typical SCADA system for wind turbines (Adopted from WT Manufacturer's Manual)*

A user can access the wind turbine from any remote location through the SCADA server, as shown in Figure 4-1. SCADA, as the name suggests, has two levels of function:

1. A control level which allows the user to turn on or turn off and control the power output from wind turbines
2. A monitoring level where the user can get an instantaneous status update of operating condition of wind turbines and the historical data about its behavior

Various measurement sensors are placed at different locations in the wind turbine. Parameters like wind speed, wind direction, ambient and nacelle temperatures, lubrication oil temperature and pressure, different bearing temperatures are measured continuously for wind turbines. In addition to these measurements, electric quantities like voltage, current, frequency and power factor are also measured. These measurements are stored as a 10-min average value on a server in remote location. The user can access this data through the server at any point of time. In addition to this, the SCADA system also generates alarms and warnings based on pre-set threshold values. For example, if the bearing temperature value is above a pre-set threshold value, then the wind turbine is stopped and an alarm is generated. The SCADA generated alarms and warnings deliver different level of information to the operator. The function of alarms and warnings is described below:

- *Alarms*: The main function of an alarm is to avoid the operation of components under high stress conditions, which have the possibility to reduce the operating life of the component significantly. An alarm results in to a shutdown of the wind turbine. Alarms can be acknowledged in three different ways
    1. *Auto-acknowledge:* The controller acknowledges the alarm and restarts the wind turbine after the condition causing the alarm no longer exists. There is a maximum number of auto-acknowledge after which the alarm has to be acknowledged remotely
    2. *Remote-acknowledge:* The alarm has to be manually acknowledged at a remote location, for example, control centre to restart the wind turbine. The main function is to inform the operator that a component might need some kind of inspection
    3. *Local-acknowledge:* The alarm has to be acknowledged manually at the wind turbine. These alarms are mainly related to safety of operation, for example, the alarm generated in the fire safety system
- *Warning*: The main function of warnings is to inform the operator that attention is needed to a particular component. Warning is generated in a situation when there is no immediate danger of damage to the component but the reduction in life of the component could be more than normal. This could be, for example, low oil level indication, which is not critical but needs attention. Warning could result in to an alarm if no attention is given, which will lead to a shutdown of a wind turbine

SCADA records and provides valuable information. However, an intelligent use of SCADA data in maintenance planning application still lacks application in wind turbine industry. An ANN based condition monitoring approach is presented which not only uses the historical data recorded in the SCADA but also uses the alarms and warnings to make a detection of deterioration in critical components in wind turbine.

4.2 ANN Based Condition Monitoring Approach

Even though the SCADA system generates warnings and alarms in order to notify the operator/maintenance personnel about a possible deterioration in a wind turbine component, these warnings and alarms have not been fully integrated in to the maintenance planning process. The lack of integration is mainly due to the fact that the SCADA system either gives the indication too late to do anything useful or that there are so many alarms and warnings being generated that it becomes overwhelming to consider all of them and take action. Moreover, SCADA records a large number of measurements of different parameters in the wind turbines. An intelligent analysis of this stored data along with a systematic analysis of alarms and warnings can provide an accurate estimate of operating conditions for some critical components in the wind turbine.

Artificial neural network (ANN) has been successfully applied for condition monitoring of a component in wind turbine using data stored in SCADA (refer Section 3.4). The main philosophy of most of the approaches can be summarized in Figure 4-2.

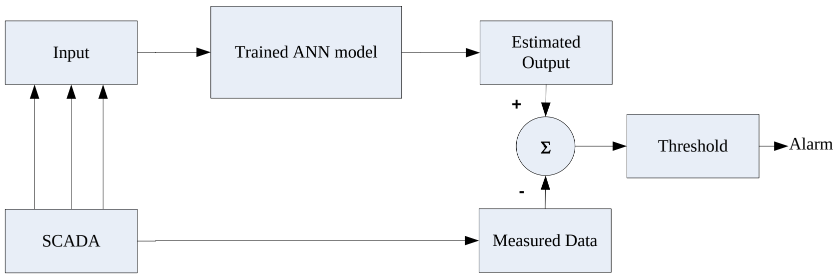


Figure 4-2 *The ANN based condition monitoring approach*

The historical data from the wind turbine SCADA system is used to train an ANN model. The ANN model is used to estimate an operating parameter of the component being monitored for a given operating condition. The operating parameter being modeled could be, for example, the temperature of the bearing and the operating conditions could be the nacelle temperature, rotational speed and power being generated by the wind turbine. Once the ANN model is trained it can be used in real time to estimate the operating parameter of interest and then can be compared to the actual value of the parameter. If the difference between the estimated and actual value is found to be higher than a pre-set threshold, an alarm is issued indicating abnormal behavior of the component, which could be because of deterioration.

Conceptually, the ANN model described above can be called a normal behavior model. At any given operating condition there exists equilibrium in the physical system, which decides the value of the parameter being modeled. Given that the ANN is able to model this equilibrium condition between the inputs, i.e. the operating condition, and the output, i.e. the parameter being modeled, with accuracy; it can detect a situation when the equilibrium does not exist anymore. In normal conditions if the equilibrium is not disturbed the estimated and the measured value for the modeled parameter are very close. If the equilibrium is disturbed due to deterioration in the component, the measured parameter will deviate from normal condition. However, as the ANN has modeled only the equilibrium condition, the output from the ANN model will still be the same as before. This will increase the difference between the estimated and actual parameter values indicating damage in the component. An analysis of the difference between the modeled and the measured parameter values will indicate an anomaly, which might lead to determination of deterioration.

4.2.1 An Automated Approach for Selection of Training Dataset

The ANN model needs to be trained with the help of data which is representative of the environment or system being modeled, refer Section 3.3. The representative data is called ‘*training data*’. Conventionally, the training data is selected manually to represent the behavior of a system [37]. If the number of wind turbines is large selecting training data manually for each wind turbine is an arduous and time consuming task. Another approach to the problem is to make one average model, which is used for all wind turbines. However, as shown in Figure 4-3, the behavior of wind turbines subjected to similar operating conditions differ considerably.

Figure 4-3 shows the gearbox bearing temperature over a year of operation for five different wind turbines. The bearing temperature values are averaged over a period of three months, a typical length of one season in Sweden. The wind turbines are rated 2 MW and are of the same make and manufacturer. They are located in the same geographical area, which means that all the five wind turbines are subjected to similar operating conditions throughout the year. In spite of these similarities there is a considerable difference between average gearbox bearing temperatures.

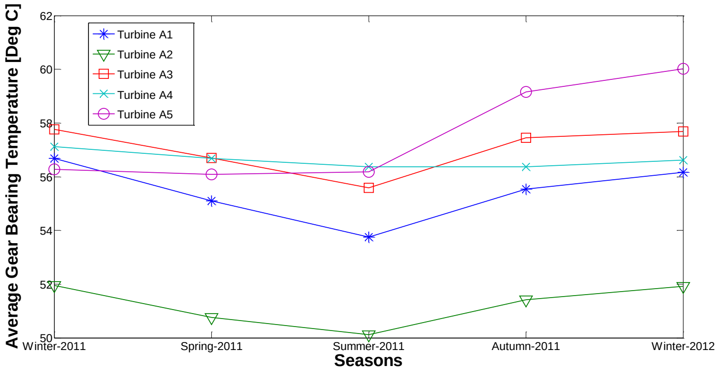


Figure 4-3 *The behavior profile of five wind turbines located in same geographical area [WT28 Database]*

It can be concluded that only one gearbox bearing temperature ANN model will not be able to model the equilibrium condition for all these wind turbines. Hence, there is a necessity to train different ANN models, which are tailored to the operating condition of individual wind turbines.

In order to overcome the limitations of an averaged ANN model and to make the ANN model training procedure automated, an '*Automated training data selection approach*' is proposed. Figure 4-4 shows the outline of the procedure for selection of training data set for training ANN model.

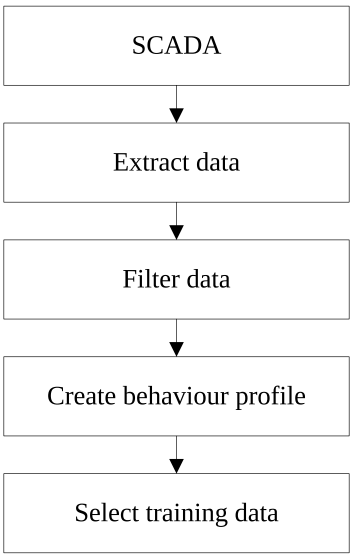


Figure 4-4 *An outline of procedure for training data selection for training ANN model*

Data Extraction:

Historical sensor measurement data for wind turbines is stored on the server in the SCADA system, refer Figure 4-1. Data extraction is a manual process, where a user with appropriate level of access extracts the historical data from the SCADA system to a user computer for further analysis. The data extracted from SCADA is referred to as '*raw data*'.

Data Filtering:

The extracted raw data from SCADA cannot be used directly, as it often contains erroneous data. The two main reasons for such erroneous data are described below:

1. SCADA records negative power signals, when the wind speed is below the cut-in limit and the wind turbine is in idling mode
2. due to communication failure SCADA does not record any data for some duration

Such data with errors cannot be used to train the ANN model as it is not representative of the normal operation under physical equilibrium condition. Hence, the data has to be filtered for ANN model training. The filtering of raw data is done using the logic described in Eq. 4-1.

$$[Training\ data]_i = [Operating\ parameters]_i |\ P_i > 0, \forall\ i \in N \qquad \textit{Eq. 4-1}$$

$[Training\ data]_i$ is the i^{th} vector of the training data set, which contains the operating parameters used to model the ANN and P_i is the output power from the wind turbine while N is the total number of sample points in the raw data. Hence, the data where the wind turbine is producing positive power is considered and the rest is filtered out.

Creating Behavior Profile:

The *behavior profile* of a wind turbine is defined as the specific operating characteristic of a wind turbine with respect to the parameter being monitored. Figure 4-3 shows the average gear bearing temperature for a set wind of turbines of same make located in same geographical area. The average gearbox bearing temperature is calculated for four seasons each consisting of three months. This specific seasonal behavior of the wind turbine is termed as the behavior profile and is used for final selection of the training data set. The reason for looking at the seasonal behavior is due to the fact that wind turbine population under consideration has a season dependent behavior due to different power production levels seen during these seasons. In this particular case, the power output from wind turbines is higher in the winter than in summer and hence the average gearbox bearing temperature in winter is higher than for summer season.

Selection of Training data set:

The ANN model will be accurate if the training data set contains all the normal operating conditions for the wind turbine. In order to ensure that all the operating points are covered the logic presented in Eq. 4-2 is used.

$$DM = \mathrm{arg}_{\mathrm{max}} \left\| \tau_{\mathrm{av_i}} - \tau_{\mathrm{av_j}} \right\|, \forall\, i,j \leq n\,, i \neq j \qquad \textit{Eq. 4-2}$$

DM is an indicator, called diversity measure, indicates which two seasons should be considered for selection of training data set. n is the number of seasons, τ_{av} is the seasonal average value of the operating parameter that is intended to be modeled using ANN. For example, referring to Turbine A1 in Figure 4-3, 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 selection of training data set is the addition of more operating points with an aim to include the maximum number of operating points that the wind turbine has seen. The addition of these extra points is performed using the control equation presented in Eq. 4-3.

$$[(\mathrm{A_{max}} - \mathrm{B_{max}}) + (\mathrm{B_{min}} - \mathrm{A_{min}})] + N \ \leq\ \varepsilon \qquad \textit{Eq. 4-3}$$

$\mathrm{A_{max}}$ is a vector of maximum values of input parameters in actual data set which includes data from one year. For example; vector $\mathrm{A_{max}}$ can be described as shown in Eq.4-4.

$$A_{max} = \left[Oiltemp_{max}^{Act}, Nactemp_{max}^{Act}, Power_{max}^{Act}, RPM_{max}^{Act}\right] \qquad \textit{Eq. 4-4}$$

The ‘max’ values in Eq.4-4 denote the maximum value of the parameter in data set containing data from one year. Similarly, $\mathrm{B_{max}}$ is the vector of maximum values of input parameters in training data set. $\mathrm{A_{min}}$ and $\mathrm{B_{min}}$ are vectors of minimum values of input parameters in actual and training data sets respectively. The value N is the number of sample points in the training data set and ε is called a control parameter. The control parameter limits the number of sample points to a maximum value.

The SCADA system records 10-min average values. The maximum number of recorded data points in one month, considering 24 hours per day and 30 days in a month, can be 4320 data points. Hence, the value of control parameter ε can be selected to be in range of 8500 to 9000 to ensure that the training data set contains data from at least two months.

The batch learning method is used to train the ANN model, refer Section 3.3.1. A training data set with redundant sample points does not have any benefit in improving the performance of the ANN model using batch training [31]. Moreover, with too many sample points in the training data set, the training of ANN model takes longer. Hence, it is intended 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 and the training speed is increased. The proposed automated training data selection approach ensures that the number of training samples is not large and at the same time the entire operating range of the wind turbine is covered.

4.2.2 Validation: Automated training data selection approach

The automated approach presented in the previous section is different from the conventional approach of manual data selection used for training the ANN model. Hence, a validation is deemed necessary to ensure that the accuracy of the trained ANN model is not compromised due to the automated approach. Hence, a case study is presented here with the application of the automated approach to a sample ANN model and the output is compared with same ANN model trained using the conventional approach.

Sample ANN model:

The feed-forward multilayer perceptron ANN, presented in Section 3.2.3, is used for modeling the normal behavior of gearbox bearing temperature. The ANN model has 14 neurons in the hidden layer and one neuron in the output layer. The sigmoid activation function is used for the neurons in the hidden layer and the threshold function is used for the output neuron. The inputs and the output for the ANN model are presented in Table 4-1.

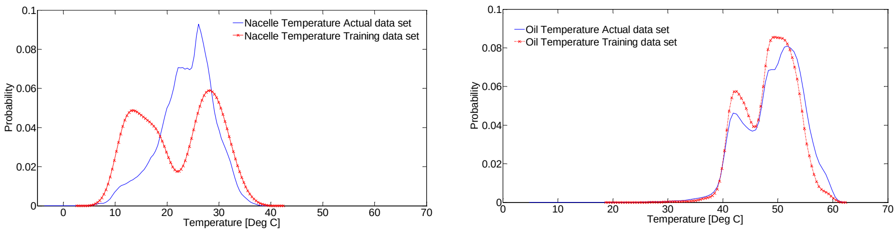
Table 4-1 *The inputs and output for the sample normal behavior ANN model for gearbox bearing*

ANN model Input	ANN model Output
Nacelle temperature	Gearbox (HSS) bearing temperature
Gearbox oil temperature	
Turbine power	
Rotor RPM (Rotations per minute)	

The inputs have been selected on the intuitive understanding of the physical system. It is assumed that there exists equilibrium between different external temperatures like the nacelle temperature and the lubrication oil temperature and the operating parameters of the wind turbine like turbine power output and rotor rpm and the temperature of the bearing of gearbox. The ANN model is trained to emulate this equilibrium.

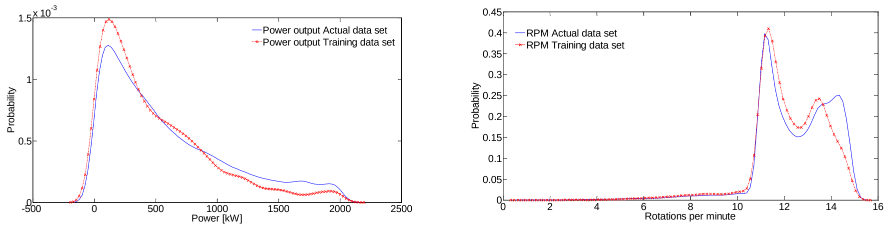
Automated training data selection:

The automated approach presented in Section 4.2.1 is applied to data from *Turbine A1* presented in Figure 4-3. The data from year 2011 is used to decide the training data set. The comparison of the probability distributions of input data in the selected training data set and the overall data set consisting of one year data is presented in Figure 4-5 and Figure 4-6. Figure 4-7 presents the probability distribution of the output parameter, i.e. gearbox bearing temperature, for the actual data set and the selected training data set.



(a) (b)

Figure 4-5 *The probability distribution for (a) Nacelle temperature (b) Oil temperature [44]*



(a) (b)

Figure 4-6 *The probability distribution for (a) Turbine power (b) Turbine RPM [44]*

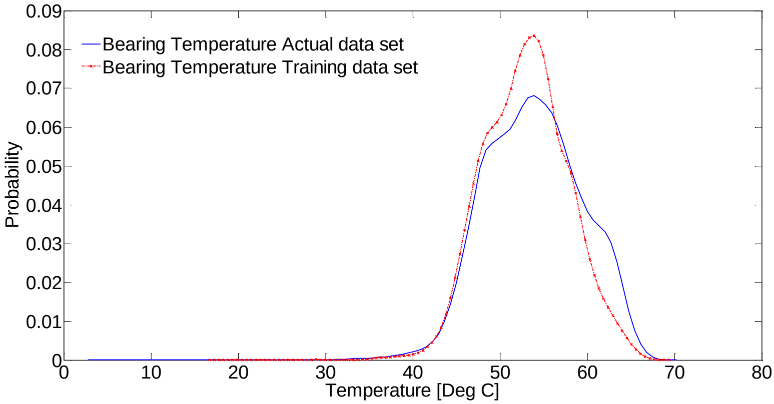


***Figure 4-7** The probability distribution for gear bearing temperature in actual data set and selected training data set [44]*

It can be concluded that the data in the training data set covers the entire range of data compared to the set of data spanning over one year of wind turbine operation. Hence, the aim of selecting the training data set which covers the complete range of operating conditions is achieved. In the current demonstration case study the value of control parameter ε is selected to be 8500 so that the training data set has sample points from at least two months of operation of the wind turbine. The total number of sample points in the training data set is 8473.

Conventional training data selection:

Condition monitoring based on ANN method using SCADA data has been developed by various researchers, refer Section 3.4. However, training data selection, which is an important step in building good ANN models, is seldom discussed in literature. Eventually, the training data set is either assumed to be available or is selected manually [37]. Hence, the approach of manual selection is considered as the conventional approach for selection of training data set.

For comparison purpose a conventional data set was selected. The selection of data set was done based on the value of power output from the wind turbine. The output power was arranged in ascending order and the corresponding values of operating parameters for each output power value was selected. All repeated values of the power were rejected in such a way that only one vector of inputs and output is obtained for each value of power output from wind turbine. The resulting final training data set selected contained 17533 sample points. Figure 4-8 shows the conventionally selected training data set.

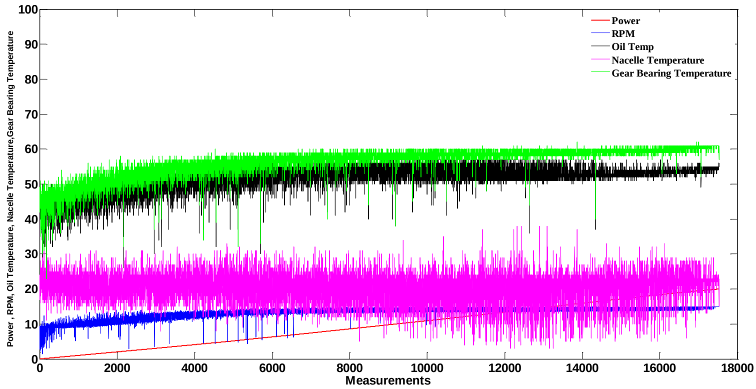


Figure 4-8 *A conventionally selected training data set [45]*

Calculation of error from ANN model:

An error is defined as the difference between the estimated parameter output from the ANN model and the actual measured value of the parameter stored in SCADA. The error is defined in Eq. 4-5.

$$E_i = \mathrm{y}_\mathrm{i}^{\mathrm{measured}} - \mathrm{y}_\mathrm{i}^{\mathrm{ANN\ output}}, \forall\, i \in N \qquad \textit{Eq. 4-5}$$

E_i is the i^{th} value of error, $\mathrm{y}_\mathrm{i}^{\mathrm{measured}}$ is the i^{th} measured parameter value recorded in SCADA and $\mathrm{y}_\mathrm{i}^{\mathrm{ANN\ output}}$ is the i^{th} value of the estimated output from ANN model and *N* is the total sample points over which the ANN model is applied.

Comparison of the Conventional and the Automated approaches:

The errors generated from two ANN models are compared. ANN model 1 is trained using the conventional approach and ANN model 2 is trained using the automated approach.

Table 4-2 *The details for the sample ANN models used for comparison of training data selection approaches*

ANN Model	**Type of ANN model**	**Number of neurons in hidden layer**	**Type of training data selection approach**
ANN Model 1	Multilayer perceptron	14	Conventional
ANN Model 2	Multilayer perceptron	14	Automated

In order to be comprehensive in comparison, the errors from both the models are considered over a condition monitoring period of 33 weeks. As the training of the ANN model is done based on data selected from year 2011, the ANN model is presented with data from the year 2012. In order to make the results clear and easy to understand the root mean squared error (RMSE) is used, which is calculated over a period of one week as defined in Eq. 4-6 .

$$RMSE_j = \sqrt{\frac{\sum_{i=1}^{n_j}\left(y_{ij}^{\text{measured}} - y_{ij}^{\text{ANN output}}\right)^2}{n_j}} \qquad \textit{Eq. 4-6}$$

$RMSE_j$ is the root mean squared value of error for the j^{th} week, where n is the total number of data points in week j. Figure 4-9 presents the output of ANN models 1 and 2 over the condition monitoring period of 33 weeks. It can be observed that the RMSE output from both ANN models are very similar over the entire period. However, the training with lesser number of training samples is faster and furthermore, the automatic selection is much simpler compared to the conventional procedure for training data set selection. In this thesis, the ANN models used for condition monitoring are trained using the proposed automated data selection approach.

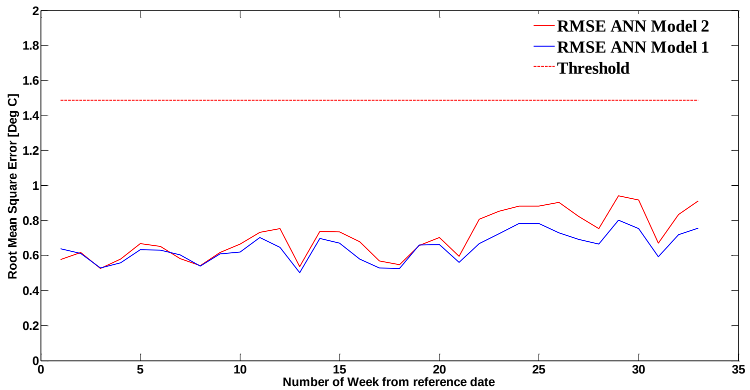


Figure 4-9 *A comparison of ANN model outputs for ANN model 1 and ANN model 2 [45]*

4.3 Self-evolving Approach for ANN Modeling

Wind turbines operate in a dynamically changing environment. The variations in the operating conditions can; for example, be hourly, daily or over seasons. With the changing operating characteristics the behavior of the components also changes in the wind turbines; for example the changing operating temperature for gearbox bearings, which is season dependant.

Wind turbine operation and maintenance providers, generally, follow a six month preventive maintenance regime. The scheduled maintenance activities are performed with an objective to keep the performance of the wind turbines at a normal level. However, after a failure of a major component, like gearbox, a replacement is performed. The replacement can drastically change the operating characteristics of the wind turbine components. The ANN model built to model equilibrium with the old component cannot be applied for condition monitoring of the new component. Hence, it becomes necessary to update the ANN model with new data, in order to avoid false alarms. A Self-evolving approach, which considers major maintenance actions; like replacement of a critical component, and updates the ANN model is presented in Figure 4-10. The aim is to keep the ANN model up-to-date by re-training after certain maintenance actions.

The first step of the approach is to select a component to be monitored. The decision of the component to be monitored is based on Stage 1 of RCAM approach, refer Section 2.3. The next step is to accumulate the un-faulted data consisting of relevant operating parameters to model the normal behavior of the selected component. The automated approach outlined in section 4.2.1 is used to select the training data set and further the trained ANN model is used for condition monitoring of the selected component.

If there is a major maintenance activity leading to replacement of the component being monitored, a re-training of the ANN model is initiated. In accordance with outlined approach, the SCADA based CMS will not be available for three months after the major replacement. During this time the fingerprinting of the new component is done, wherein the data is collected to learn the behavior of the new component in the system. During these three months the vibration based CMS will be the only monitoring provided to the equipment. However, the probability that the newly replaced equipment fails within three months is low.

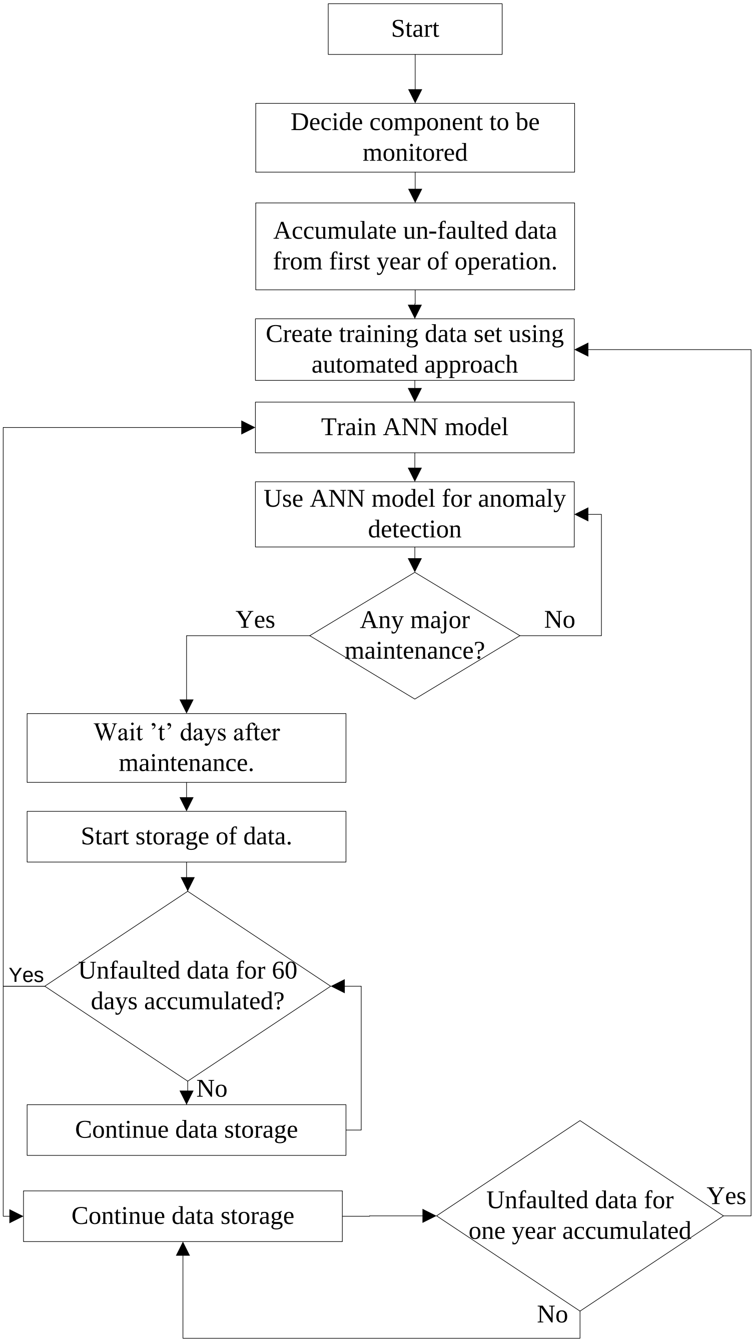


Figure 4-10 *The self-evolving approach for ANN modeling*

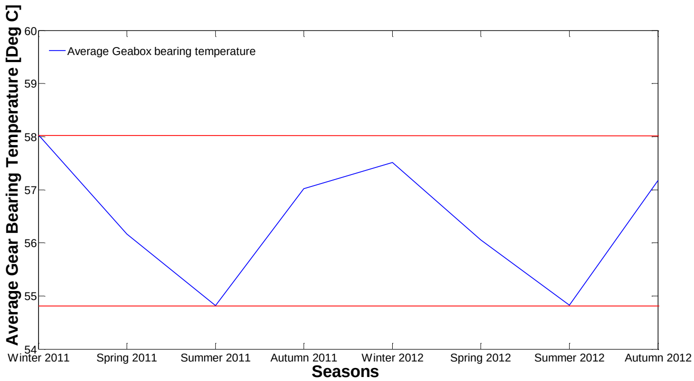


Figure 4-11 *The average gearbox bearing temperature shown over a period of two years [WT28 database]*

Figure 4-11 shows the seasonal average gearbox bearing temperature for one wind turbine over the period of two years. It can be observed that the gearbox bearings show a cyclic temperature behavior. Time based service maintenance was performed on the wind turbine and there was no gearbox failure. It can be inferred, from this information, that once the ANN model has been trained, it can be used to monitor the gearbox bearings as the operating conditions do not change drastically over the year if there is no damage. It can also be argued that the service maintenance activities helped in retaining the operating characteristics of the wind turbine gearbox. Hence, in the Self Evolving approach an update of the ANN model on a yearly basis is not felt necessary.

4.3.1 Validation: Self-evolving Approach for ANN Modeling

A case study based on real SCADA data from a wind turbine is performed to validate the proposed self-evolving approach. The validation case study contains data from a wind turbine where the gearbox was replaced after a gear failure. In line with the self-evolving approach for ANN modeling, presented in Figure 4-10, data for year 2010 during which period there were no recorded gearbox failures, was accumulated for the wind turbine. Based on the automated training data selection approach the ANN model was trained and applied for anomaly detection for wind turbine gearbox. Figure 4-12 shows the ANN model output for the year starting from 31st Jan 2011 to 31st Jan 2012.

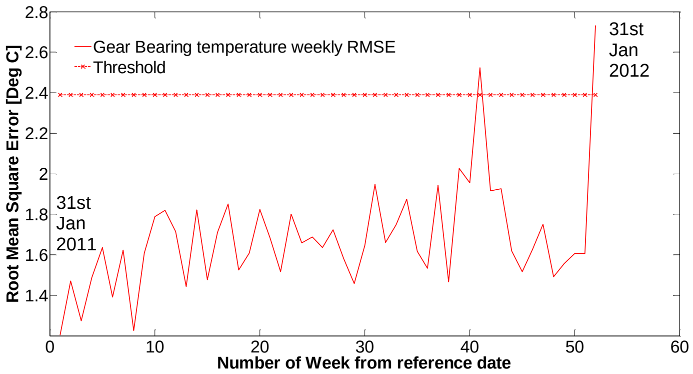


Figure 4-12 *The ANN model output for condition monitoring period of one year [44]*

From Figure 4-12 it can be observed that the RMSE value of error has an increasing trend throughout the period of condition monitoring. Further, in week 41 the RMSE is greater than the pre-set threshold value. An inspection at this point could have revealed the damage in the component.

It is important to note the ANN model presented in this section is simplistic in structure and is used for demonstration purpose only. A more advanced model might be able to model the physical equilibrium condition with better accuracy and may give better diagnosis. Moreover, the ANN model is emulating the gearbox bearing temperature and is not designed to directly monitor the gears in the gearbox. However, any damage in the gearbox will result in disturbance of the modeled equilibrium condition, it can be safely assumed that the ANN based condition monitoring may detect indirect damages as well.

At end of the condition monitoring period on 31^{st} Jan 2012 it was realized that the high speed shaft gear was damaged and needed to be replaced. The same can be observed from the ANN model as well, where the RMSE has crossed the threshold value. The new gearbox had a distinctly different behavior as compared to the old gearbox. Figure 4-13 shows the probability distribution for the period of January to May 2011; i.e. before gearbox replacement and period of January to May 2012; i.e. after the replacement of the gearbox.

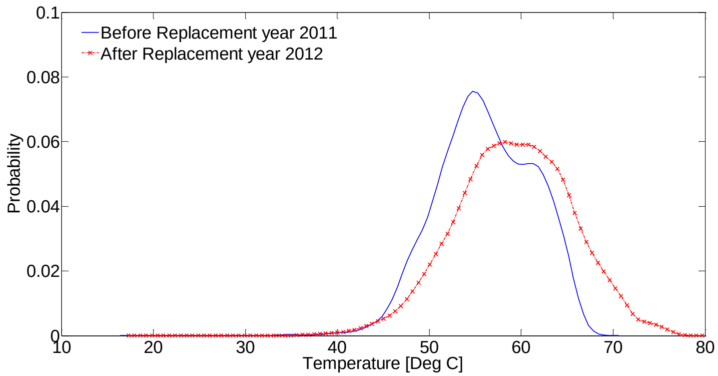


Figure 4-13 *The probability distribution of gearbox bearing temperature before and after gearbox replacement [44]*

It can be observed that the behavior of the gearbox has changed considerable after being replaced. However, from the maintenance records and the SCADA data it was confirmed that the new gearbox was operating normally, albeit the higher operating temperature. The ANN model trained with the data for the old gearbox was applied to the new gearbox and the RMSE value of the error for the period June to December 2012 is presented in Figure 4-14. It can be observed that according to the ANN model output, the gearbox is constantly operating in a state of fault. This can be attributed to the fact that the ANN model is trained to emulate the equilibrium condition which existed with the old gearbox and did not exist after replacement of gearbox.

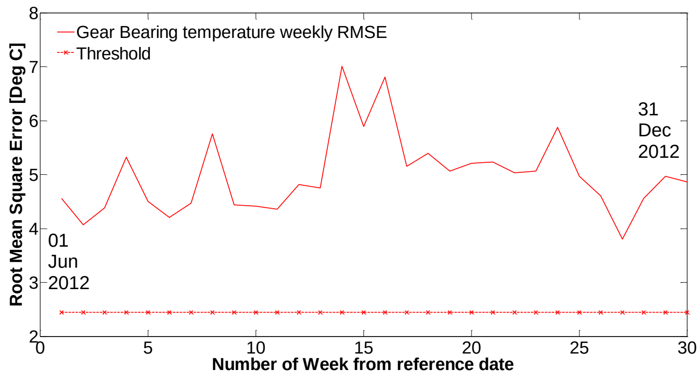


Figure 4-14 *The RMSE value averaged over a week from ANN modeled applied to new gearbox [44]*

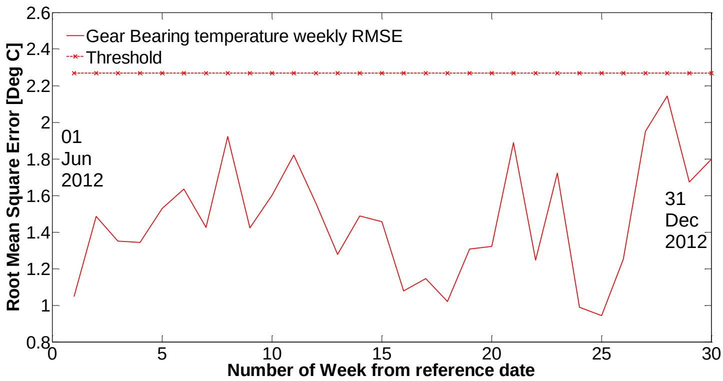


Figure 4-15 *The RMSE value averaged over a week from ANN modeled applied to new gearbox [44]*

In line with the self-evolving approach for ANN modeling, the data from SCADA for the month of February was discarded. This filtering of data is motivated by the assumption that the new component will take some time to adjust in to a routine operation in the system. Collecting data from the '*settling in*' period might result in to erroneous ANN model. Hence, the data from the next two months that are March and April was accumulated and used to train a temporary ANN model which will be used for condition monitoring. Figure 4-15 shows the RMSE output from the newly trained ANN model for the period of condition monitoring from June to December 2012. It can be observed that the RMSE value has not crossed the threshold, which indicates a normal operation of the gearbox. The ANN model output is in line with the maintenance records and the SCADA data.

4.4 ANN Model for Condition Monitoring

In Section 4.2.1 an approach for automated selection of training data set was presented. The presented approach can be used for training ANN model irrespective of its structure. In this Section the specific structure of ANN model selected for condition monitoring application in wind turbines using SCADA is discussed and presented. Further, a statistical approach for analyzing the output from the ANN model to detect an anomaly using the Mahalanobis distance measure is presented and the methodology to decide the threshold is discussed. For training the ANN models, the supervised batch learning procedure describe in Section 3.3.1 is applied and the Levenberg-Marquardt training algorithm is used to decide the synaptic weights.

4.4.1 ANN model architecture

In Section 3.2.3, different ANN architectures were presented. The recurrent neural networks have proven to have better performance than the feed-forward structure

[32]. Consequently, a particular form of recurrent neural network called Non-linear Auto-regressive neural network with exogenous input (NARX) is selected in this thesis work. NARX models have been successfully applied to modeling of non-linear physical systems like heat exchangers and waste-water treatment [46, 47]. Figure 4-16 presents the schematic structure of NARX ANN model used in this thesis.

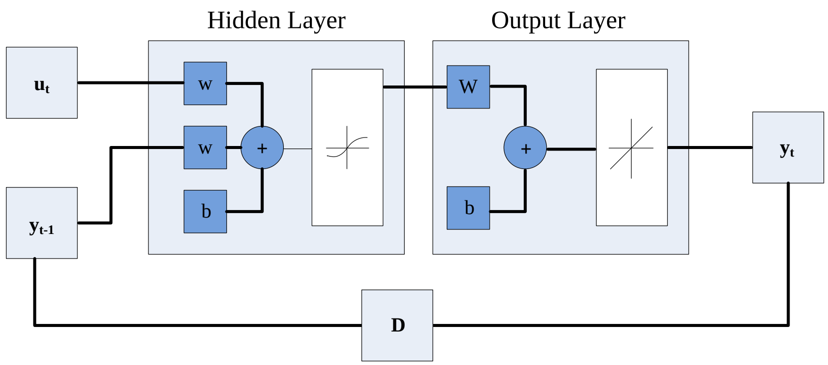


Figure 4-16 *A Non-linear Autoregressive network with exogenous input (NARX) structure for ANN*

u_t represents the input vector at time instant 't' and y_t is the corresponding output. 'w' is the weight vector in the hidden and the output layer. D is the delay vector, which decides the delay in feedback between output and input.

The input u_t represents the exogenous inputs as they originate from outside the neural network. The ANN model output y_t is regressed on delayed value of output y_{t-1}. The generalized behavior of the NARX model of Figure 4-16 is expressed in Eq. 4-7.

$$y_t = F(y_{t-1}, \dots, y_{t-D}; u_t) \qquad \textit{Eq. 4-7}$$

In order to decide the value of the delay vector D it is important to consider the dynamic behavior of the system being modeled. In this thesis, ANN based condition monitoring approach is applied for gearbox condition monitoring. Hence, it is desirable to model the dynamic behavior of the gearbox. It is assumed that the gearbox has a certain thermal inertia and the value to temperature for the bearing at instant *(t-1)* will influence the value of bearing temperature at instant *t*. However, as the measurements are 10-min average measurements, no further delayed temperature signals were included in modeling of gearbox bearing temperature at time instant *t*. Hence, the delay vector *D* is considered to have only one delay value, which results in only y_{t-1} being fed back to the input side. Hence, the specific formulation of the ANN model is described in Eq. 4-8.

$$y_t = F(y_{t-1}; u_t) \qquad \textit{Eq. 4-8}$$

4.4.2 ANN model structure

There is no standard methodology to decide the optimal number of neurons in the hidden layer of the ANN. An iterative process was adopted where the output of the neural network outputs with different number of neurons in the hidden layer were compared. It was found that the neural network with 20 neurons in the hidden layer gives the best performance for cases with different number of neurons investigated.

In addition, it is important to verify the influence of each input on the output. If it is found that an input does not have an influence on the output it can be neglected. However, in order to give a physical significance to the model, the inputs that have a physical effect on the gearbox bearing temperature have been selected. The ANN model inputs and outputs will be discussed in more detail in Section 4.6. However, for the purpose of demonstration an ANN model and its output are presented in this section. Table 4-3 shows the details for the ANN model used for the purpose of demonstration.

Table 4-3 *The specific details for the ANN model*

NARX ANN Model	Model specific details
Number of neurons in hidden layer	20
Number of neurons in output layer	1
Activation function for neuron in hidden layer	Sigmoid function
Activation function for neuron in output layer	Threshold function
Inputs	*u(t)=[Power, Nacelle temperature, Oil temperature, RPM, PCB_B temperature]*
Output	*y(t)=[PCB_A temperature]*

The ANN model selected is designed to model the temperature of the rotor end planet carrier bearing (PCB-A), refer Figure 2-5. Power produced by the wind turbine, nacelle temperature, gearbox oil temperature, rotations per minute and the bearing temperature of non-rotor end planet carrier bearing are used as inputs for the modeling. Figure 4-17 shows the comparison of the ANN predicted output and the actual temperature measured, extracted from SCADA, for 1000 sample points. It should be noted that these 1000 sample points are different from the one used for training of the ANN model. Hence, the output of the ANN model is based on the inputs that the trained ANN model has not seen before.

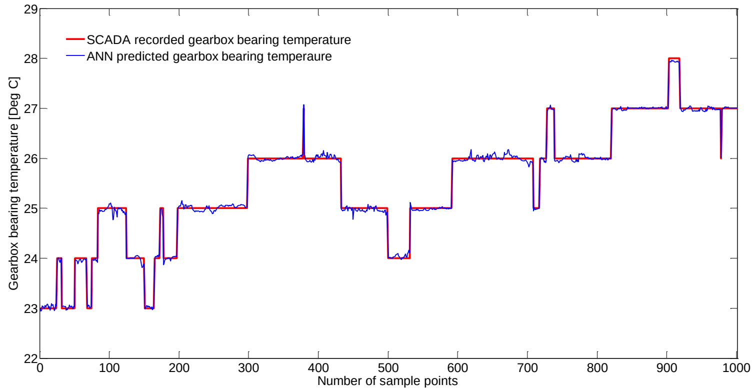


Figure 4-17 *A comparison of ANN modeled output and actual SCADA recorded temperature values*

It can be observed that the ANN model is able to predict the temperature value as well as the gearbox bearing dynamics very accurately. In line with the result, all further ANN models presented have 20 neurons in the hidden layer and 1 neuron in the output layer. However, the inputs and output will vary depending on the specific bearing which is being modeled.

4.4.3 Anomaly detection

An error from the ANN model is defined in Eq. 4-5, it is the difference between the estimated parameter value from the ANN and the real measured parameter value stored in SCADA. At any given time there exists some error in the ANN model due to inaccuracies during modeling stage. Anomaly detection is the process of differentiating any normal error with the ones that might be important from condition monitoring perspective. Hence, anomaly detection is an important step in the process of condition monitoring using ANN.

A major drawback of ANN methods is the lack of physical understanding of the system being modeled. As there is no analytical modeling involved, ANN methods are black box models wherein the relationship between the input and the output is derived solely based on understanding of representative data provided to the ANN model. Even though care can be taken to ensure that the training data is free from errors, it cannot be ensured that the ANN can model the system without any errors. This could also be attributed to the fact that ANN models have the tendency to get stuck in local minimum during training, giving rise to inadvertent errors.

To overcome this drawback of the ANN modeling method, a statistical approach for anomaly detection using a distance measure called Mahalanobis distance is suggested in this thesis.

Mahalnobis Distance measure:

Mahalanobis distance (MD) is a unit less distance measurement, which has the ability to capture correlation of variables in a process or a system. Mahalanobis distance gives a univariate distance value for a multi-variate data. Mahalanobis distance has been applied successfully to capture outliers in different fields of application; see for example [48, 49]. Figure 4-18 shows a simple example case for Mahalanobis distance measurement, this example has been adopted from Matlab demonstration files. The reference data set is shown by a scatter of points on the XY axis. The dark highlighted points are the new data points for which Mahalanobis distance is intended to be calculated. As can be observed from Figure 4-18, all the four points are equidistant from the centre of mass of the reference data set. However, Mahalanobis distance considers the covariance of data and hence is able to determine that the points highlighted in '*red*' are, in fact, outliers as compared to the spread of the reference data. This strength of outlier detection of Mahalanobis distance measurement is utilized for anomaly detection.

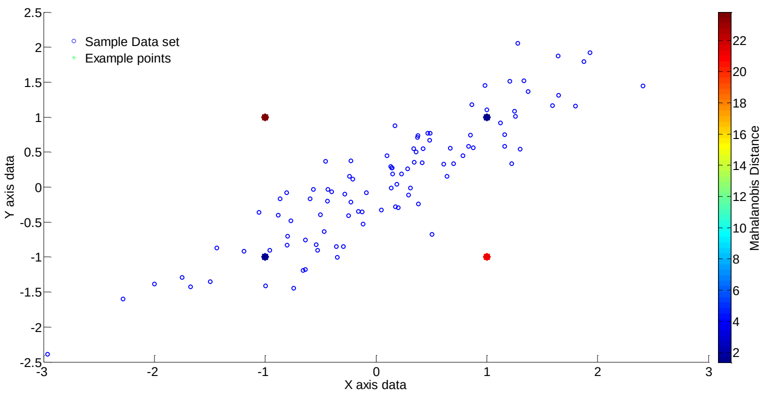


Figure 4-18 *An example for Mahalanobis distance*

Mahalanobis distance measure can be calculated using Eq. 4-9.

$$MD_i = \sqrt{(X_i - \mu)C^{-1}(X_i - \mu)^T} \qquad \textit{Eq. 4-9}$$

$X_i = [X_1, X_2, \ldots, X_m]$ is the i^{th} observation vector where m is the total number of parameters. $\mu = [\mu_1, \mu_2, \ldots, \mu_m]$ is the vector of mean values obtained from the healthy/training data set and C is the covariance matrix for the healthy data set.

A new value of MD, obtained during the condition monitoring stage is calculated using Eq. 4-10 and Eq. 4-11

$$X_{CMstage} = [Error_{CMstage}, SCADA\ record] \qquad \textit{Eq. 4-10}$$

$$(MD_{CMstage})_i = \sqrt{\left((X_{CMstage})_i - \mu_{ref}\right) C_{ref}^{\ -1} \left((X_{CMstage})_i - \mu_{ref}\right)^T} \qquad \textit{Eq. 4-11}$$

The '$SCADA\ record$' in Eq. 4-10 is the actual temperature recorded in the SCADA during the condition monitoring stage and '$Error_{CMstage}$' is the difference between the ANN estimated and actual measured quantities during the condition monitoring stage. Figure 4-19 shows the application of Mahalanobis distance measurement to the ANN based condition monitoring for gearbox bearings. The example application shows 300 sample points. It can be observed from Figure 4-19 that the ANN model estimated and real temperature values for the gearbox bearings are similar with little difference. However, the Mahalanobis distance is high for some sample points.

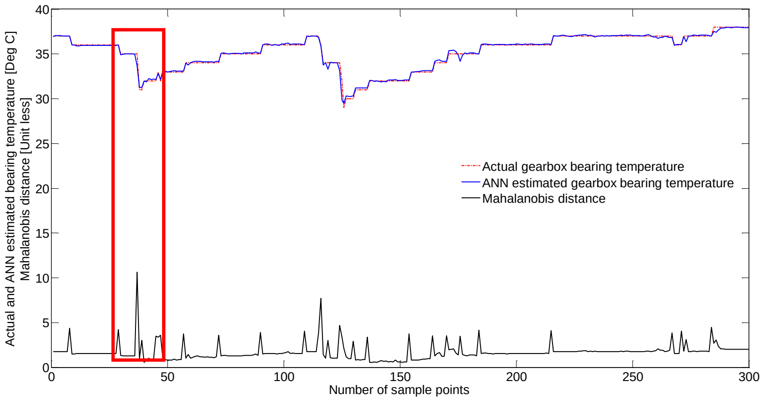


Figure 4-19 *The application of Mahalanobis distance to ANN based condition monitoring of wind turbine gearbox*

Figure 4-20 shows the zoomed in picture for the highlighted part in Figure 4-19. It can be observed that a small deviation between the ANN estimated and actual measured temperature is accompanied by an observable increase in the value of Mahalanobis distance. The ANN is able to model the gearbox bearing temperature accurately; hence, the standard method of using RMSE is considered insufficient. In this regards, Mahalanobis distance measurement gives robust method for outlier detection.

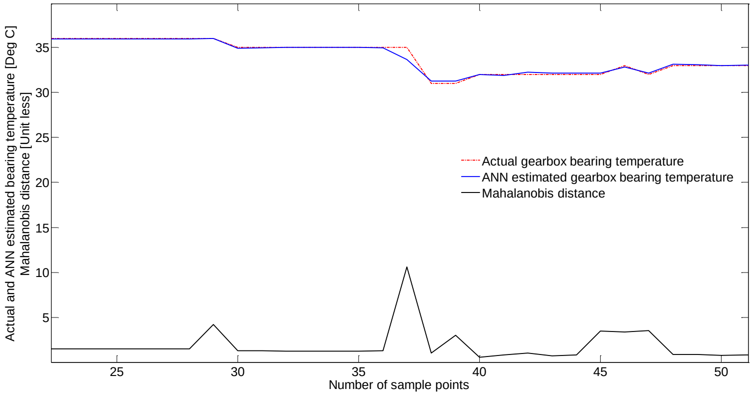


Figure 4-20 *The application of Mahalanobis distance to ANN based condition monitoring of wind turbine gearbox [Zoomed in]*

However, it is important to note that small variations, as demonstrated in Figure 4-20, could occur in the monitored component, which may not point to damage in the component. In order to avoid false alarms during condition monitoring, an averaging of the Mahalanobis distance is done over a pre-defined time period to ensure that the anomaly has existed over a period of time rather than just one instant.

The Threshold value:

For successful anomaly detection, deciding the correct threshold value is important. It has been pointed out that one of the drawbacks of ANN method is the lack of analytical modeling. Hence, in order to ensure that the anomaly is due to deterioration in the component being monitored and not due to inaccuracies in the ANN model, a statistical approach is adopted to decide the threshold value.

The training of ANN model is performed on data set specifically selected from a time span, where there have been no reported failures in the gearbox or the gearbox bearings. Hence, it is natural to consider that the errors between the ANN output and the real temperature value (also refer Eq. 4-5) obtained during the training stage are due to the inaccuracies in the ANN model. This information is used further to decide the threshold value for anomaly detection.

The threshold for anomaly detection is calculated based on the Mahalanobis distance values for errors obtained during the training stage. The Mahalanobis distance for the training data set is calculated using Eq. 4-12 and Eq. 4-13.

$$X_{ref} = [Error, Target\ value] \qquad \text{Eq. 4-12}$$

$$(MD_{ref})_i = \sqrt{\left((X_{ref})_i - \mu_{ref}\right) C_{ref}{}^{-1} \left((X_{ref})_i - \mu_{ref}\right)^T} \qquad \textit{Eq. 4-13}$$

The reference vector is used to calculate the covariance matrix C_{ref} and the mean value vector μ_{ref}. $(MD_{ref})_i$ represents the Mahalanobis distance for the i^{th} row of reference vector. The '*Error*' in Eq. 4-12 is the difference between the temperature estimated by the ANN model and the measurement recorded in SCADA and '*Target value*' is the recorded SCADA measurements used during ANN model training.

The MD values obtained during the training stage can be represented accurately by a two-parameter Weibull probability distribution function [48], defined in Eq. 4-14.

$$f(x) = \beta \eta^{-\beta} (x)^{\beta-1} \, e^{\left(-\frac{x}{\eta}\right)^{\beta}} \qquad \textit{Eq. 4-14}$$

x is the Mahalanobis distance value calculated during the training stage; i.e. MD_{ref}. The shape and scale parameters β and η for the Weibull distribution can be estimated using maximum likely hood method. However, in this thesis work in-built Matlab functionality has been used to estimate the parameters.

The threshold is decided such that the probability of occurrence of the Mahalanobis distance has low probability compared to the spread of data obtained from the training stage. Conceptually, this is done by using the logic that the MD value is an anomaly if $f(MD_{CMstage})_i < 0.01$. Hence, any MD value obtained during monitoring stage, which has a probability of occurrence less than 0.01 is considered to indicate an anomaly in the component. Figure 4-21 shows the schematic representation of the ANN based condition monitoring approach.

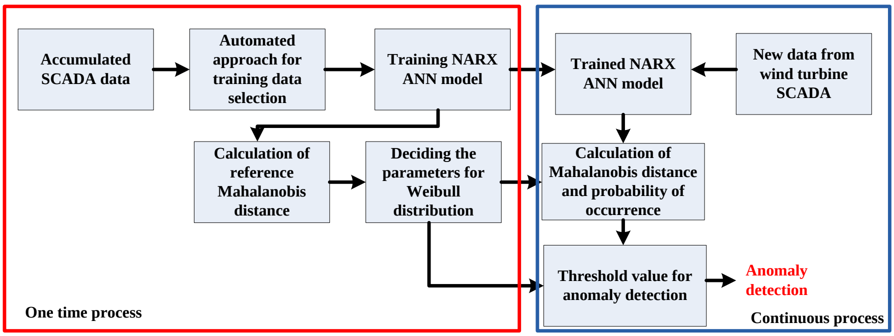


Figure 4-21 *A schematic representation of the ANN based condition monitoring approach*

4.5 SCADA Alarms and Warnings Classification

The SCADA alarms and warnings are important indicators of health condition of components in the wind turbine. The wind turbine manufacturers have their own coding structure in which all the alarms and warnings are coded. This type of coding structure makes it simpler to handle the SCADA alarms and warning. There exists a specific coding structure for SCADA alarms and warning classification for the wind turbines in WT28 database. However, following an analysis on the manufacturer suggested coding structure, it was realized that it could not be adopted along with the ANN based condition monitoring approach proposed in Section 4.4. Hence, a separate coding structure is developed to suit the desired application. The alarms and warnings occurring in the SCADA system are classified using a three character classification system. This classification is done by extracting the raw alarm and warning data in to Microsoft excel and further using basic functions available in excel to generate the desired codes.

The alarms and warnings are divided in nine major categories depending on the component which is responsible for the alarm or warning. The second character of the classification is decided based on the sub-component, which is responsible for the SCADA alarm or warning. The first and second characters are classified as per Table 4-4. The third character is based on the way the alarm is acknowledged and is carried out as per Table 4-4.

Table 4-4 *The first two characters in the coding structure for SCADA alarm and warning classification*

1 st character		2nd Character	
Which component has caused the alarm		**Which subcomponent has caused alarm**	
Environment	1	Wind Speed	1
		Ambient Temperature	2
		Shadow Detection	3
		Ice Detection	4
		Environment Other	5
Generator	2	Generator Control System	1
		Electrical machine	2
		Mechanical components + cooling	3
		Rotor and Control	4
		Invertor/Convertor	5
		Generator Other	6
Grid	3	Transformer	1
		Grid Control System	2
		Grid Other	3
Nacelle	4	Temperature control	1
		Nacelle Other	2

1 st character		2nd Character	
Which component has caused the alarm		Which subcomponent has caused alarm	
Rotor	5	Blades and Pitch System	1
		Hydraulic System	2
		Rotor Control System	3
		Rotor Other	4
Tower	6	Tower	1
Transmission	7	Gearbox Lubrication System	1
		Mechanical Brake	2
		Gearbox	3
		Gearbox Lubrication Control System	4
		Main Shaft	5
Turbine	8	Turbine Control System	1
		Manual Stop	2
		Turbine Other	3
Yaw	9	Yaw Control System	1
		Mechanical Components	2

Table 4-5 *The 3rd character in the coding structure for SCADA alarm and warning classification*

3rd Character	
How is acknowledgment done	
Auto	1
Remote	2
Local	3

The classification can be visualized through an example; the classification code 712 represents a remote acknowledged alarm in the transmission system in gearbox lubrication system.

The classified SCADA alarms and warnings are then displayed together with the ANN based condition monitoring output. This will improve the confidence in the output from the proposed condition monitoring approach.

4.6 Case Study on Two Wind Turbines from WT28 Database

The ANN based condition monitoring approach along with the SCADA alarms and warnings analysis is applied to real data from two wind turbines, rated 2 MW and located in south of Sweden. Due to confidentiality agreement in the project it is not allowed to reveal the names of the wind farm owner or the wind turbine manufacturer. Hence, the wind turbines will be referred to as '*Turbine A1*' and '*Turbine A2*'.

An analysis of the service reports for both wind turbines revealed that there was a gearbox replacement carried out in *Turbine A1* in the month of February in year 2012. A rotor end planet carrier bearing (PCB_A) failure had resulted into the replacement of the gearbox. It was also found that there were no faults or failures reported in the gearbox for the *Turbine A2*. Hence, these two wind turbines were selected for case study so that the proposed ANN based condition monitoring approach can be validated.

The SCADA data for three years starting from December 2010 to December 2013 is available for both the wind turbines. In line with the automated training data selection approach, training data has been selected from year 2011, as there have been no reported gearbox failures for both wind turbines.

Figure 4-22 shows a schematic representation of a three stage planetary gearbox. SCADA temperature measurements are available for five bearings, which have been highlighted. Hence, five separate NARX ANN models are constructed and used at the same time detect anomaly in the system as a whole.

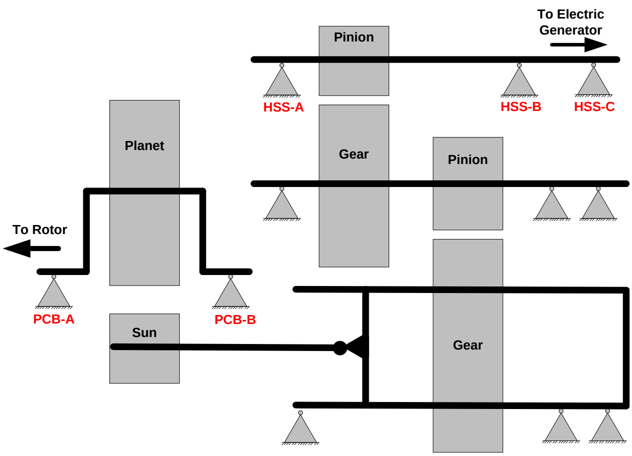


Figure 4-22 *A schematic representation of a three stage planetary gearbox*

The five different ANN models for the above mentioned bearings have a different set of inputs. The power produced by the wind turbine, gearbox lubrication oil temperature, nacelle temperature and rotor RPM are common inputs which will be used in all the models. However, each model has some more model specific inputs which are shown in Table 4-6. The results for the anomaly detection are provided for the condition monitoring period of one year from 1st January 2012 to 31st December 2012. As discussed in Section 4.4.3, in order to avoid false alarms, the Mahalanobis distance measure has been averaged over a period of three days. The averaging period of three days has been selected based on a consideration that the maintenance personnel will check the output of the ANN based condition monitoring once every three days to ensure that the system performance is within limits. If an anomaly is detected a maintenance planning and optimization routine is initiated according to the SEMS framework described in Section 2.5.

Table 4-6 *The inputs for the five different ANN models for gearbox bearings*

Output/ Input	**PCB-A**	**PCB-B**	**HSS-A**	**HSS-B**	**HSS-C**
Power Generated	**x**	**x**	**x**	**x**	**x**
Gearbox oil Temperature [Deg C]	**x**	**x**	**x**	**x**	**x**
Nacelle Temperature [Deg C]	**x**	**x**	**x**	**x**	**x**
Rotor Rotations Per Minute	**x**	**x**	**x**	**x**	**x**
PCB-A Temperature [Deg C]	-	**x**	-	-	-
PCB-B Temperature [Deg C]	**x**	-	-	-	-
HSS-A Temperature [Deg C]	-	-	-	**x**	**x**
HSS-B Temperature [Deg C]	-	-	**x**	-	**x**
HSS-C Temperature [Deg C]	-	-	**x**	**x**	-

4.6.1 Turbine A1: Turbine with recorded gearbox bearing failure

The output from the anomaly detection using ANN based condition monitoring approach for the five bearings are presented. The threshold value has been decided individually for each ANN model based on its own training data.

Figure 4-23 shows the mean value of Mahalanobis distance for PCB-A bearing in *Turbine A1* for the condition monitoring period of one year. It can be observed that the mean Mahalanobis distance has crossed the threshold value in late February. However, there were no accompanying SCADA alarms and warning. In such situations it is recommended that the maintenance service provider or wind turbine operator take a subjective decision based on experience gained through continued application of the proposed approach. Moreover, it should be noted that an inspection at such an early stage could have revealed the deterioration at very initial stages. Information about deterioration in very early stages of development can be useful from maintenance management perspective.

From Figure 4-23, it can also be observed that the mean Mahalanobis distance value has crossed the threshold on 17th Nov 2012 and the difference between the threshold and the mean value of Mahalanobis distance is noticeably large. In addition to this fact, the number of SCADA alarms and warnings which have occurred in the same time period have been higher than normal. These two indication coupled together give a strong indication of deterioration in the gearbox bearing.

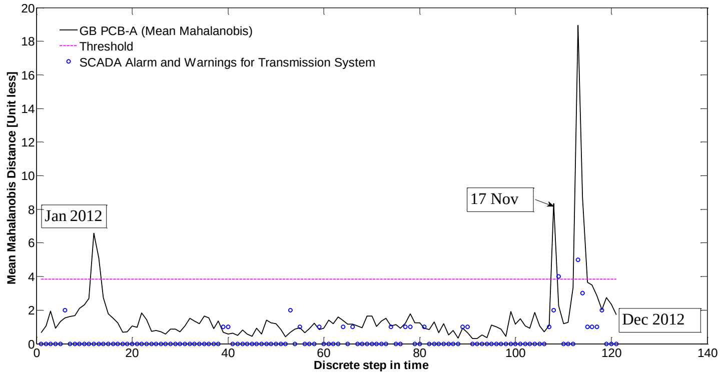


Figure 4-23 *The Mean Mahalanobis distance calculated for PCB-A bearing (Turbine A1)*

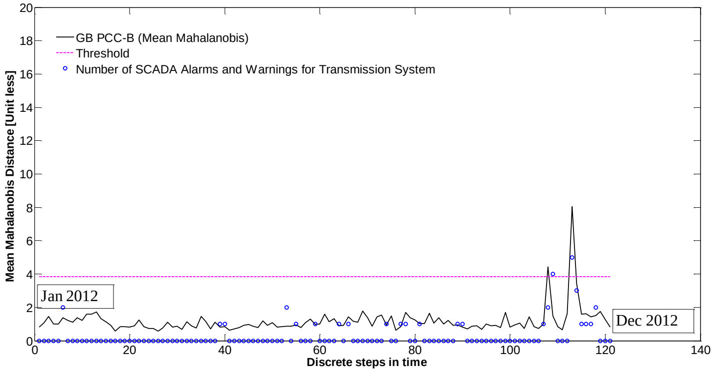


Figure 4-24 *The Mean Mahalanobis distance calculated for PCB-B bearing (Turbine A1)*

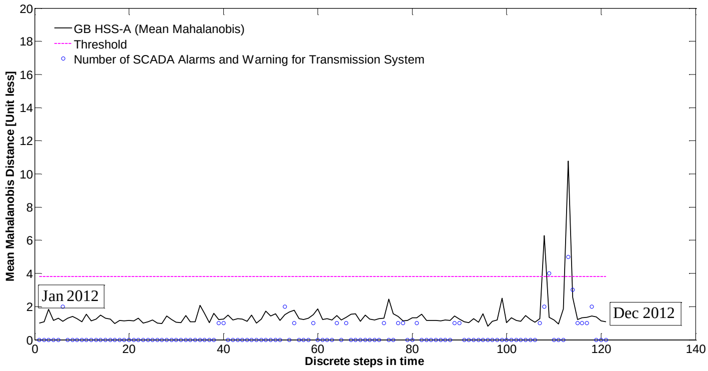


Figure 4-25 *The Mean Mahalanobis distance calculated for HSS-A bearing (Turbine A1)*

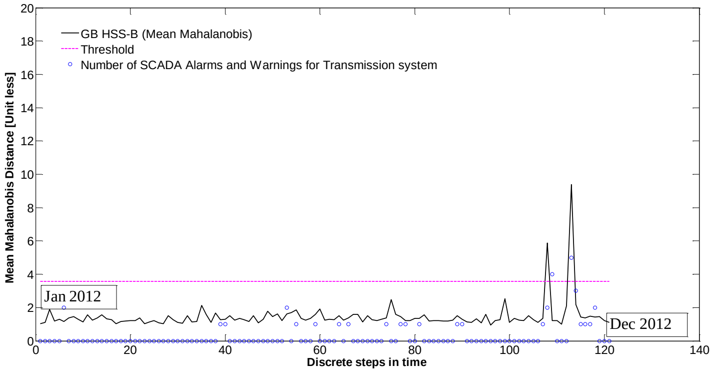


Figure 4-26 *The Mean Mahalanobis distance calculated for HSS-B bearing (Turbine A1)*

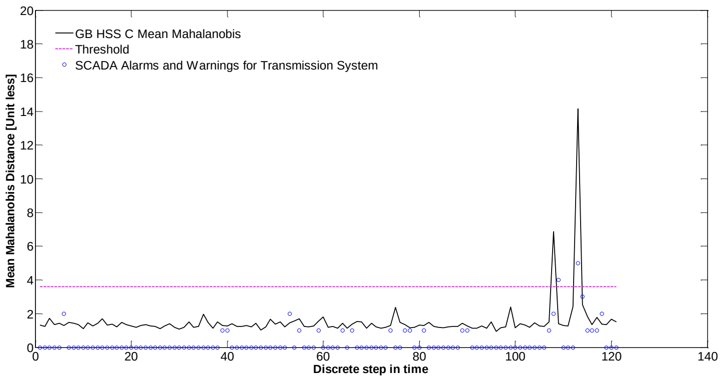


Figure 4-27 *The Mean Mahalanobis distance calculated for HSS-C bearing (Turbine A1)*

Figure 4-24, Figure 4-25, Figure 4-26 and Figure 4-27 present the mean value of Mahalanobis distance calculated over a condition monitoring period of one year for PCB-B, HSS-A, HSS-B and HSS-C bearings respectively. It can be observed that all the bearings show deterioration during the period of 17th Nov. The ANN based condition monitoring shows damage in all the bearings as during this period, due to damage in one of the bearings, all the bearings in the gearbox were operating outside the ANN modeled equilibrium condition. Hence, it can be concluded that even though the ANN based condition monitoring is designed to directly monitor only the gearbox bearings, any damage in the immediate vicinity, for example, in the gears, will also reflect on the bearing measurements.

The vibration based condition monitoring issued an alarm for damage on 23rd Nov and an inspection done on 28th Nov on the wind turbine revealed that the planet carrier bearing on rotor end was damaged due to spalling. Figure 4-28 shows the damaged bearing, the picture was taken during the inspection.

Figure 4-28 *Turbine A1 bearing damage due to spalling (Adopted from WT service report)*

From the presented output results it can also be observed that the Mahalanobis distance value for PCB-A bearing, which was damaged, is the highest compared to all other bearings. This gives an indication as to which bearing might be responsible for the anomalous operation in the gearbox.

4.6.2 Turbine A2: Turbine without recorded gearbox bearing failure

In Section 4.6.1 the ANN based condition monitoring approach was validated with an application to a case with recorded gearbox bearing failure. In order to complete the validation process, the same approach is applied to a gearbox without any recorded gearbox bearing failures.

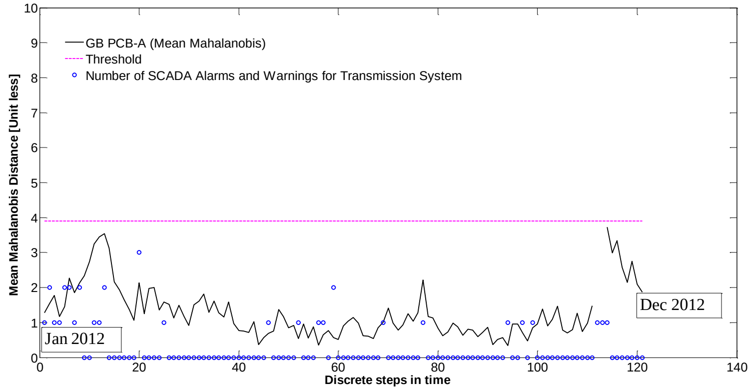


Figure 4-29 *The Mean Mahalanobis distance calculated for PCB-A bearing (Turbine A2)*

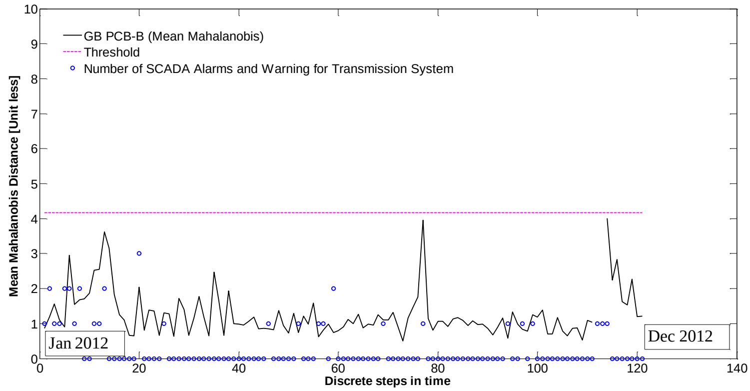


Figure 4-30 *The Mean Mahalanobis distance calculated for PCB-B bearing (Turbine A2)*

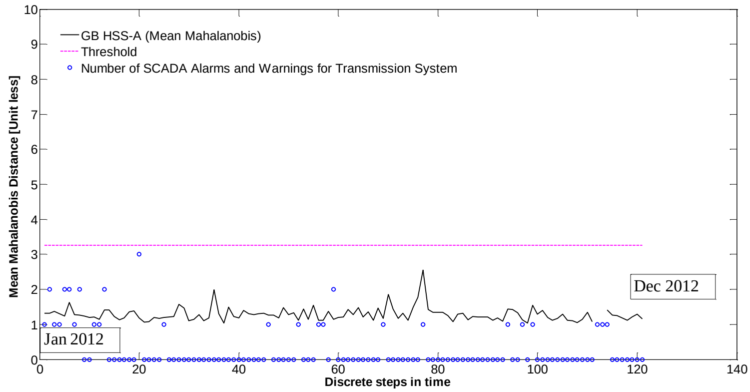


Figure 4-31 *The Mean Mahalanobis distance calculated for HSS-A bearing (Turbine A2)*

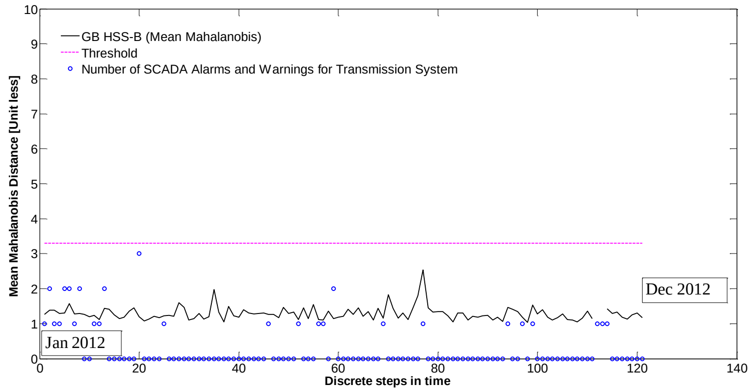


Figure 4-32 *The Mean Mahalanobis distance calculated for HSS-B bearing (Turbine A2)*

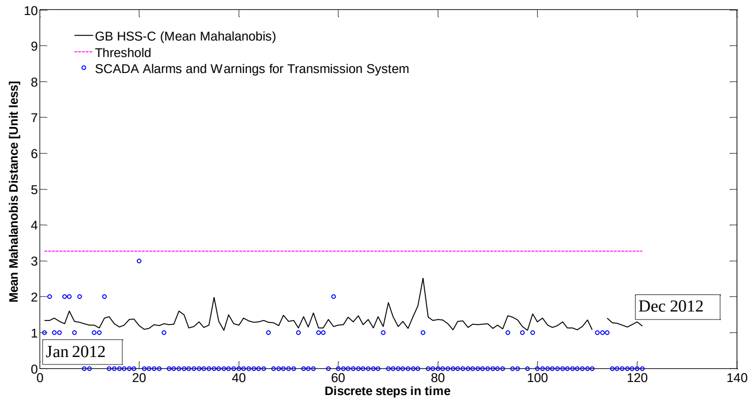


Figure 4-33 *The Mean Mahalanobis distance calculated for HSS-C bearing (Turbine A2)*

Figure 4-29, Figure 4-30, Figure 4-31, Figure 4-32 and Figure 4-33 presents the output of the ANN based condition monitoring for PCB-A, PCB-B, HSS-A, HSS-B and HSS-C bearings respectively for *Turbine A2*. It can be observed that during the entire period of the condition monitoring the mean Mahalanobis distance has not crossed the threshold and there have been no false alarms. Hence, the proposed ANN based condition monitoring approach has been validated for a case without any failures.

4.7 Comparative Analysis

Various researchers have presented ANN based condition monitoring methods using data stored in SCADA system. Most of the previously presented methods are based on a similar philosophy of using the ANN to model the normal behavior characteristics of the component being monitored, in order to detect an anomaly in real time operation. In this subsection the ANN based condition monitoring approach proposed in this thesis is compared to two frequently quoted ANN based condition monitoring approaches [36, 37].

In [36], SIMAP (Intelligent System for Predictive Maintenance) has been introduced. The proposed approach uses ANN to model the normal behavior of the gearbox bearing temperature. A similar model is presented in [37], where the 10-min average temperature data is used to model the normal behavior of the temperature characteristics of the gearbox bearing using neural networks. In both the proposed approaches, anomaly detection is done based on the error between the ANN estimated temperature and the actual measured temperature. In [36], the anomaly is detected based on increasing error value in relation to a pre-defined confidence interval and in [37] the anomaly is detected based on increase in the duration and frequency of errors. However, with regards to the two case studies presented previously, a simple error value; i.e. the difference in estimated and actual temperature, was found insufficient for anomaly detection.

As presented in Figure 4-17 the ANN estimated gearbox bearing temperature is very close to actual SCADA recorded temperature value. Closer analysis of the failure case of *Turbine A1* shows that the operating temperature of the gearbox during the fault condition did not vary significantly from the normal operating temperature. Hence, the RMSE of temperature is not a good indicator of anomalous operation. Figure 4-34 shows the RMSE value for the condition monitoring period of one year for *Turbine A1*.

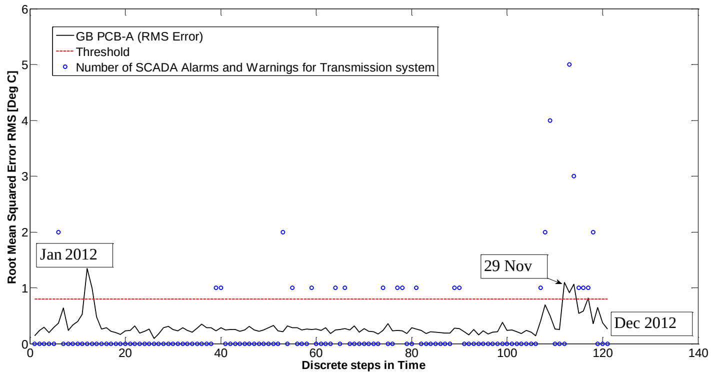


Figure 4-34 *The RMSE value from condition monitoring period for Turbine A1*

It can be observed that even with a low threshold value of 0.8 ^{o}C, it is not possible to detect the anomaly in advance as the difference between the estimated and the actual gearbox bearing temperatures is very small. Hence, in order to overcome this drawback, in this thesis the Mahalanobis distance method, introduced in Section 4.4.3, is used.

Furthermore, the approach proposed in [37] does not define a simple threshold value for anomaly detection. The approach proposed in this thesis provides an easy understanding of the output of the ANN model by providing a threshold value, which is calculated based on the training data. The provision of such a threshold value makes the application of the ANN based condition monitoring simpler, mainly due to the following advantages:

- A subjective judgment about the anomaly by an expert is not required
- There is no need to store the details about the averaged MD value from previous inspection point for anomaly detection

The ANN models presented in [36] and [37] are trained on data set created manually. However, the ANN model proposed in this thesis is using an automatic approach to decide the training data set. The automated training data selection makes it simpler to use the proposed ANN based approach, especially when the number of wind turbines is large. As opposed to both [36] and [37], the approach presented in the thesis also considers the SCADA generated alarms and warnings and aids the maintenance/operation personnel to distinguish the important alarms and warnings. Table 4-7 shows the summary of comparison of the previously proposed ANN based approaches with the approach presented in this thesis.

Table 4-7 *The summary comparison of previously proposed similar approaches with the approach proposed*

Points of comparison	Models in [36] and [37]	ANN based approach proposed in this thesis
Training data set selection	Not discussed in [36], manual in [37]	Automated approach
Anomaly detection	Using difference between estimated and actual temperature	Mahalanobis distance
Threshold value	95% confidence bands in [36], not defined in [37]	A statistical approach for deciding the threshold based on healthy data from training data set
SCADA Alarms and warnings	Not considered	An coding system is proposed to include the information of alarms and warnings together with the condition monitoring

4.8 Drawbacks with ANN Modeling and Mitigation

The advantages of using the ANN based artificial intelligence approach in extracting hidden information in the SCADA date has been highlighted in this Chapter. However, there are few disadvantages of ANN based approach which are discussed in this subsection.

Individuality of wind turbine operations:

- ***Issue:*** Wind turbine is a system made up of a number of sub-systems and components. Even though wind turbines are located in the same geographical area, it cannot be said with certainty that they will behave exactly in the same manner to a set of similar operating conditions. Hence, using one ANN model which could be applied for condition monitoring in all wind turbines is not possible. The conventional method for training data set selection for creating individual ANN models could be very time consuming and a limiting factor in the application of ANN methods.
- ***Mitigation:*** In order to overcome this problem, an automated approach for data selection was created for selection of training data set. The automated approach not only selects an appropriate training data set, but also updated the ANN model after a major maintenance.

Lack of analytical model in ANN method:

- ***Issue:*** ANN is a black box model, which lacks analytical formulation. Hence, an error from ANN model cannot be attributed to a particular reason and has no real physical significance. In case of application to wind turbines, it is also difficult to judge if the error is because of inaccurately modeled ANN or because of anomaly in the monitored component.
- ***Mitigation:*** To overcome the issue of lack of analytical model, a statistical approach is adopted to detect anomalous operation in the monitored component. A statistical distance measurement called Mahalanobis distance is used to detect an error value, which is away from the main centre of mass for normal operating condition error values. In addition to this, a statistical approach is used to decide the threshold value for anomaly detection. The error values, which have a probability of occurrence less than 0.01 are considered to be because of anomaly in the monitored component, all other errors are attributed to inaccuracies in ANN modeling.

Chapter 5

Closure

This chapter summarizes the research work and results in this thesis work. The future work is described and a preliminary mathematical model for SEMS framework is presented.

5.1 Conclusions

The thesis has focused on development of methodology to utilize the information stored in SCADA to estimate the health of a critical component in wind turbine. Furthermore, a maintenance strategy for maintenance optimization based on information about deterioration from condition monitoring system is proposed. The main contributions from the thesis are listed below:

a) Through application of RCAM approach for maintenance management it was realized that gearbox is a critical component in wind turbines and focusing maintenance planning on gearbox has a potential to reduce maintenance costs
b) An ANN based condition monitoring approach based on SCADA data has been proposed for early detection of bearing failures in gearboxes. The proposed approach uses statistical outlier detection method and also incorporates SCADA alarm and warning analysis
c) A self evolving approach to re-train the ANN model has been presented
d) A Self Evolving Maintenance Scheduler (SEMS) maintenance management framework is proposed, which focuses on maintenance optimization in critical components showing visible signs of damage
e) The ANN based condition monitoring approach along with the SCADA alarm and warning analysis is applied to two case studies and the results validate the performance of the proposed approach

5.2 Future Work

The thesis has focused on development of artificial intelligence based method to extract signs of damage from the data stored in SCADA. The results for gearbox bearing condition monitoring using ANN based condition monitoring approach are presented. The future work from this thesis can be listed as follows:

a) Development of similar ANN based model for other critical components in the wind turbine like generator and blades
b) Integration of vibration based CMS with the proposed ANN based condition monitoring approach towards a more robust fault diagnosis
c) Development of detailed mathematical model for the SEMS framework

Preliminary mathematical model for maintenance optimization is presented in this Section. The preliminary models will be developed in detail as future work.

5.2.1 Preliminary Mathematical modeling for SEMS

The SEMS framework provides an opportunity to optimize the maintenance of wind turbines with a focus on critical components, especially the ones which have shown visible signs of damage. The SEMS framework can be developed to optimize the maintenance of one wind turbine or for a collection of wind turbines. In the present case all the wind turbines do not belong to same owner but are managed by same maintenance provider, the SEMS framework can be applied to such cases because of its flexibility.

In order to generalize the model consider a wind farm with $m \in M$, wind turbines and system with a set of $\mathrm{N} := \{1, \dots, \mathrm{n}\}$ components, with condition monitoring system. The maintenance can be done at discrete time steps of $\mathrm{T}_i := \{1, \dots, \mathrm{T}_i^{\max}\}$ after damage in component i ∈ N in wind turbine $m \in M$ is realized. The planning horizon $\mathrm{T}_i^{\max}$ is understood as the maximum time after which the damaged component i has to be replaced. This can be realized by a mathematical model predicting the remaining useful life of the damaged component or by the aid of inspection. However, the replacement can only be done after the spare component is available after a lead time $LT \in T_i$.

A planned maintenance (PM) activity contains two type of maintenance activities denoted by $j \in PM; PM = \{1,2\}$, each planned maintenance activity generates a cost ${C_{ij}}^{PM}; i \in N, j \in PM$. $j = 1$, denotes a small repair done on component i and $j = 2$ represents replacement of the damaged component i; for example replacement of gearbox. Each kind of maintenance activity is associated with time taken to perform the maintenance, denoted by $\tau_j; j \epsilon PM$. The loss of revenue due to downtime during the maintenance is considered by multiplying the term τ_j with the expected cost of energy Cel_t and the expected power production P_t at time $t \in T_i$.

As the component under consideration has already shown signs of deterioration, it is probable that it fails before the scheduled replacement. It is assumed that in such a case, the planned replacement will be shifted to the time of failure. The risk of such an unscheduled maintenance will generate cost, which is presented as '*Risk Index*'. The minimization problem is then represented by Eq. 5-1.

$$min \sum_{t\epsilon T_i}\sum_{m\epsilon M}\sum_{i\epsilon N}\sum_{j\epsilon PM} C_{ijt}{}^{PM} * z_{ijt}{}^{m} + \sum_{t\epsilon T_i}\sum_{j\epsilon PM}\sum_{m\in M} P_t * \tau_j{}^{PM} * Cel_t * y_t{}^{m} + Risk\ Index \qquad Eq.\ 5\text{-}1$$

Variables in the optimization:

$$z_{ijt}{}^{m} = \begin{cases} 1, if\ maintenance\ action\ j\ is\ performed\ for\ component\ i\ at\ time\ t \\ 0, otherwise \end{cases}$$

$$y_t{}^{m} = \begin{cases} 1, if\ maintenance\ is\ performed\ at\ time\ t\ in\ wind\ turbine\ m \\ 0, otherwise \end{cases}$$

Parameters in the optimization:

$P_t =$ Expected average power generated at time t [MW]

$\tau_j{}^{PM} =$ Expected time required for planned maintenance action j [h]

$Cel_t =$ Expected average cost of electricity at time t [SEK/MWh]

$$w_t{}^{m} = \begin{cases} 1, if\ weather\ permits\ maintenance\ in\ wind\ turbine\ m\ at\ time\ t \\ 0, otherwise \end{cases}$$

Constraints in the optimization:

$$\sum_{t\epsilon T_i}\sum_{j\epsilon PM} z_{ijt}{}^{m} \geq 1$$

$$z_{ijt}{}^{m} = 0\ , \qquad j = 2, t \in \{1, \dots, LT\}, i \in N, m \in M$$

$$z_{ijt}{}^{m} \geq y_t\ , \qquad i \epsilon N, j\epsilon PM, m \epsilon M, t \epsilon T$$

$$w_t{}^{m} \geq z_{ijt}{}^{m}\ , \qquad i \epsilon N, j\epsilon PM, m \epsilon M, t \epsilon T$$

$$z_{ijt}{}^{m} \epsilon \{0,1\}\ , \qquad i \epsilon N, j\epsilon PM, m \epsilon M, t \epsilon T$$

$y_t{}^m \in \{0,1\}$, $m \in M, t \in T$

Cost parameters:

$C_{ijt}{}^{PM} = v_{ij} * Sp_{ij} + ScEx_{ij} + ScIn_{ij} + IC_{i(t-1)}$

v_{ij} is number of spares required for maintenance action *j* on component *i*, Sp_{ij} is cost of spare required for maintenance on component *i* for maintenance action *j*. The cost of scheduled external resource required for maintenance action *j* on component *i* is denoted by $ScEx_{ij}$. $ScIn_{ij}$ is the cost of scheduled internal resource required for maintenance action *j* on component *i* and $IC_{i(t-1)}$ is the inventory holding cost for component *i* for time *(t-1)*.

Risk Index:

As the component under consideration is already damaged there is a possibility that the component fails before the predicted end of life. In such a situation any planned maintenance activity will be rescheduled to the point of failure. The rescheduled maintenance activity will be more expensive that the planned activity due to requirement of immediate mobilization of resources. The rescheduling is considered along with a risk factor based on a probabilistic model for failure of the component as per Eq. 5-2.

$$Risk\ Index = (C_{is}{}^{CM} - C_{ijt}{}^{PM}) * \left(\frac{1-\gamma}{\gamma} * \left(\frac{s}{\alpha_i}\right)^{\frac{\beta_i}{\mu}} \right) \qquad \text{Eq. 5-2}$$

$C_{is}{}^{CM}$ is the cost of unscheduled replacement of component i at time $s \in \{t-1, .., T_i - 1\}$ and is defined by Eq. 5-3.

$$C_{is}{}^{CM} = v_{ij} * Sp_i + \pi_s(s) * ScEx_i + \eta_s(s) * ScIn_i + IC_{i(s-1)} \qquad \text{Eq. 5-3}$$

$\pi_s(s)$ and $\eta_s(s)$ are cost functions for external resources and internal resources respectively. These cost function denote the change in price with time, for example; the cost function can be modeled as a linear increase in price for resources with the base value as the cost of scheduled resources. γ is a weighting factor, which decides the amount of risk that the wind turbine owner is willing to take in terms of maintenance optimization. γ close to one is a high risk situation, wherein the wind farm owner focuses on reducing the maintenance cost and is willing to risk the cost that will arise if there is an early failure. However, γ close to zero will make the make the replacement risk free by scheduling the replacement as early as possible to avoid the risk of early failure.

In Eq. 5-2 a factor μ is specified, which is called the '*maintenance incentive factor'*. Conceptually, any maintenance done on the component can extend the remaining useful life of the component. However, it will strongly depend on the component under consideration. The maintenance incentive factor aims at modeling the effect of such a maintenance action with regards to failure rate function for the damaged component. The maintenance incentive factor gives an incentive to perform maintenance action on the component even though there are indications of damage. The formulation of Eq. 5-2 is for demonstration purpose only and will be developed further in the future work.

In Eq. 5-2 it is assumed that the damaged component follows a Weibull function towards the end of its life. α_i and β_i are the scale and the shape parameter for component i respectively. These values can be calculated from the historical data for failures and suspensions for component i. However, the degradation process can also be modeled as other functions like the Gamma function or the Weiner process, depending on the availability of data. Another popular model which helps in tracking the residual life estimates, based on deterioration in a component using predefined covariates, is the Proportional Hazards Model (PHM) [50, 51], which is defined in Eq. 5-4.

$$h(t;\theta) = h_o(t)e^{(\bar{v} * \bar{z}(t))} \qquad \textit{Eq. 5-4}$$

$h_o(t)$ is the base line hazard function, which can be defined as a Weibull hazard function [51]. $h(t;\theta)$ is the hazard function which is influenced by θ, which is a vector of unknown covariates $\bar{z}$ and $\bar{v}$ is a model parameter which gives weight to each covariate in vector $\bar{z}$. The covariates could be the vibration signals from the condition monitoring system or the other parameters which can be extracted from SCADA data.

In addition to the PHM model, various researchers have developed different methods for residual life prediction and degradation modeling. A degradation modeling framework using signals from the condition monitoring system and past history of failures is presented in [52]. An approach for determining the residual life distribution using ANN and CMS data is presented in [53]. In [54] a similar ANN based method for residual life prediction is presented, which uses Weibull fitted condition monitoring series for each failure history to eliminate the effect of data irrelevant to degradation. A Bayesian updating method for updating the stochastic parameters of an exponential degradation model using real-time condition monitoring signals is presented in [55]. A dynamic failure rate model is proposed in [56], which takes into account the historical data about operating conditions and failures for each operating condition to update the failure rate of a component under consideration. In [57] a residual life time prediction model is presented which can be used without prior knowledge of the distribution of failure time signals. The failure time signals at the time of failure are fitted to a Bernstein distribution whose parameters are used to determine the priori distribution of failure signals, which can then be used for future prediction purposes. A data-fitted rolling bearing life prediction model was presented in [58], which can be used for spalling life prediction in rolling element bearings.

Future work in this regard will be development of residual life prediction models based on already presented models or by developing new models which could fit better to the data and purpose at hand.

List of Figures

List of Tables

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