MACHINE PERFORMANCE AND CONDITION MONITORING USING MOTOR OPERATING PARAMETERS THROUGH ARTIFICIAL INTELLIGENCE TECHNIQUES

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DECLARATION

No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

DEDICATION

This work is dedicated to my

Husband,

Who has stood by my side and patiently supported me throughout these past years. Your encouragement and assistance on all things, large and small, are greatly appreciated. Without you, none of this would be possible.

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PUBLICATIONS

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ABSTRACT

Condition monitoring (CM) of gearboxes is a necessary activity due to the crucial importance of gearboxes in power transmission in most industrial applications. There has long been pressure to improve measuring techniques and develop analytical tools for early fault detection in gearboxes.

This thesis develops new gearbox monitoring methods by demonstrating that operating parameters (static data) obtained from machine control processes can be used, rather than parameters obtained from vibration and acoustic measurements. Such a development has important implications for the future of CM techniques because it could greatly simplify the measurement process.

To monitor the gearbox under different operating and fault conditions based on the static data, three artificial intelligence (AI) techniques: a general regression neural network (GRNN), a back propagation neural network (BPNN), and an adaptive neuro-fuzzy inference system (ANFIS) have been used successfully to capture nonlinear variations of the electric motor current and control parameters such as load settings and temperatures.

The three AI systems are taught the expected values of current; load and temperature for the gearbox in a given condition, and then measured values obtained from the gearbox with a known fault introduced are assessed by each of the AI models to indicate the presence of this abnormal condition. The experimental results show that each of GRNN, BPNN and ANFIS are adequate and are able to serve as an effective tool for gearbox condition monitoring and fault detection.

The main contributions of this study is to examine the performance of a model based condition monitoring approach by using just operating parameters for fault detection in a two stage gearbox. A model for current prediction is developed using an ANFIS, GRNN and BPNN which captures the complicated inter-relations between measured variables, and uses direct comparison between the measured and predicted values for fault detection.

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ABBREVIATIONS

AC	Armature current
AI	Artificial intelligence
ANFIS	Adaptive neuro-fuzzy inference system
ANNs	Artificial Neural Networks
BPNN	Back propagation neural network
CBM	Condition based maintenance
CM	Condition monitoring
CP	Control parameters
CT	Current transformer
DAQ	Data acquisition
D_{th}	Threshold
FDD	Frequency division duplex
FFT	Fast Fourier Transform
FIS	Fuzzy inference system
GA	Genetic algorithm
GRNN	General Regression neural network
MF	Membership function
MSE	Mean Square Error
MTBF	Mean time between failures
NNs	Neural Networks
PCI	Peripheral Card Interface
PM	Preventative maintenance
PV	Peak Value
RBF	Radial-basis function
RMS	Root mean square
RMSE	Root mean squared error
STD	Standard deviation

STFT Short Time Fourier Transform

SVMs Support vector machines

TLU Threshold logic unit

WT Wavelet transforms

WVD Wigner-Ville Distribution

CHAPTER 1: INTRODUCTION

This chapter begins by presenting the general background to the research undertaken, which includes a brief review of maintenance strategies. This is followed by an explanation of why operating parameters obtained from machine control processes (static data) can be used for condition monitoring rather than the traditional measurements of, for example, surface vibration and airborne sound. Then there is a short description of the development of condition monitoring techniques. Next the motivation for the project is given and finally the objectives, expected contributions of the research work and layout of the thesis are given.

1.1 Background

Engineering machinery has high capital cost so its cost-efficient use depends on low operating and maintenance costs. Many companies and consumers are now aware of the impact plant failure has on their investments and profitability, and as a result, they are increasingly willing to address maintenance problems before they become serious and affect production. Such an approach will help avoid unscheduled downtime and optimise maintenance activities, effectively reducing per unit cost of production.

As a result condition monitoring (CM) and diagnosis of machinery condition have become established industry tools [1]. CM has become increasingly important, in many and different industries due to an increased need for uninterrupted processing and use of equipment. CM systems using data collection and analysis of parameters which indicate machine condition have become acceptable and even popular due to their ability to provide early warning of machine problems [2].

CM is an organized activity, the monitoring of the condition of an item of machinery to certify its continued ability to perform its required function [3]. CM plays an important role in ensuring both the reliability and minimum-cost operation of industrial facilities by enabling early discovery of machine faults and allowing suitable action to be taken before that fault causes an unforeseen breakdown and, possibly, a catastrophic accident [4]. CM also allows a machine to be monitored during its operation and repaired at planned intervals, which helps to achieve economical operation and reduce possible emissions.

The CM of high integrity plants is a difficult task because it includes a wide range of disciplines, including mechanical, fluid power, electrical, electronic, system control, computers, system modelling and software engineering. Selecting an appropriate and validated CM system is important to ensure increased machine availability, performance and life span, also reduction of spare parts inventories and breakdown maintenance [5]. Many companies have been involved in research in this field, to improve the applicability, accuracy and reliability of CM monitoring services and systems [6,7].

In a control system, the output signal changes according to the control command. It is the measurement of several parameters related to the electrical and mechanical condition of the machinery for example; surface vibration, acoustic emission, temperature, oil pressure, oil debris, voltage, current, conductivity and corrosion which make it possible to determine whether the machine is good and healthy. In addition, machinery models can be established for simulating and predicting the trend of changing parameters [8].

Effective maintenance combines both technical and administrative actions, both are necessary to restore a machine or process to a state in which it can perform a required function [8, 9]. The base of this method is detection of fault, severity assessment and diagnosis of the fault [10].

However, the indicative changes in a machine's condition may be so small that they are hidden by the noise in the system. Many CM books and journal papers are available and much industrial interest has been expressed both in research and provision of services to detect and analyise these signals [11-13]. Current interest is to combine modern transducers and signal processing techniques to differentiate between noise and significant trends, to detect the presence of a fault at the earliest stage and even predict likely time to failure [14].

In summary, CM provides many advantages, such as:

- Avoiding unexpected catastrophic breakdowns with expensive or dangerous consequences.
- Reducing maintenance costs by reducing the number of machine overhauls to a minimum.
- Eliminating unnecessary intervention and subsequent risk of introducing faults on previously healthy machines.
- Reducing the intervention time and thereby minimising production loss (as the fault to be repaired is known in advance and overhauls can be scheduled when most convenient and with parts pre-ordered).
- The clear advantages offered by the application of CM have in recent years led to the development of a vast number of techniques for condition monitoring [15-18].

Of course, there are also certain disadvantages of CM such as the cost of monitoring equipment, operational process and the consequences of false warnings.

1.2 Maintenance Strategies

The core objective of investment for private companies and industries is to achieve maximum profit from minimum spend on plant and equipment. This means increasing machine throughput, reducing maintenance costs per machine and preventing unscheduled delays. Today's plant investors may be fully aware that machine maintenance consumes a significant proportion of plant operating costs, but not appreciate that a well-structured CM programme is necessary to maximise profit [19-20]. However, recently, many companies and consumers have become more aware of the impact plant failure has on profits and, as a result, they are increasingly willing to address maintenance issues. Translating this increased understanding into action will help avoid unscheduled downtime and optimise maintenance activities, effectively reducing per unit cost of production.

It is well known that equipment fails because some of its parts deteriorate and fail. There are usually hundreds of combinations of causes that can make a single item of equipment fail. Fortunately, these causes can be categorised into a fairly short list [20].

1. Over-stressed components.
2. Physical attack.
3. Errors or mistakes.
4. Poor design choices and-or poor manufacturing / assembly quality.
5. Lack of maintenance and care.
6. Unimagined incidents and knock-on effects.

Reducing the maintenance costs can be accomplished by implementing correct maintenance strategies. Maintenance can be defined as work undertaken to maintain (or reinstate) equipment and machines in a good state of repair. [19, 21]

The objectives of maintenance actions are to produce required outputs, maximise designed life span, abide by safety standards and minimise maintenance costs [8].

1.2.1 Pre-emptive detection and elimination

Strategic maintenance planning using this approach should start with appropriate design choices of plant and machinery to reduce the amount of maintenance required. Hence, the planning of strategic maintenance ought to start on the drawing board where the design of machine and equipment determines the maintenance requirements. A simple way to implement this approach is to consider it as a series of answers to ‘what-if’ questions used on each part of the equipment. Depending on the consequence of the effects, one would put into place suitable design features to reduce the impact of failure [19, 20].

Pre-emptive maintenance strategies are the least expensive way to reduce maintenance! Their beauty and wonder is that they are an equipment lifetime strategy that brings continual better operation for the equipment’s entire operating life. The results of using a pre-emptive detection and elimination maintenance strategy are that expected failures from such equipment do not happen [19-20].

1.2.2 Quality control and assurance

This strategy is based on the appropriate and accurate control of manufacture and assembly so that machine and equipment are built exactly as designed. This type of strategy involves tracking a specific, written set of steps and rules on how the work should be done. Operating equipment that is accurately and properly assembled using the right components has longer intervals between repairs, as a result it will have a longer mean time between failures (MTBF). The results of adopting this form of strategic maintenance can be seen immediately through the elimination of mistakes in the design and assembly of the equipment [19-20].

1.2.3 Preventative maintenance

The preventative maintenance (PM) strategy specifies the maintenance tasks (repairs, servicing, or component replacement) to be carried out at set time intervals (or duty cycles), in order to prevent equipment breakdown [22-23]. A planned maintenance strategy can lead to savings in maintenance cost when compared to breakdown maintenance [19-20].

A PM strategy can be divided into two forms.

• The first form is known as the inspection and observation approach and involves inspecting and assesses the condition of equipment and its parts for signs of age and wear, and that includes the regular base services. If evidence of potential failure is found, the damaged part is replaced immediately or at the earliest convenient time before breakage can occur [20]. It is not, however, an efficient use of maintenance resources as work is undertaken regardless of the condition of the machinery, whether needed or not [19,20].

• The second form is known as shutdown overhaul maintenance, and involves intervention and replacement of a part at a certain age, based on experience of the degradation of that part. The replacement is fixed on a set interval shorter than the MTBF. Typically such tasks are undertaken as an overhaul where the whole of the equipment is removed from operation during a shutdown and taken to a workshop to be stripped down to its component parts, and rebuilt as new [20].

1.2.4 Predictive maintenance

Predictive maintenance is a very powerful maintenance strategy which is based on monitoring the health of machinery during normal daily operations, looking for evidence of changed conditions within the machine. It starts by comparing the measured updated machine parameters against the norm, and then determining whether a maintenance intervention is required. If it is possible to detect early onset of failure then it is often possible to manage the equipment carefully and continue operation until a replacement is actually needed.

Using this maintenance strategy and detecting faults long before problems are pronounced can give time to plan maintenance schedules. This method can offer significant financial benefits because it reduces the maintenance cost of equipment operation [24]. Predictive maintenance technique include the use of vibration monitoring, oil debris analysis, thermography, and ultrasonic analysis to detect a change, and measure the rate of change, so that the equipment's continuing performance can be predicted [20].

1.2.5 Breakdown maintenance

In this maintenance strategy, maintenance takes place only when the machine fails. No predetermined action is taken to prevent failure and the emphasis is given to corrective maintenance such as the repair or replacement of the failed components [24]. This is the most costly of maintenance strategies when applied to critical equipment [25]. In general, run-to-failure maintenance is appropriate when the following situations exist [22].

1. The equipment is redundant
2. Low cost spares are available
3. The process is interruptible or there is stockpiled product
4. All known failure modes are safe
5. There is a known long mean time to failure (MTTF) or a long MTBF
6. There is a low cost associated with secondary damage
7. Quick repair or replacement is possible.

1.2.6 Condition based maintenance (CBM)

With this strategy, preventive maintenance is carried out based on knowledge of the condition of a machine or process instead of a predetermined plan or schedule. Ideally this maintenance is able to exploit the maximum running time of a machine or process and yet keep the maintenance cost to a minimum. The key to CBM is knowledge of the condition of the machine. This can be obtained by employing various monitoring techniques that constitute the so-called “condition monitoring” which will be discussed in detail in the following section.

Other maintenance strategies include automatic maintenance, running maintenance, controlled maintenance, off-line maintenance and remote maintenance. They all may be employed in specific situations. Although this involves the interaction of various departments the condition is the predominant factor in scheduling appropriate maintenance actions. [8]

1.3 Condition Monitoring Using Vibration Analysis

Considerable effort has been spent developing reliable methods for gear fault detection. Techniques which have been proven successful include analysis of lubricating oil, the acoustic signal generated by the gearbox when in operation, temperature and performance monitoring, electrical motor current analysis, angular speed of crank and drive shafts and, most popular today, vibration analysis.

Unfortunately, no one technique is able to detect all machine faults. However, it has been suggested that vibration measurement, which is the most widely used CM technique in industry, can accurately identify 90% of all machinery failures by the change in vibration signals which they produce and the level of signal can give an accurate prediction of future failure [26].

1.4 Advantages of Using Operating Parameters Obtained from Machine Control Processes Over Traditional Measurements?

Conventional CM techniques invariably need additional equipment such as data acquisition, sensors, and data processing systems which are expensive and complicated. Alternatively, modern machine control processes provide several different data accessible for machine control and which might be used for CM and which need to be explored.

These parameters are readily available in most industrial applications and do not requires specialist sensor and/or external sensor installation. If these parameters could be used for CM this would substantially reduce the cost of the process while making it substantially easier to implement in industrial environments.

If these parameters could be used for CM a definite advantage would be parallel streams of date providing a rich set of information for CM and fault diagnosis. Furthermore, control parameter based monitoring can be implemented using remote monitoring well away from the machines. It would be unnecessary to have direct access to the machine being diagnosed, there would be no need to access the machine to fix, e.g. mechanical sensors for gathering data. This would be a particularly useful method for inaccessible areas. Such an approach would also overcome the problems associated with with sensor ‘poisoning’ or contamination and changes in sensor sensitivity due to prolonged exposure to harmful materials [27]. Therefore, there would be definite disadvantages of using mechanical sensors:

1. Sensors often operate in a noisy environment and may be adversely affected by it;
2. The different sources may interfere;
3. Transducers may not fit easily into the space available;
4. The instrumentation and transducers will usually require special arrangements and special handling;
5. Data collected will, to a certain extent, be dependent on the position of the transducer.

1.5 Historical Development of CM Techniques

Various effective CM techniques have been developed for machine monitoring and fault diagnosis, these include; visual inspection, electrical, thermal and vibration monitoring [1]. These techniques mainly focus on extracting pertinent signals or features from measured equipment health parameters. However, the related yet more important problem is what methods to use to analyse the information obtained?

Various traditional methods have been used to process and analyse this information. These techniques include conventional computation methods, such as simple threshold methods, system identification and statistical methods. The main shortcoming of these techniques is that they require a skilled specialist to make the diagnosis. This shortcoming has led to the use of computational intelligence techniques for CM. The value of artificial intelligence (AI) can be understood by comparing it with natural human intelligence as follows [28].

• AI is more permanent, natural intelligence is perishable from a commercial standpoint since specialists leave their place of employment or forget information. AI, however, is permanent as long as the computer systems and programs remain unchanged.

• AI offers ease of duplication and dissemination. Transferring knowledge from one person to another usually requires a long process of apprenticeship; even so, expertise can never be duplicated completely.

• AI being a computer technology is consistent and thorough. Natural intelligence is erratic because people are unpredictable, they do not perform consistently.

• AI can be documented. Decisions or conclusions made by a computer system can be more easily documented by tracing the activities of the system. Natural intelligence is difficult to reproduce, for example, a person may reach a conclusion but at some later date may be unable to re-create the reasoning process that led to that conclusion or to even recall the assumption that were a part of the decision.

Various computational intelligence techniques such as neural networks, support vector machines, have been applied extensively to the problem of CM. However, many computational intelligence based methods for fault diagnosis rely heavily on having an adequate and representative set of training data. In real-life applications it is often common that the available data set is incomplete, inaccurate and changing. It is also often common that the training data set becomes available only in small batches and that some new classes only appear in subsequent data collection stages. Hence, there is a need to update the classifier in an incremental fashion without compromising on the classification performance of previous data. Due to the complex nature of online CM, it has been accepted that the software module such as intelligent agents can be used to promote extensibility and modularity of the system [29].

1.6 Research Motivation

Several of research has been carried out into the condition monitoring of gearboxes, but it is a fact that gearbox monitoring methods using the operating parameters obtained from machine control processes rather than the traditional measurements such as vibration and acoustics has not been studied.

This research focuses on developing a new sensor-less method to examine a broken tooth fault with two levels of magnitude of a gearbox transmission system based on the parameters learned from control systems and to demonstrate that the AI methods could detect a fault and could be usefully used to discern the different levels of that fault. The control data, which are available in most machines, including armature current, speed demand, load set point, torque feedback motor current, and speed feedback. The use of these parameters for CM and fault detection has been explored using a gearbox test system.

The motivation for this research is to develop an intelligent system for machine fault detection and condition prognosis based on the use of signal obtain from a controller analysed using AI techniques.

1.7 Research Objectives

The aim of this study is to develop gearbox monitoring methods using the operating parameters (static dataset) obtained from machine control processes rather than the traditional measurements such as vibration and acoustics. The research will incorporate knowledge obtained from both mechanical engineering and computing science.

The main objectives of this study are as follows:

Objective one: To present and discuss machine condition monitoring and its application to a gearbox.

Objective two: To illustrate the fundamentals of a two stage helical gear transmission, including gear types and components, their failure modes and methods of monitoring.

Objective three: To review different techniques being used for fault detection and diagnosis in gearbox condition monitoring using vibration signals and various artificial intelligence based methods.

Objective four: To develop experimental procedures for CM of a two stage helical gear transmission system focusing on a faulty gear (pinion) in the first stage gear transmission system.

Objective five: To examine the performance of a model based condition monitoring approach by using just operating parameters for fault detection in a two stage gearbox.

Objective six: To develop the model by apply different AI techniques such as a general regression neural network (GRNN), a back propagation neural network (BPNN), and an adaptive neuro-fuzzy inference system (ANFIS) to capture the complicated connections between measured variables.

Objective seven: to carry out a comparative study of three methods (GRNN, BPNN.ANFIS) to appraise the accuracy of these AI methods.

Objective eight: To provide useful information to guide future research in this field.

1.8 Thesis contribution

The main contributions of this study can be stated as follows:

- It develops gearbox monitoring methods using the operating parameters obtained from machine control processes rather than the traditional measurements such as vibration and acoustics.
- This research examines the performance of a model based condition monitoring approach by using just operating parameters for fault detection in a two stage gearbox.
- A model for current prediction is developed using an ANFIS, GRNN and BPNN which captures the complicated connections between measured variables for using a direct comparison between the measured and predicted values for fault detection.
- The author has suggested a novel scheme for machine fault detection which utilizes control parameters from embedded sensors and available in most industrial applications. An underpinning technique has been developed and successfully tested. It has the potential to achieve cost effective monitoring system because it is available in most systems.

1.9 Tool and Approaches

In order to achieve the objectives of this study, the following methods have been used:

- The data were collected for the three gear sets: Gear07, Gear08 and Gear09, which were all collected under the same gear operating conditions. Gear08 and Gear09 were induced with 50% and 75% tooth breakage respectively. Gear07 healthy gear is taken as the baseline for model development.
- Acquire the operating parameters obtained from machine control processes as static data.
- Examine the performance of a model based condition monitoring approach for fault detection in a two stage gearbox.

- Applying AI techniques involving GRNN, BPNN, and ANFIS to demonstrate that the AI methods could detect a fault and could be usefully used to discern the different levels of that fault
- Carrying out a comparative study to appraise the accuracy of these methods.

The procedure used for the fault detection is shown in Figure 1.1.

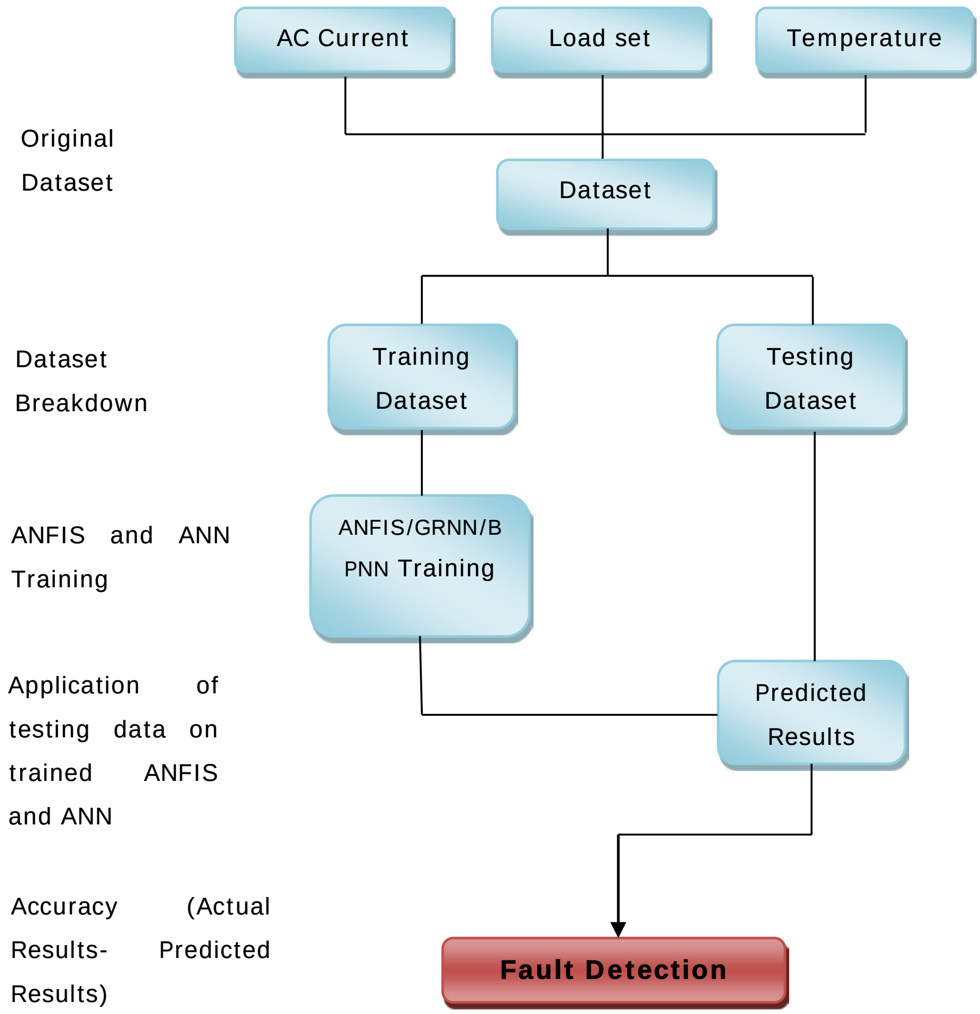


Figure 1.1 Frameworks for gear fault detection

1.10 Organization of thesis

This thesis is organised in nine chapters describing the work that was done to achieve the aims and objectives of this study. This thesis is laid out as follows:

Chapter 2: Gearbox Transmission Systems, their faults and condition monitoring.

This chapter provides a brief description of general condition monitoring techniques followed by a review of the different techniques being used for fault detection in gearbox condition monitoring and various artificial intelligence based methods. Finally, overview of gear types and their operation are given and a brief explanation of why gears fail, and gear failure modes is given.

Chapter 3: Background Knowledge.

This chapter covers the theory underlying the implementation of techniques that will be used later in this thesis. A theory on how to apply model-based diagnosis is covered. Furthermore, this chapter demonstrates the use of residuals in fault detection and diagnosis. The artificial intelligent (AI) methods are introduced in this chapter. Then, Artificial Neural Network (ANN) including General Regression Neural Network (GRNN) and Back Propagation Neural Network (BPNN) are introduced. The reasons for using the chosen modelling technique are discussed. Finally, the Adaptive Neuro-Fuzzy Inference System (ANFIS) and fuzzy logic are described.

Chapter 4: Describes the test rig facility and fault simulation.

This chapter addresses the facilities and fault simulation for the experimental study of the gearbox. It starts by describing the test rig components and control systems. It then briefly explains how the local fault was simulated and how the data was collected. Finally, it describes the load mechanism used in the test rig.

Chapter 5: Condition Monitoring Using Datasets from a Gearbox Rig.

This chapter presents a literature review of signal processing techniques which are used to monitor the condition of geared transmission systems based on vibration signals. Then discusses the dynamic and static datasets collected from the gearbox test rig. As the rig has a typical drive system, the datasets are considered representative for CM practices. Dynamic dataset were analysed to diagnose the condition of the gear: healthy and faulty, using conventional signal processing techniques such as time domain and frequency domain analysis.

The static data was also analyzed by comparison to evaluate the detection performances. This procedure of data collection and analysis allowed gaining a full understanding of CM datasets and paved the way for developing a more effective AI approach and efficient database.

Chapter 6: Model Based Method for Gearbox Fault Detection Using Motor Operating Parameters and General Regression Neural Network.

This chapter examines the performance of a model based method by applying it to the detection of one fault at three levels in a gearbox dataset. The model is developed using a GRNN to capture the complicated connections between measured variables.

Chapter 7: Gearbox Fault Detection using Static Data and Back Propagation Neural Network.

This chapter examines the performance of a BPNN model by applying it to the detection of one fault at three levels in a gearbox dataset. The model is developed using Neural Networks (NNs) to capture connections between measured variables.

Chapter 8: Gearbox Fault Detection using Static Data and an Adaptive Neuro-Fuzzy Inference System.

This chapter develops gearbox monitoring methods using the operating parameters obtained from machine control processes. To monitor the gearbox conditions, an adaptive neuro-fuzzy inference system (ANFIS) is used to capture the nonlinear connections between the electrical motor current and control parameters such as load settings and temperatures. The predicted values generated by the ANFIS model are then compared with the measured values to indicate the presence of an abnormal condition in gearbox.

Chapter 9: Conclusion and Suggestions for Future Work.

This chapter summarises the achievements of the research and explains how the objectives were met. It includes a summary of the author's contribution to knowledge and the novel aspects of the research work. The key results of the research work on the condition monitoring of the helical gearbox using AI with the aid of operator parameter are drawn together. Finally, the chapter ends by recommending areas for future work.

CHAPTER 2: GEARBOX TRANSMISSION SYSTEMS, THEIR FAULTS AND CONDITION MONITORING

This chapter provides a brief description of general condition monitoring techniques followed by a review of the different techniques being used for fault detection in gearbox condition monitoring and various artificial intelligence based methods. Finally, Gear overview types and their operation given and a brief explanation of why gears fail, and gear failure modes are given.

2.1 Overview of Condition Monitoring

In today's industry there are many sources of information on machine health available to an organization's maintenance and operations personnel. The most commonly used sources of information are scheduled inspection of machinery and machinery condition monitoring. CM is defined as the use of technology to assess the condition of a machine's health and, potentially, predict when failure will occur. It should be applied only where the detection methods are reliable and the cost of monitoring is a fraction of the plant reliability benefit [30].

The main principles of CM of machinery are to identify physical characteristics that indicate the current condition of the machine, and to use these measures to identify changes in the condition of a machine that may indicate and identify potential failure. CM is most frequently used as a predictive or condition-based maintenance technique. However, there are other predictive maintenance techniques that can also be used, including the use of the human senses (look, listen, feel and smell) [31].

2.2 General condition monitoring techniques

Modern CM techniques include advanced computerised signal processing and data acquisition systems that have made monitoring and diagnostic systems accessible to all industrial production processes. These techniques are used to detect, diagnose and localise faulty operating conditions at an early stage in order to prevent system failure, and allow predictive and condition oriented maintenance [32].

The optimum method for CM depends deeply on the kind of processes, or machines being monitored and the maintenance services targets. Human sense inspection, for example, could be sufficient to assess the health of an electrical or mechanical process when near to break down; on the other hand an advanced CM approach may be required for a more sophisticated course of action. The selection of CM techniques should take into account both the monitoring objectives and costs. Some of the most commonly used machines and processes for CM methods in today’s industry are discussed in the following sections [32].

2.2.1 Visual inspection

Visual inspection is one of the most basic forms of CM, a very simple technique which makes the use of all the human senses, not just sight, to monitor a machine. Not only does the person inspecting the machine observe, she/he also listens to and touches the machine. The method is simply to listen for a change in the machine noise or, by placing a hand onto the casing detect a change in the temperature or vibration level. Visual inspection offers a flexible and instant assessment of the health condition of a machine, but requires experience and personal skill. Indeed, a significant disadvantage of this method is that different conclusions may be deduced by different inspectors for the same machine due to their individual skills and experiences [33].

The cost of visual inspection is relatively low compared with alternative CM methods. As portable machines become more powerful this technique has improved and been made more objective. The technique now uses a range of tools including simple magnifying glasses or low power microscopes, to stroboscopes, hand-held vibration pick-ups and infrared cameras and endoscopes. Visual inspection has been found particularly useful for detection of cracks, corrosion, leakage, and sub-surface defects [33].

2.2.2 Trend monitoring

This monitoring technique involves repeated measurements of a parameter such as pressure, temperature, torque, noise, electrical current, etc. to detect the changing characteristics of a machine. During the period of the final life phase of rotating machines and equipment, the system condition will deteriorate far from its normal operating condition and faults can occur at almost any time. One significant maintenance strategy goal is to extend the machine's final period life and requires the collection of accurate data .Typically, the measured data is recorded and plotted on a graph as a function of time, to be compared with another set of measurements collected as representative of acceptable or normal machine operation. Differences between the two are used to identify if there is any machine abnormality, to diagnose any fault and assess whether or not corrective measures have to be taken. However, failure of an electronic component in the monitoring system, for instance, could produce false readings using this type of monitoring technique [34, 35].

2.2.3 Vibration monitoring

Vibration monitoring represents a widely used CM technique applied to industrial machinery. Although vibration analysis has been widely used for online monitoring for rotary machine such as bearings, gearboxes, gas turbines, etc [36, 37].

Vibration of equipment is detected by means of an accelerometer, which normally consists of three parts: the sensing element, the transducer body and a seismic mass [38]. There are several reasons for the wide use of vibration monitoring and one is that almost every machine or process will produce vibration in one form or another while in operation. Another reason is that the vibration mechanisms of most machinery and structures are theoretically understood making it possible to predict the characteristics of vibration responses due to these faults. A third reason is the reliable performance of vibration instrumentation such as wide band transducers and portable analysers.

Also the development of vibration signal processing methods and computing facilities contribute to its wide applications.

The difficulties with this monitoring technique may stem from the combination of different vibration sources and noise, the presence of non-linear, non-stationary phenomena and the influences of transmission paths [39]. However, Vibration monitoring is not suitable for all-purpose condition monitoring as it mainly provides vibration related information. Certain types of faults such as wear may not produce significant change in vibration. Nevertheless, vibration condition monitoring has evolved as the predominant and most cost-effective technique.

2.2.4 Performance monitoring

Any machine or process is designed to give or perform certain functions. In this monitoring technique, the main aim is to insure that the concerned machine performs the required functions such as: converting energy from one form to another, generating power output and producing quality products as illustrated in Figure 2.1 [40].

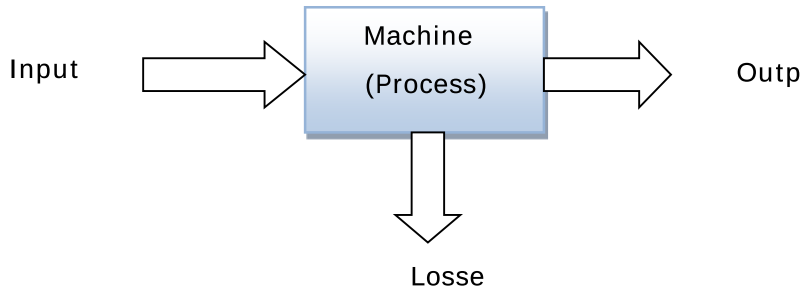


Figure 2.1 Performance monitoring parameters

The condition of a machine or a component can be indicated by the information obtained from Performance monitoring. For example, tool wear may result in an increase of product dimensions and so by checking the product quality, the extent of tool wear can be controlled. This technique employs a variety of transducers to detect changes in load, pressure, speed, power, flow, and temperature [39]. It is a steady state monitoring technique and its problem is that its feedback information may not be provided on time or well enough in advance before the fault occurs. It also requires highly accurate transducers in order to determine outputs.

2.2.5 Acoustic monitoring

Acoustic based CM of machines has been around for many years. Machines when operating create vibration and generate noise, and this technique analyses the acoustic and/or noise signals generated. Generally, microphones pick up the acoustic signals to be analysed, and the relevant monitoring information about the health of the machine is extracted. Acoustic analysis has long been a recognised technique of non-destructive testing. Non-intrusive data collection using, cheap, easy to mount and sensitive microphones is an attractive option for online CM, including gearboxes, bearings, tools and engines [34, 41]. Laboratory results have shown that acoustic monitoring can be particularly useful for the CM of gearboxes [42].

Acoustic monitoring has its own advantages especially when the problem of noise is under investigation; this technique provides a more direct explanation of noise sources and generation mechanisms. However, the influence of the acoustic environment definitely plays an important part in condition monitoring of machines, one of the main problems being the contamination of acoustic signals by background noise. These include influences such as interference from related sound sources (the driving motor, loading generator and cooling fan) and reflecting surfaces [42].

2.3 Gear overview types and their operation

Gears have been used as a mean of power transmission for a very long time. Their function is to accomplish a change of speed, usually rotational. Gearboxes, essentially, consist of a set, or sets, of gears mounted on shafts and supported by bearings. The entire system is enclosed and supported within housing, complete with lubrication. A power source such as an electric motor drives the gearbox input shaft, normally at a relatively high speed. The gears inside the gearbox transmit a reduced speed to the output shaft. When the speed is reduced, there is generally an increase in output torque [102].Gears, in general, operate in groups of two, or more, with the teeth of one engaging the teeth of another and, thereby, transmitting power without slippage. When the teeth of two gears are meshed, turning one gear will cause the other to rotate; such an arrangement allows the speed and direction of rotation to be changed. The gear with the fewer teeth is called the pinion. The speed of rotation is increased when the gear drives the pinion, and reduced when the pinion drives the gear.

The speed reduction ratio of the arrangement is the ratio: (number of pinion teeth)/ (number of gear teeth).

2.3.1 Helical and spur gears

As with most power transmission products, gears come in a wide variety of shapes and sizes to suit different operational functions: spur and helical are among the most used in today’s industry.

Spur gears, have straight cut teeth that run parallel to the shaft driving the gear, see Figure 2.2, and are only suitable when the input and output shafts run parallel to each Other. Spur gears are best suited for moderate speed applications since, during engagement and disengagement, spur gears mesh with a rolling and sliding motion which often causes excessive wear on the gear teeth. Spur gears offer the advantage of producing no axial thrust, and this feature, along with their lower costs, has made them very widely used in general machine applications. Unfortunately, this type of gear produces audible noise which may become objectionable at high speeds [102-103].

Figure 2.2 Spur gear

Helical gears ,Figure 2.3, differ from spur gears because their teeth are skewed at an angle to the axis of the shaft, the helix angle, which can be from a few degrees up to 450 (higher angles tend to reduce load capacities). Hence, teeth enter the meshing zone smoothly and progressively, and mesh with less vibration and less noise than spur gears. The contact line of the meshing teeth progresses diagonally across the face from the tip at one end to the root at the other reducing vibration and noise [103]. In addition, the helix angle creates an extended length of contact line, which results in a higher tooth contact ratio and the load is thus distributed over a greater area. A helical gear can transmit more torque because it has greater tooth strength due to the helical wrap around, and more teeth being engaged (4-5), both factors help it to carry more load than spur gears of the same size [102, 104]. Helical gears can be manufactured in both right and left-handed configurations to transmit motion and power.

Due to their angular cut, teeth meshing results in thrust loads along the gear shaft. The higher the helix angle, the greater the thrust produced. This must be taken into consideration when choosing supporting bearings for the shaft and requires thrust bearings to absorb the thrust load and maintain gear alignment; also the longer the surface of contact the less the efficiency of a helical gear relative to a spur gear [103].

The load over helical gears is transferred by a sliding rather than chopping action, which gives quieter running than spur gears, a better wear rate, and may carry a heavier load than spur gears. They are also capable of transferring power between shafts that run at an angle to each other. By meshing two gears of different diameters, a variation in both speed and torque between the two shafts is obtained. Pinion and gear have different rotational periods, though they both share the same tooth meshing frequency [105]. Helical gear units offer reduction ratios in the range of 3:500, with the higher ratios being achieved by use of multiple stages in the gearbox [106].

Figure 2.3 Helical gear

2.3.2 Gearbox failures

Most gear failures occur when a gear is operated under higher stress conditions than it can tolerate [107]. Gear faults can be classified into two main failure modes, distributed and local faults. In distributed faults, the time between failure initiation and the complete loss of serviceability is usually long and the fault progresses slowly. The gear can still transmit power during the developing fault. These types of faults are usually uniformly distributed on the gear surface and a typical example of this would be the wearing, pitting and scuffing. The second types of failures are known as local faults and they are more insidious. This type of fault develops rapidly once it is initiated and most often it significantly affects the transmission of power. It may have dramatic consequences if it is not detected early. Typical examples of this are a tooth breakage, a cracked tooth and local wear involving one or more teeth. They are briefly summarized below.

Tooth Breakage - There are various reasons for tooth breakage, but most frequently an excessive load is the common cause of the breakage. Often, the tooth breakage starts with a crack in the root of the tooth. It propagates and eventually causes the tooth to break. In some instances, there may be breakage (chipped tooth) at a point in the working tip. The tooth breakage may progressively advance in a single tooth by losing some portions of the faulty tooth. When the faulty gear is operated under this condition the shock of a mating gear may cause the breakage of several consecutive teeth [108]. This type of faults is the main focus of this research. In this work, mainly the progression of a fault in a single tooth is investigated.

Gear Crack - Gear tooth cracks ordinarily start in the root fillet and progress inwardly. The direction of the propagation of the crack is usually unpredictable, but in the majority of the cases it propagates downwards towards the rim of the gear [108, 109].

Localised Tooth Wear - The sliding motion of mating teeth tends to pull the metal away from the tooth surface. If the layer removed from the surface is thick, it will affect the load carrying capacity of the tooth. It usually occurs right across the face width. It may take place in the form of localised wear, which involves a small number of teeth.

2.3.3 Causes of gearbox failures

There are various reasons which may cause gears to fail and they are summarised below [108, 109]:

1. The actual tooth loading may exceed the nominal value for long periods of operation.
2. Non-uniform load distribution over the teeth even if the overall transmitted load is correct.
3. Manufacturing errors - this may be related to incorrect design, inadequate processing or material defect etc.
4. Mishandling - Careless or incorrect usage of gears.
5. Lubrication failure - it often results in loss of oil due to leakage and sometimes a contamination of the lubricant

6. Gearbox bearings – they are usually sensitive to various effects, including misalignment, debris, lubrication and shock. They are likely to start to fail sooner than the gear teeth. Undetected bearing problems may lead to gear failures
7. Imbalance – it initially causes overloading and this gradually destroys the teeth accuracy
8. Misalignment - it affects the accuracy of the mesh contact in the mating gears and it eventually causes gears to fail prematurely.

2.4 Literature review for gearbox condition Monitoring

A wide range of approaches can be employed to extract features and obtain the condition indicative information in rotating machinery. The machine's condition can be estimated by comparing the normal and probable fault conditions. The approaches used vary from simple measuring techniques to sophisticated signal processing methods. This section will provide a summary of most fault detection techniques applied in rotating machinery, particularly in gearboxes.

2.4.1 Time Domain methods

One method is to look at the statistical properties of the vibration signals. They are easy to understand and simple to use. They include measurement of *RMS* (root mean square), *crest factor, peak-to-peak value, skewness, shape factor* and evaluating *Kurtosis* (fourth statistical moment). Applications of these measurements are given in [43-48].

Another frequently used approach is based upon time domain averaging of the vibration signals. This technique is suitable for many applications where a periodic signal needs to be extracted from noisy signals. The applications of this method for gearbox diagnostics can be found in [43, 49-52]. Residual analysis, which requires the removal of major frequency components from the averaged vibration signal can also be used to detect gear faults [43, 49].

2.4.2 Frequency Domain and Cepstrum Analysis methods

Spectral analysis is a simple and widely used technique in vibration analysis and is also frequently employed in gearbox diagnostics. Particularly, the development of the Fast

Fourier Transform (FFT) [44] has made a significant contribution for its wide acceptance to examine signals in terms of their frequency components.

Gearbox vibration is mainly created by the gear teeth action in the mesh. This generates predominant frequency peaks at tooth meshing frequencies and their higher harmonics. With faults, this structure of the spectrum will change. Faults in the gearbox can be detected by comparing the vibration spectra of good and deteriorated conditions. A wide range of applications, including the condition monitoring of gearboxes can be found in [53, 58].

2.4.3 Time-Frequency methods

The standard Fourier transform decomposes a time signal into individual frequency components and it represents the spectrum of a stationary signal without the time information. However, if the signal is non-stationary the spectral composition of the signal will change with time. In this case, the Fourier transform cannot describe the signal properties adequately.

In the presence of an advancing local fault, the gear vibration signal is non-stationary and the Fourier analysis is limited to reflect changes in the gear vibration signals. Therefore, some other methods are required to signify the time-varying properties of the signal. A time-frequency distribution is an ideal tool to define how the spectral content of a signal is changing with time. It can either be performed at constant or at varying time-frequency resolutions. Today, combined time and frequency analysis is increasingly used in gear fault diagnosis and is gradually replacing conventional time-domain analysis and frequency-domain analysis.

The Wigner-Ville Distribution (WVD) is one of the early time-frequency methods and it has been widely used in machinery diagnostics. The early application of the time-frequency methods to gear faults began with the work of Forrester. He applied both Short Time Fourier Transform (STFT) and the WVD to detect gear failures [59-62]. He showed that different faults such as a tooth crack and pitting could be detected by the WVD. Later, Wang and MacFadden, and Staszewski and Tomlinson successfully applied the normal WVD and weighted version of the WVD to detect gear faults [63-66]. The smoothed version of WVD was applied by Baydar and Ball to detect various gear failures [67,68].

Another method of time-frequency analysis is the Instantaneous Power Spectrum (IPS). The technique was used by Baydar and Ball to detect advancing local faults in a gearbox [69-71].

2.4.4 Wavelet transform

With interesting features, the wavelet transform (WT) has gained popularity during the 1990s. The WT has been applied in many applications for fault detection. Gears, as one kind of the most important components in machines, were probably the most exploited objects by wavelets, The successful application of the WT to gear fault detection started with Wang and Staszewski [72,73]. In 1999 Newland used the harmonic wavelet to identify the ridge and phase of the transient signals successfully [74].

Boulahbal et al. [75] used the scalogram on the residual vibration signal of gears. Some distinctive features of the cracked tooth were obtained and the precise location of a crack was detected. Wang et al. [76] experimentally investigated the sensitivity and robustness of the currently well-accepted techniques for gear damage monitoring, including the wavelet transform, and the results show that the wavelet transform is a reliable technique for gear health condition monitoring, which is more robust than other methods. Staszewski [77] made a review on structural and mechanical damage detection using wavelets. Besides gears and cracks, many other objects have been the clients of wavelets. After that the WT has been applied in various ways by different researchers for gear fault detection [78-81].

2.4.5 Artificial intelligence based methods

Artificial_intelligence methods usually include fuzzy logic, neural networks, support vector machines, expert systems and genetic algorithms. Four first ones are widely used in the field of fault detection and diagnostics, either alone or combined with some other method.

A Neural network is the only method that doesn't need the prior knowledge of the component or system's modelling and dynamic character. It is also the best way to overcome the accuracy problem when modelling a system [82].

Using a neural network, one can simulate the behaviour of any system, both linear and non-linear. The advantage of the neural network is that it doesn't need any knowledge of the design of the system [83].

In this section Artificial Neural Network techniques were applied to detect fault in gearbox were described also In the process of development of methods for fault diagnosis, the different Artificial Intelligent techniques, such as, fuzzy inference, neural network, and genetic algorithm have been hybridized. The hybrid techniques used for identification of fault are deliberated in this section.

The Artificial Neural Networks (ANNs) have been used as promising technique in the domain of inverse problem. Saravanan et al [84] dealt with the robustness of an artificial neural network, wavelet and, proximal support vector machine based on fault diagnostic methodology for a gear box. Wu and Chan [85] described a condition monitoring and fault identification techniques for rotating machineries using wavelet transform and neural network method. Samanta [86] compared the performance of gear fault detection using artificial neural network (ANN) and support vector machines (SVMs) and found that the classification accuracy of SVMs is better than ANN without genetic algorithm (GA) optimization while with GA optimization performance of both classifiers is comparable. Jack and Nandi [87] used support vector machines (SVMs) and artificial neural network (ANN) with genetic algorithm (GA) optimization technique to detect faults in rotating machinery. Tran et al. [88] presented a fault diagnosis technique based on adaptive neuro fuzzy inference system in combination with classification and regression tree. The ANFIS controller has been trained with the results obtained from the least square algorithm. They observed that the developed ANFIS model has the potential for fault diagnosis of induction motors. Ye et al. [89] developed a new online diagnostic algorithm to find out the mechanical fault of electrical machine using wavelet packet decomposition method and adaptive neuro fuzzy inference system. According to them the new integrated fault diagnostic system significantly reduces the seal complexity and computational time of the system. They validated results from the diagnostic technique for a 3-phase induction motor drive system. Zio and Gola [90] presented a fault diagnostic problem using neurofuzzy approach. They used this approach for the purpose of high rate of correct classification and to obtain an easily interpretable classification model. The efficiency of the approach was verified by applying to a motor-bearing system, and the results obtained were quite encouraging. Altmann and Mathew [91] presented a novel method, which was based on an adaptive network-based fuzzy inference system, to select the wavelet packets of interest as fault features automatically. Mufti and Vachtsevano [92] fuzzed the fault features extracted by the wavelet transform; and then, a fuzzy inference was applied. Essawy et al. [93] presented an automated integrated predictive diagnostics method for the monitoring of the health of complex helicopter gearboxes. In this method, the neuro-fuzzy algorithm and the sensor fusion were used, and the wavelets were used to analyse the vibration data and to prepare them for neural network inputs. Zhang et al. [94] proposed a bearing fault detection technique based on multiscale entropy and adaptive neurofuzzy inference system (ANFIS) to measure the nonlinearity existing in a bearing system. They conducted experiments on electrical motor bearing with three different fault categories, and the results obtained from the experimentation were used to design and train the ANFIS system for fault diagnosis. Wu and Hsu [95] designed a fuzzy logic-based fault diagnosis system for a gearbox system. Rafiee, Arvani, Harifi, and Sadeghi [96] used a multiple- layer perceptron ANN to classify three different fault conditions and one no-fault condition of a gearbox. Saxena and Saad [97] prepared an ANN for fault diagnosis of ball bearings and applied the genetic algorithm to find the best subset of the ANN input features and the number of neurons in the hidden layer of the ANN and improved the accuracy of fault diagnosis. A. Hajnayeb et al [98] designed a multiple layer perceptron ANN to classify four different conditions of a gearbox using its vibration signals. Zuber N,el [99] demonstrated the use of SOFM and ANN for automatic identification of missing and worn teeth in gearboxes that work under steady loads. It is shown that SOFM can be used for pre-processing phase where a reduced set of vibration features should be defined as inputs in ANN algorithm.

2.4.6 Static data

Static data obtained from machine control processes can be used, rather than parameters obtained from vibration and acoustic measurements.

Benghozzi et al. [100] proposed a new method to monitor and diagnose different faults of a gearbox transmission system based on the parameters acquired from control systems. A nonlinear regression model is adopted to correlate the datasets to obtain residuals from the observed and the predicted control parameters. Subsequently a model based method is implemented to detect common faults such as lower oil levels and shaft misalignment in the gearbox system. The results confirm that it is possible to use existing control parameters for monitoring such faults. Abusaad et al. [101] employed polynomial models to describe nonlinear relationships of variables available from such drives and to generate residuals for real time fault detection and performance comparisons. Both transient and steady state system behaviours have been investigated for optimal detection performance. Amongst 27 variables available from the drive, the torque related variables including motor current, Id, Iq currents and torque signals show changes due to mechanical misalignments. So only these variables are explored for developing and optimising detection schemes. Preliminary results obtained based on a motor gearbox system show that the torque feedback signal, in both the steady and transient operations, has the highest detection capability whereas the field current signal shows the least sensitivity to such faults.

In this research will be examine the performance of a model based condition monitoring approach by using just operating parameters for fault detection in a two stage gearbox. A model for current prediction is developed using an ANFIS, GRNN and BPNN which captures the complicated inter-relations between measured variables, and uses direct comparison between the measured and predicted values for fault detection.

2.5 Summary

This chapter presents a brief description of general condition monitoring techniques and a review of the different techniques being used for fault detection in gearbox condition monitoring and various artificial intelligence based methods. Finally, Gear overview types and their operation given and a brief explanation of why gears fail, and gear failure modes has been presented.

CHAPTER 3: BACKGROUND KNOWLEDGE

This chapter covers the theory underlying the implementation of techniques that will be used later in this thesis. A theory on how to apply model-based detection was covered. Furthermore, this chapter has shown the use of residuals in fault detection. The artificial intelligent (AI) methods are introduced in this chapter. Then, Artificial neural network (ANN) including General Regression Neural Network (GRNN) and Back propagation Neural Network (BPNN) are introduced. The reasons for using the chosen modelling technique are discussed. Finally, Adaptive Neuro-fuzzy inference system (ANFIS) and fuzzy logic are given.

3.1 Introduction

A fault model is a formal representation of the knowledge of possible faults and how they influence the process. More specific, the term fault means that component behaviour has deviated from its normal behaviour. It does not mean that the component has stopped working altogether. The situation where a component has stopped working is, in the diagnosis community, called a failure. So, one objective is to detect faults before they cause failure. [110]

Faults may be modelled as deviations of normally constant parameters from their nominal values. These deviations can be modelled as multiplicative or additive, or a combination thereof. In the case of multiplicative faults, the value of a system parameter changes without an offset. In the case of an additive fault, an offset is introduced without changing the slope of the relation. Typical faults that are modelled in this way are gain errors and bias errors in sensors. Process faults modelled as a deviation of physical parameters.

Another important factor is the choice of residuals as well as functions used for residual generation since residuals are fundamental components in a diagnosis system. A residual is often time-varying, signal that is used as a fault detector. Normally, the residual is designed to be zero (or small in a realistic case where the process is subject to noise and the model is uncertain) in the fault-free case and deviate significantly from zero when a fault occurs. Note, however, that other approaches exist. In case of a likelihood function based residual generator where the residual indicates how likely it is that the observed data is generated by a fault-free process, the residual is large in the fault-free case and small in a faulty case. For the remainder of this text it is assumed, without loss of generality, that a residual is zero in the fault-free case. [110]

3.2 Model based Methods

The aim of model-based fault/defect detection and diagnosis is to create a model based on known and accepted mathematical and scientific principles verified and fine-tuned by past experience to generate accurate predictions of faults and defects likely to occur in target systems. Such models may be quantitative, qualitative or a combined system model. The model-based method is often referred to as an analytical method and has the enormous advantage that it is much less costly than constructing a real-life system for testing (possibly to destruction). Typically, the model of the target system is a continuous-variable dynamic system, with input(s) *u(k)* and output(s) *y(k)* in the presence of an unknown fault. [111]

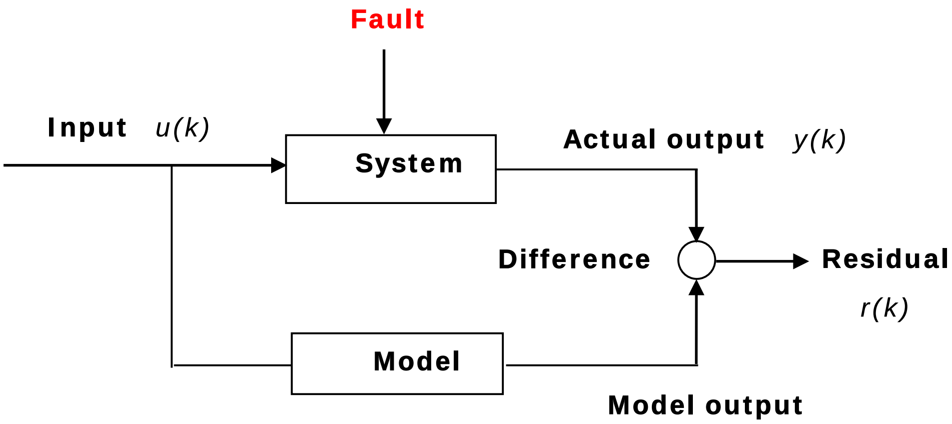


Figure 3.1 Concept of Model Based fault detection

The model based fault detection method can easily find the fault of the system as shown in figure 3.1. Residual *r(k)* in the figure is the difference between the outputs of the model and the actual system. The aim of the model is to generate a residual which can be used to indicate whether a fault is present and to identify that fault. However, the model can also be used “in reverse” information representing the behaviour of the system can be input to the model which produces an output that predicts what change in system components and/or features have taken place to produce that behaviour. The model can then predict likely causes of the change and even suggest other symptoms to search for to aid diagnosis.

A frequency division duplex (FDD) system includes three stages (procedures) with different functions: system modelling, residual generation and fault diagnosis. Firstly, a precise mathematical model is required to accurately predict system performance as model-based methods require such a model of the supervised process [112]. For most systems, such models are often very difficult to obtain. The robustness of the FDD system is often achieved by designing algorithms where the effects of model uncertainties and un-modelled dynamic disturbances on residuals are minimised and sensitivity to faults is maximised [113, 114]. Secondly, a set of residuals is generated to represent the deviation between actual and nominal features. Finally, the residuals are evaluated to relate to certain faults and to locate the fault if it is present. The model implementation and residual generation compose the model-based fault detection system.

3.2.1 Modeling of faults by means of residual generation

These methods generally consist of two basic steps: Residual generation and a decision process to identify the cause. When faults occur, model and process differ and a residual $r \neq 0$ occurs, where broadly residuals represent the differences between various outputs and the expected values of these outputs.

To construct a model-based detection system, a model of the system is needed as well as fault models which describe the effects of different faults. A fault model is the formal representation of the knowledge of possible faults and how they influence the process. In general, better models imply better diagnosis performance, e.g. smaller faults can be detected and more different types of faults can be isolated. [110]

3.2.2 Residual evaluation

With this approach, faults are modelled by signals $f(t)$. Central is the residual $r(t)$ which is a scalar or vector signal of which the elements are zero or small in the fault-free case when $f(t) = 0$, and is nonzero when a fault occurs, i.e. $f(t)\neq 0$.

Diagnosis can be considered as detecting and isolating faults in processes. The diagnosis system is then separated into two parts: residual generation and residual evaluation. This view of how to design diagnosis systems is well established on research conducted by [115]. Thus (Karlsson. 2001) defines the model-based FID as a two-stage process: (1) residual generation, (2) decision making (including residual evaluation). This two-stage process is accepted as a standard procedure for model-based FD nowadays. Residual evaluation can be done using decision logic or a neural net, amongst others. These two methods will now be further discussed.

Residual evaluation by decision logic is an established procedure. The method is often called structured residuals and is primarily an isolation method [115]. A diagnosis system using structured in this method, the first step of the residual evaluation is essentially to check if each residual is responding to the fault or not, often achieved via simple threshold. By using residuals that are sensitive to different subsets of faults, isolation can be achieved. What residuals those are sensitive to what faults is often illustrated with a residual structure.

3.2.3 Threshold definition

In order to detect fault quantitatively, the thresholds have to be defined for the residuals. It is very important that the definition of thresholds for the residuals is independent of disturbances. The disturbances come from unknown input noise signals, modelling errors, etc. Because of the presence of noise disturbances and other unknown signals acting upon the monitored variable, the residuals are usually stochastic variables with mean value and standard deviation for fault free processes.

If the distribution and variance of the noise is known, it is easy to determine the threshold. This method employs a fixed threshold and is therefore easy to implement. Analytic symptoms are obtained as changes of residual signals with reference to the normal values. To separate normal from faulty behaviour, usually a fixed threshold has to be selected. By this means, a compromise has to be made between the detection of small faults and false alarms. The start of the fault can be easily detected by the positive peak (maximum) and the end of the fault can be detected by the negative peak (minimum). This means that when a fault occurs, one or more components of the residual vector will change in magnitude and make it possible to recognise that some change has taken place.

The problem with a fixed threshold is that some part of the signal is ignored. Fixed thresholds are only concerned with the maximum and minimum peak of the signal. However, the basic idea of adaptive thresholds is that since disturbances and other uncontrolled effects vary with time, the thresholds should also vary with time instead of being fixed at a constant value. The adaptive threshold adapts to the disturbances and therefore follows the test quantity as long as there are no faults.

One way of setting the thresholds is to perform a large number of simulations. No two simulations will give exactly the same result since noise is present. The threshold is then set according to a worst case scenario. This will give a system that is unlikely to fire false alarms but unfortunately there is a risk for missed detection instead. The thresholds might be set so high that an alarm is not even generated when a fault is present [110].

3.3 Artificial intelligence (AI) based methods

Model-based fault diagnostics methods require precise mathematical model of the process under consideration, and based on the model and process measurements they monitor the health of the system. In real systems, this may become a problem, since any un modelled dynamics can effect on fault diagnostics process. Model-based methods are still widely used in fault diagnostics, but different kinds of AI based methods have also been developed to overcome problems with model-based methods. AI methods have also been combined to more traditional methods e.g. in failure isolation and identification tasks or in building the system models [116], [117].

In order to carry out fault diagnostics, some representation (or reference) of correct or normal behaviour has to be developed. This reference is the most important part of a fault diagnosis system. The consequences of a poorly defined reference are a failure to detect faults or the generation of false alarms. A model-based approach to diagnostics involves using a mathematical description of the system as a reference of correct behaviour. A diagnostics scheme can use various types of models, such as, neural networks models, fuzzy rules, characteristic curves, etc. This research advocates the use of artificial neural networks models (ANNs) and Adaptive Neuro-fuzzy inference system (ANFIS) which is briefly described in this section.

Unlike with statistical methods, the models of artificial intelligence (AI) methods are usually implicit, and the parameters have no physical meaning. Basically, AI methods have two types of parameter, user-defined and training-data-defined [118]. Here, the parameters are the training-data-defined. AI techniques are useful for determining the relationship data has with its input variables of applications where conventional methods such as statistics are too complicated or not valid. Non-linear systems are an example of applications which can be evaluated by AI techniques and which are difficult or impossible to analyse with conventional techniques [118].

Artificial neural networks (ANNs) are the most widely used AI methods. These models are flexible and able to accommodate different methods to enhance classification results. Adaptive Neuro-fuzzy inference system (ANFIS) is one of the ANN models which hybridize the knowledge-based inference system of fuzzy logic technique and learning capability of neural networks. For ANN and ANFIS, all training data are used to determine their models.

3.3.1 Artificial Neural Networks (ANN)

Neural network (NN) models are inspired by the human thought processes. Over 100 billion biological neurons are present in the human brain. The connections between these neurons are called synapses and when the brain learns their strength is modified. Figure 3.2 shows the structure of a biological neuron. [119]

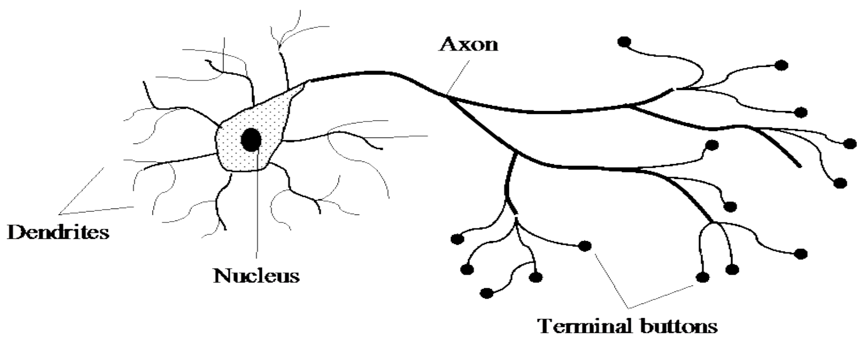


Figure 3.2 Schematic of Biological Neuron

A NN is an attempt at a mathematical model of neuron activity in the brain. This model assumes the neurons are simple processing units. Figure 3.3 show the structure of an artificial neuron. The neurons are arranged into layers and each connection between them has an adjustable weight that is shown in Figure 3.5. In general there are three kinds of layers: Input, Output and Hidden or Processing. Each of the *n* inputs into the neuron has a weighting, w_i (that can be positive or negative), and is the value of this weighting determined as the network is trained. The nucleus arithmetically sums the input values.

Let *n* inputs be a_1, a_2, a_3... a_n and corresponding weights be w_1, w_2, ...w_n. The total input (activation) is thus $A = a_1w_1 + a_2w_2 + a_3w_3 + \ldots + a_nw_n$

It is the fact that the weightings are adjustable that give the NN the capability of learning. Consider just three layers, every neuron in the input layer sends a signal to every neuron in the hidden layer, and every neuron in the hidden layer sends a signal to every neuron in the output layer. Thus if there are N_1 neurons in the input layer and N_2 neurons in the hidden layer, then there are N_1*N_2 paths to each of the output neurons. Obviously the number of possible different arrangements of the layers and the ways of interconnecting neurons offer a vast number of NNs each with a range of possible different methods used to tune the adjustable weights [119].

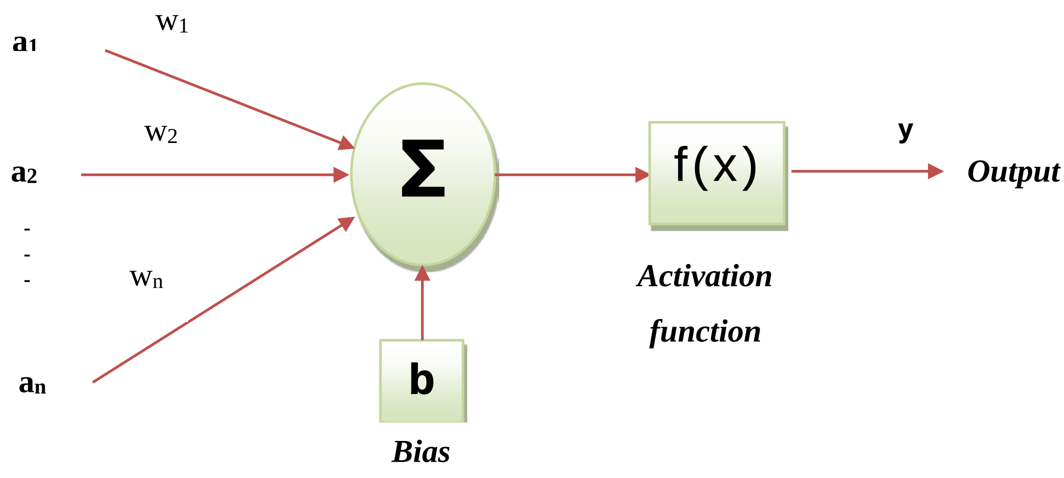


Figure 3.3 Schematic of an artificial neuron

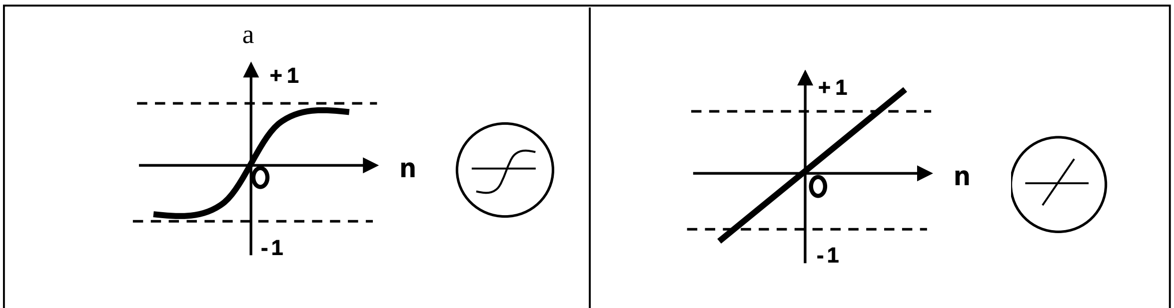
The output of the neuron is given by:

$$y = f(x) = \mathrm{f}(\textstyle\sum_{i=1}^{n} w_i a_i) \qquad (3.1)$$

where: $w_1 a_1$ is the threshold value (polarization), *f (x)* is the neuron activation function, *x* is the summation output signal and *y* is the neuron output, *b* is bias which is added to the network .

Changes can be made to the binary output function, otherwise known as the nodes transfer function. two common transfer functions are shown in Figure 3.4, the pure linear (purelin) and tangent sigmoid (tansig) functions.

these functions give the neuron output range of possible output values between[1,-1], the nature of the transfer function determines the distribution of the outputs [120].



a= tansig(n)
Tan-Sigmoid Transfer Function

a= purelin(n)
Linear Transfer Function

Figure 3.4 The sigmoid and linear neuron transfer functions

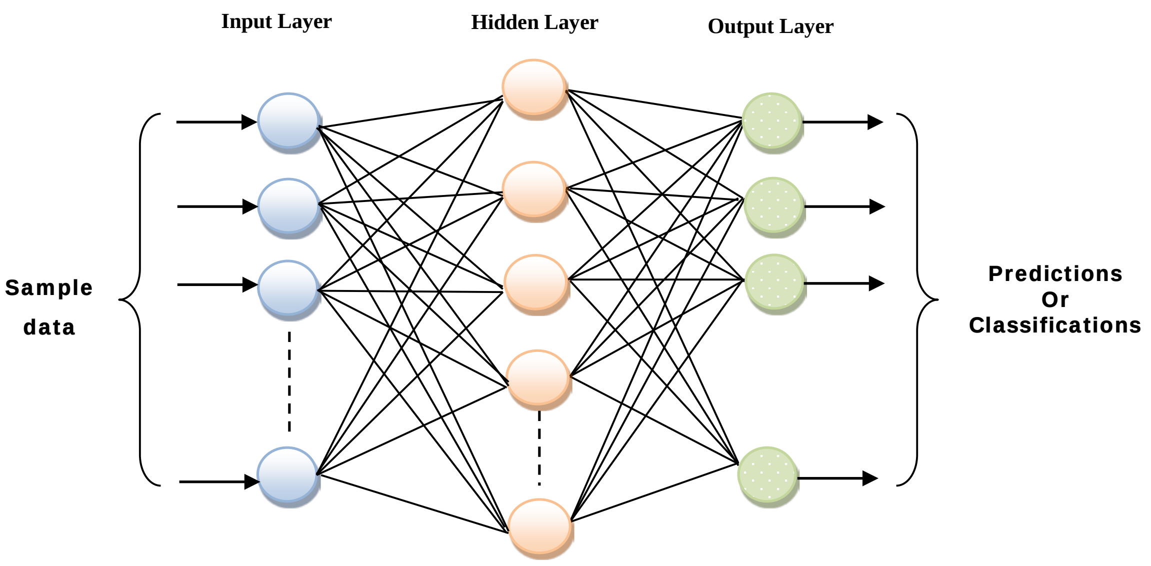


Figure 3.5 General structure of a neural network

There are many different types of neural networks, each of which has different strengths particular to their applications. The abilities of different networks can be related to their structure, dynamics and learning methods.

ANNs are particularly suited to deal with the problem of system identification in dynamic processes for several reasons (for a general reference on neural networks see [121].

The biggest advantage of ANNs manifests itself when dealing with hard problems, e.g. in the case of significantly overlapping patterns, high background noise, and dynamically changing environments. The ANN'S characteristics of adaptive learning generalisation ability, fault tolerance, robustness to noisy data and parallel processing makes it a very interesting candidate for approaching the identification of dynamic events.

3.3.1.1 Analysing the problem

Where processes to be modelled are complex enough to be described mathematically, neural networks are considered to outperform the conventional, deterministic models most of the time. However, one should be aware of the applicability of neural networks to a specific problem and the basic conditions for getting the best performance out of it. In many cases neural networks for research are used 'blindly' by choosing all the possible input variables and without considering much of the possibilities to maximise the performance.

In general, neural networks are suitable for problems where the underlying process is not known in detail and the solution can be learned from the input-output data set. Nevertheless, the following points have to be stressed:

- It has to be made sure that the problem is difficult to be solved by conventional methods and that neural networks can be used as a good alternative.
- If there are logical non-chaotic relationships or structural properties that similar initial configurations indicate mapping to the similar solutions, one can expect a generalisation by neural network. It simply means the same input should always result in the same output.
- If the data set to train the network is impossible to be represented or coded numerically, the problem cannot be solved by a neural network approach.
- Non-linearity and the change of variables in time are possible to be dealt with by neural networks.

Training the network has to be started by defining the topology of the neural network. The best topology is found by adjusting the parameters by trial and error, therefore it is better to start with a small network which learns fast and is easy to change the parameters. When the appropriate network topology is defined, it is possible to speed up or slow down the process by changing the learning rate and fine-tuning.

This is one of the most important stages of any neural network application because the accuracy of the solution for most of the networks depends on the quality and quantity of the training data set. Although neural networks can accept a wide range of inputs, they work with data of certain format encoded numerically.

3.3.1.2 Training of neural networks

Artificial neural networks are designed to operate in a similar manner to their biological counterparts. Biological neural networks in the brain have neurons that receive input stimuli, which are amplified or attenuated by other neurons based on past learning experience, and the outputs are passed to other neurons through synapses. The final output is based on a combination of the output of other neurons.

Artificial neural networks use a similar method by training the network using known inputs and expected outputs. The network continuously adjusts a series of weights associated with each neuron as the network is trained.

A neural network is required to go through training before it is actually being applied. Training involves feeding the network with data so that it would be able to learn the knowledge among inputs through its learning rule. There are two types of training algorithms supervised learning and unsupervised learning.

In supervised learning, the network is shown a series of input and expected output examples. The expected output is compared with the actual output from the network. The network will adjust its weights to accommodate each training example. The purpose of adjusting the weight here is to minimise the difference between the two outputs. The learning rule is used to adjust the weights and biases of the network in order to move the network outputs closer to the targets. The perceptron multilayer learning rule falls in this supervised learning category. [122]

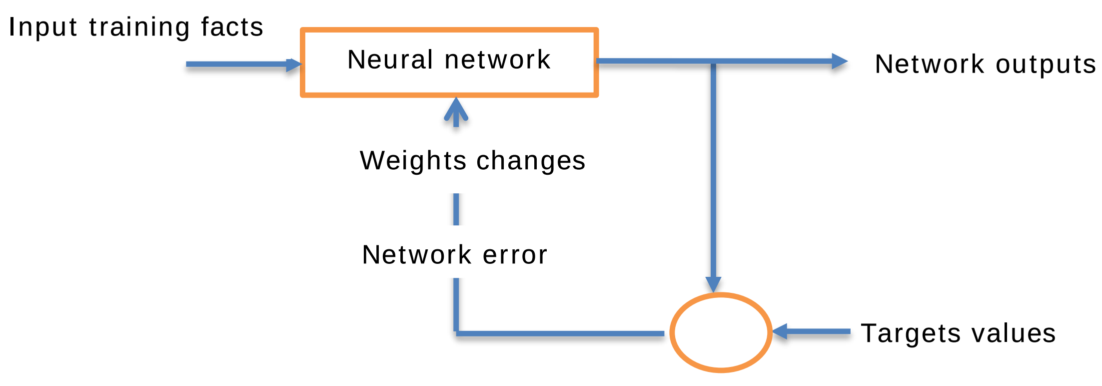


Figure 3.6 Supervised learning [122].

For unsupervised learning, the network is only presented with the inputs but not the output. The network in response to the input patterns updates the weights. That implies that there are no training data like supervised learning [122]. The neural network can only be trained by unsupervised techniques if the relationship between input and output is unknown.

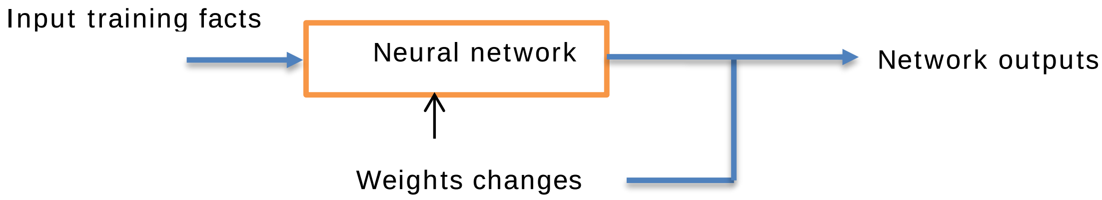


Figure 3.7 Unsupervised learning

The learning process used for the work in this research is supervised learning.

The efficiency of a chosen ANN and the learning strategy employed can be estimated by using the trained network on some test cases with known output values. This test set is also a part of the learning set. Hence the entire set of data consists of the training data set along with the testing data set. The former is used to train the neural network and the latter is used to evaluate the performance of the trained artificial neural network.

There are lots of variations of NN in use today. The aim of this work was to use ANN as a prediction tool. ANNs are efficient in modelling of complex nonlinear phenomena that are present in several types of rotating machinery faults.

3.3.1.3 Motivation for use

One of the many attributes of an ANN is its ability to model multi-input, non-linear relationships making them particularly useful for real-world applications [123, 124]. Another is their ability to learn from experience when supplied with lots of data. It is also said that ANN can develop solutions fast if an appropriate design is used, and generalise from examples. The various attributes of ANN matched the requirements of the system required for this work so it was reasonable to assume they would be a good technique to use.

3.3.1.4 Specific types of neural network

There are lots of variations of ANN in use today. The aim of this work was to use ANN as a prediction tool. We will focus on two kinds of NNs which are generalised regression neural networks (GRNN) and a Back propagation neural network BPNN for gearbox fault detection.

The following two sub-sections explain the reasons for choosing these types.

Generalised regression neural network

A generalised regression neural network (GRNN) is a term first used by Specht [125]. It is a feed-forward type and a variant of the radial-basis function (RBF) type ANN which, according to [127], can be designed in a fraction of the time it takes to train standard feed-forward ANN , GRNN features fast learning that does not require an iterative procedure and highly parallel structure. It was also chosen for this work because it is one of the simplest ANN to use [126]. The GRNN uses supervised learning. The training of an ANN involves showing it a dataset, called the training dataset, containing both the ANN inputs and corresponding outputs together. The training process effectively teaches the ANN so it learns the patterns in the dataset.

To discover the generalisation capability, or accuracy, of the ANN in predicting the output after training has taken place, it must be shown the testing dataset, this time only containing ANN input data. This testing data is processed and a number of outputs, equal to the amount of samples used for testing, is generated. The errors between the outputs from the training dataset and the predicted outputs based on the testing dataset are calculated and used to indicate the accuracy of the NN prediction.

Back propagation neural network

The back propagation neural network (BPNN) is another popular ANN and was chosen to serve as a comparison to the GRNN. Like the GRNN it is a type of multi-layer feed-forward network but it uses the back propagation algorithm.

The whole architecture of the ANN can be changed to suit the needs of the application it is intended to be used for. Parameters include the number of layers the ANN has; the size of each layer (the number of neurons); the transfer function for each layer (used to calculate the output from the input); the learning function; the number of epochs (the number of times the training process is repeated); the error goal (the required error value). Since all these parameters can be varied, it can quickly be seen that to optimise a

BPNN involves a much more intense series of tests. In addition, the number of inputs and their combinations must be varied, as was done for the GRNN [127]

3.3.2 Fuzzy logic

Information available for decision-making is usually not black and white; it generally involves some subtle “grey areas”. Fuzzy sets and fuzzy logic were developed to represent, manipulate, and utilize uncertain information and to develop a framework for handling uncertainty and imprecision in real-world applications [128]. Fuzzy logic systems provide an effective and accurate method for describing human perceptions. It accomplishes this by allowing computers to simulate human reasoning with less bias, and to behave with less analytical precision and logic than conventional computing methods [129]. Unlike the traditional hard computing techniques, such as using firm and precise mathematical formulas, soft computing strives to model the pervasive imprecision of the real world. Solutions derived from soft computing are generally more robust, flexible, and economical than those provided by hard computing [131].

Fuzzy logic provides an inference structure that enables approximate human reasoning capabilities to be applied to knowledge-based systems. The theory of fuzzy logic provides a mathematical strength to capture the uncertainties associated with human cognitive processes, such as thinking and reasoning. The conventional approaches to knowledge representation lack the means for representing the meaning of fuzzy concepts. As a consequence, the approaches based on first order logic and classical probability theory do not provide an appropriate conceptual framework for dealing with the Fuzzy logic provides an inference structure that enables approximate human reasoning capabilities to be applied to knowledge-based systems. The theory of fuzzy logic provides a mathematical strength to capture the uncertainties associated with human cognitive processes, such as thinking and reasoning. The conventional approaches to knowledge representation lack the means for representing the meaning of fuzzy concepts. As a consequence, the approaches based on first order logic and classical probability theory do not provide an appropriate conceptual framework for dealing with the representation of commonsense knowledge, since such knowledge is by its nature both imprecise and noncategorical. The development of fuzzy logic was motivated by the need for a conceptual framework which can address the issue of uncertainty and imprecision. Some of the essential characteristics of fuzzy logic relate to the following [130]:

- Exact reasoning is viewed as a limiting case of approximate reasoning.
- Everything is a matter of degree.
- Knowledge is interpreted a collection of elastic or, equivalently, fuzzy constraint on a collection of variables.
- Inference is viewed as a process of propagation of elastic constraints.
- Any logical system can be fuzzified.
- In addition, there are also two main characteristics of fuzzy systems that give them better performance for specific applications:
- Fuzzy systems are suitable for uncertain or approximate reasoning, especially for the system with a mathematical model that is difficult to derive.
- Fuzzy logic allows decision making with estimated values under incomplete or uncertain information.

In order to deal with imprecise or ill-defined systems, Fuzzy logic uses graded or quantified statements rather than ones that are strictly true or false. The fuzzy sets allow objects to have grades of membership of values ranging from zero to one. These sets, represented by linguistic variables, are used to represent a particular fuzzy set in a given problem, such as “large”, ”medium” and “small”[128]. For instance, if U is a collection of objects denoted generically by {u}, which could be discrete or continuous, U is called the universe of discourse while u represents the generic element of U. A fuzzy set F in a universe of discourse U is characterized by a membership function μ_F which takes values in the interval [0, 1]. A fuzzy set F in U may be represented as a set of ordered pairs of a generic element u and its grade of membership function as follows:

$F = [(\mu, \mu_F(u)) / u \in U]$

$F = \int_u \mu_F(u) / u \; du$

$\sum_{i=1}^{n} \mu_F(u_i)/u_i$ (3.10)

Fuzzy sets have some operations that can be applied to crisp sets, as a subset of fuzzy sets. Assume that A and B are two fuzzy sets in U with membership function μ_A and μ_B, respectively. The set theory operation of union, intersection, complement and other relations of fuzzy sets are defined by their membership function. For example, the membership function $\mu_{A \cup B}$ of the union A∪B is point-wise defined for all u ∈ U by:

$$\mu_{A_\cup B}(u) = \max[\mu_A(u), \mu_B(u)] \qquad (3.11)$$

While the membership functions $\mu_{A \cap B}$ of the Intersection A∩B is point-wise defined for all u ∈ U by:

$$\mu_{A \cap B}(u) = \min[\mu_A(u), \mu_B(u)] \qquad (3.12)$$

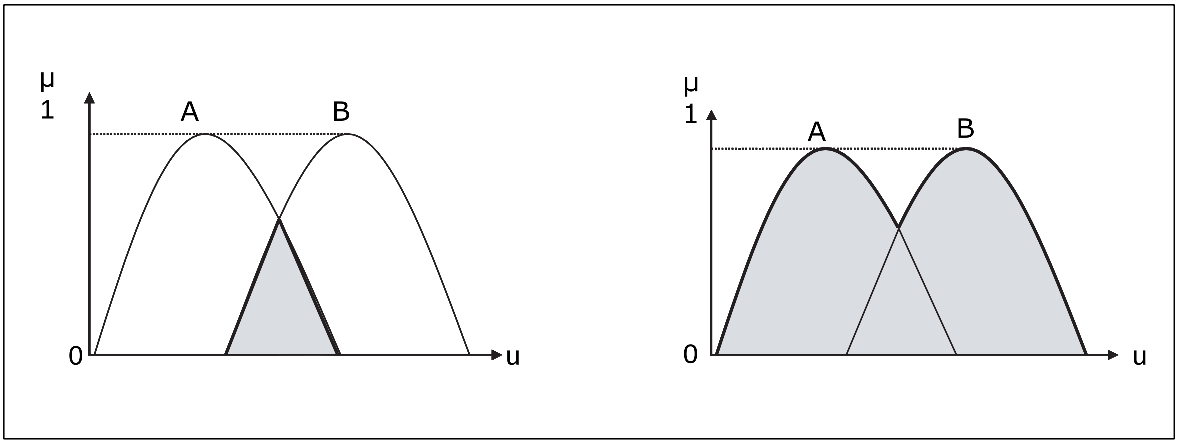


Figure 3.8 Intersection and union of two fuzzy sets

The fuzzy inference system (FIS) is the process of formulating the mapping from a given input to an output using fuzzy logic. The dynamic behaviour of an FIS is characterized by a set of linguistic description rules based on expert knowledge. This expert knowledge is usually of the form: [132].

IF - a set of antecedent conditions is satisfied

THEN - a set of consequences can be inferred.

Since the antecedents and the consequent of these IF-THEN rules are associated with fuzzy concepts (linguistic terms), they are often called fuzzy conditional statements [133]. In the case of multiple-input-single-output (MISO) fuzzy system, the fuzzy rules have the form:

R_1: if (x) is A_1 and (y) is B_1 then (z) is C_1,

R_2: if (x) is A_2 and (y) is B_2 then (z) is C_2,

... ...

R_n: if (x) is A_n and (y) is B_n then (z) is C_n,

where x, y, and z are linguistic variables representing two inputs process state variables and one output variable, respectively.

3.3.3 Hybrid System: neuro-fuzzy inference

There are benefits to using a combination of techniques; some techniques perform well for one class of problem while other techniques may be better suited to other types of problem. Hybrid systems can be constructed using multiple methods, with each method acting independently of one another. When this is the case there needs to be some central control system to decide which problems are sent to which method/sub system. This can be a very powerful approach as it allows a development to take place in sub-systems or modules. This approach also helps to ensure that problems are solved by the most appropriate solution. A flowchart for such a configuration is shown in figure 3.8.

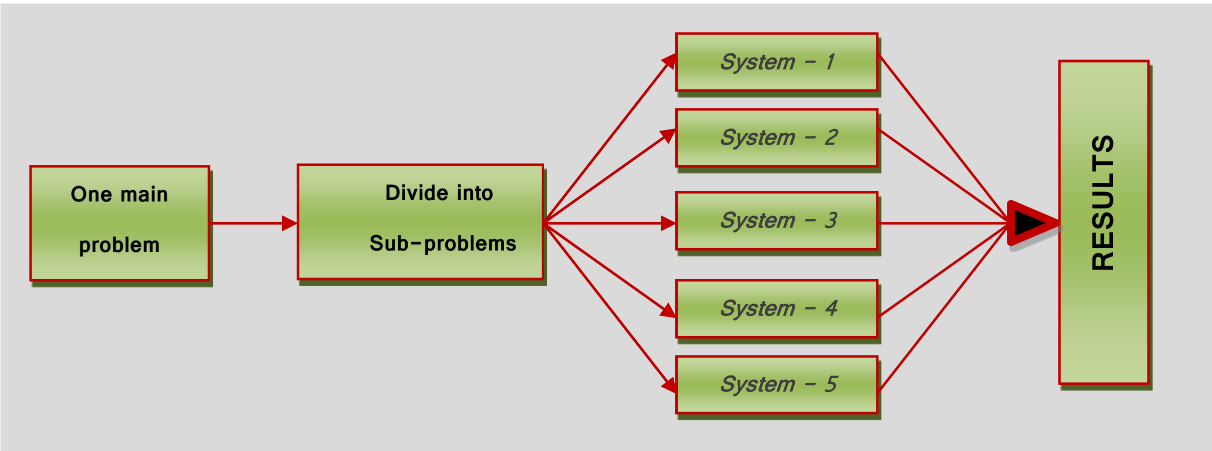


Figure 3.9 A separated hybrid system approach.

An alternative form of hybrid system is the combined use of methods to obtain one result.

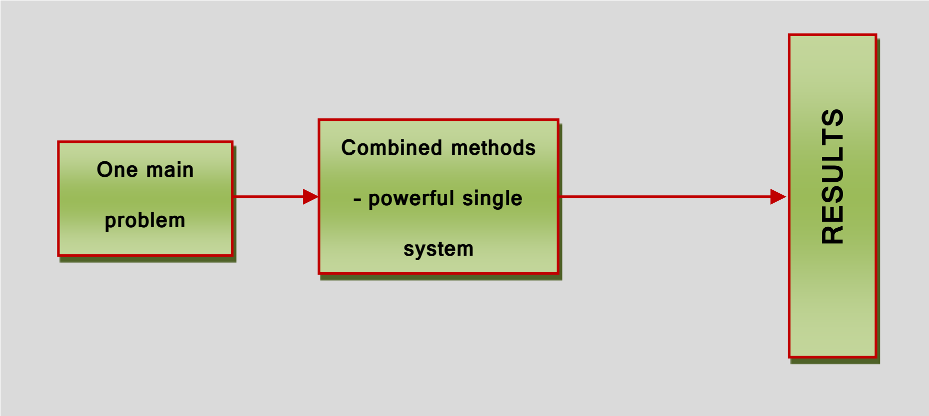


Figure 3.10 A combined hybrid system approach.

Neuro-fuzzy systems are an example of hybrid systems that use one powerful solution method where these two methods are complementary to each other [134].

A neuro fuzzy approach combines the best features of neural based systems and fuzzy systems. The most common implementation of neuro-fuzzy uses an ANN to update parameters of a fuzzy system.

Neural networks are ideal for non-linear modelling and fault classification; however, they are not good at explaining how decisions are reached, due to their 'black-box' characteristic. Fuzzy logic, which is highly suitable for reasoning with imprecise information, can easily explain the decision making process by linguistic expressions, but the rules cannot be obtained automatically for decision making. These limitations, therefore, raise the requirement for hybrid intelligent systems, where two or more techniques are combined together to overcome the drawbacks of each individual method. For instance, a fault detection and diagnosis task normally includes a signal processing task and a reasoning task, where, respectively, neural networks and fuzzy logic can be applied depending on adaptability. The combination of neural networks and fuzzy logic therefore gives the ability to learn and to deal with system uncertainties by using the advantages of each system. [134]

The models composed of neural network and fuzzy logic mainly have two classes depending on whether neural network or fuzzy logic is defined as the input interface or the decision maker. As a system input interface, fuzzy logic responds to linguistic statements and provides a fuzzy input vector to a multi-layer neural network, while the decision making is performed by the neural network. This type of combined system is normally referred to as a fuzzy neural network system. In this system, the weight and neurons are considered to be fuzzy sets. The fuzzy neurons are designed to process fuzzy inputs with linguistic expressions in the form of IF-THEN rules and the fuzzy weights are updated by back propagation algorithms to realise the learning procedure. Conversely, when fuzzy logic is employed as the decision maker, the neural network works as an input interface and receives feedback from output decisions. The architecture of this combination, which is called a neuro-fuzzy system, allows the membership functions of fuzzy logic to be automatically tuned. Since the design and tuning of membership functions are often time consuming tasks, this ability based on the neural network learning mechanism can improve system performance and reduce the time cost of system design.

With the combination of quantitative and qualitative information, the neuro-fuzzy technique is capable of handling complex systems. The neuro-fuzzy model also becomes more transparent than the simulation using a neural network, due to the linguistic expression of rules which humans can interpret. These advantages have resulted in the wide application of this method in industrial processes. [134]

3.3.2.1 Adaptive Neuro-Fuzzy Inference System (ANFIS)

In order for an FIS to be mature and well established so that it can work appropriately in prediction mode, its initial structure and parameters (linear and non-linear) need to be tuned or adapted through a learning process using a sufficient input-output pattern of data. One of the most commonly used learning systems for adapting the linear and non-linear parameters of an FIS, particularly Takagi-Sugeno fuzzy model (TS) type, is the ANFIS. ANFIS is a class of adaptive networks that are functionally equivalent to fuzzy inference systems [135]. The architecture of ANFIS and the main concepts and algorithms adopted during its learning process are described in the chapter 8. The aim of this work was to use ANFIS as a prediction tool for gearbox fault detection and comparison the performance with GRNN and BPNN.

3.4 Summary

This chapter covered the theory underlying the implementation of techniques that will be used later in this thesis. A theory on how to apply model-based detection was covered. Furthermore, this chapter has shown the use of residuals in fault detection and artificial intelligence (AI) methods are introduced. Then, Artificial neural network (ANN) including (GRNN) and (BPNN) has been introduced. The reasons for using the chosen modelling technique were discussed. Finally, (ANFIS) and fuzzy logic has been given.

CHAPTER 4: TEST RIG FACILITIES AND FAULT SIMULATION

This chapter addresses the facilities and fault simulation for the experimental study of gearbox. It starts by describing the test rig components and control systems. It then briefly explains how the local fault was simulated and how the data was collected. Finally, describes the load mechanism used in the test rig.

4.1 Description of the test rig

In order to evaluate gearbox condition monitoring and fault diagnosis, experimental work was carried out on a gearbox test rig developed at the University of Huddersfield .The test rig used in this study is shown in Figure 4.1. It consists of two stage helical gearboxes, a three phase induction motor, coupling and DC motor as a mechanical load. The induction motor is the prime driving component: (a four-pole, 11 kW, 1465 rpm, 3-phase). It is flanged in a cantilever type arrangement to the gearbox. The load component consisted of two flexible couplings and a DC generator.

The gearbox consists of two-stage helical gear transmissions. It was chosen for this research not only because it is widely used in industry, but also because it allows faults to be easily simulated and various CM techniques to be extensively evaluated.

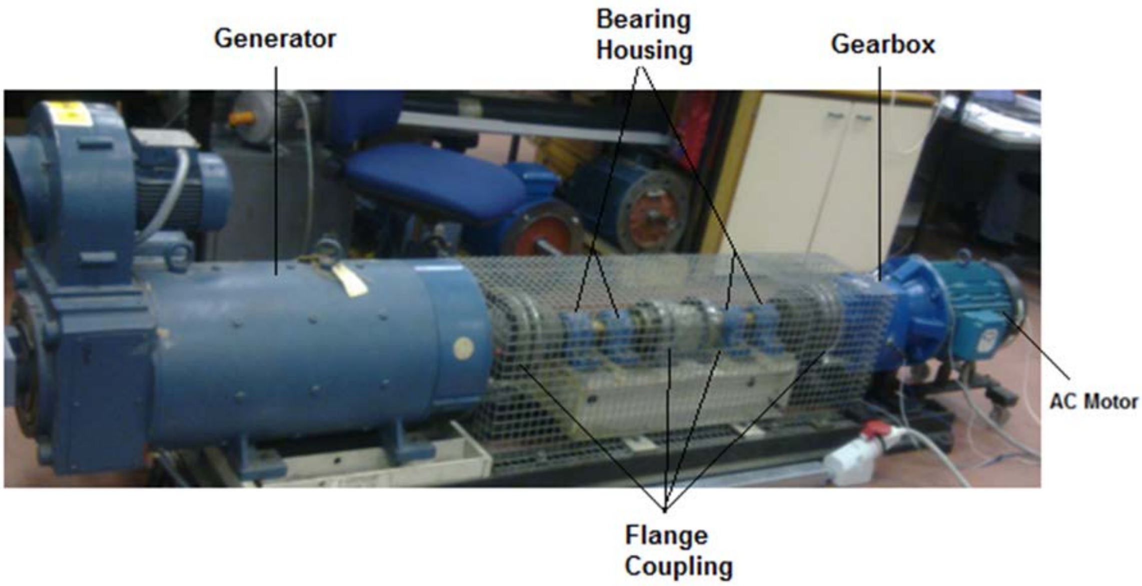


Figure 4.1 Gearbox test rig

The motor and gearbox were mounted on I-beams which were anchored to the concrete floor. Mechanically, the output of the AC motor is directly connected to the input shaft of the gearbox in order to transmit the mechanical power to the gearbox and its downstream equipment. The motor and gearbox are bolted together through two flanges integral to the motor housing and gearbox casing. This compact construction means that the whole system can be installed in a number of situations in which space is restricted or limited, for example in marine transmission. Moreover, in this study, different gear sets can be easily exchanged by unbolting the two flanges access to the inside of the gearbox.

A middle shaft supported by two bearing supports couples the mechanical power to the DC motor. The DC motor produces electricity which is consumed by the resistor bank.

In this arrangement, the AC motor absorbs electric power from the supply system via a control cabinet which generates mechanical power and a DC motor which converts the mechanical power into electricity again. By varying the resistance values different loads can be applied to the system. The details of all components used for the test-rig are given as followings:

4.1.1 AC Motor

The manufacturer's specifications of the AC motor are shown in Table 4.1.

Table 4.1 : Gearbox Specification

Description		First Stage PG0740.8/M07E	Second Stage M07-24.5B-C
Reduction ratio		0.810	4.539
No. of teeth		58/47	13/59
Contact ratio		1.450	1.469
Overlap ratio		2.890	1.289
Helix angle		27^0	13^0
Circular pitch at reference diameter	Normal	3.927	6.283
	Transverse	4.407	6.448
Circular pitch at running diameter	Normal	3.942	6.292
	Transverse	4.428	6.485
Circular pitch at base circle diameter	Normal	3.690	5.904
	Transverse	4.080	6.041

4.1.2 Motor Gearbox

The gearbox consists of two gear sets (or stages). The first set– or primary – set has two gears and the final set consists of two gears as well. The specification of the two sets is shown in the Table 4.1, and Figure 4.2 shows the schematic diagram of the two-stage helical gearbox.

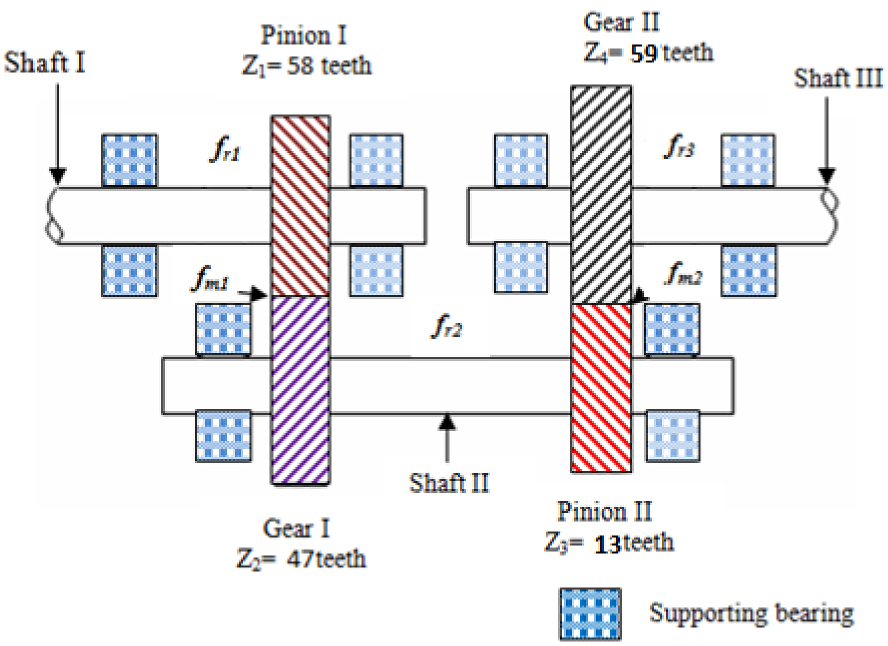


Figure 4.2 Schematic of the fundamental structure and working principles of a two-stage helical gearbox

Most motors now come with a motor-gearbox combination as an option to avoid having to couple the motor to a separately supplied gearbox. The motor is usually flange-mounted and mates directly to the gearbox front flange plate.

This combination has been popularised by machinery designers and end users requiring convenient, compact designs that come as a complete package without the need for additional mechanical components between the motor and gearbox. The requirement to drive low-speed loads that require a high-torque has also been a factor, because at any given power, torque in an AC motor is inversely proportional to speed.

High-torque, low-speed motors exist, but these are usually confined to DC machines as their AC equivalents run at a much lower power factor and generate much more heat than the high-speed motors. It is now considered more efficient to use step-down gearboxes for driving lower-speed loads at higher torque values.

4.1.3 DC Motor (generator)

The information from the DC motor rating plate is given in the table below:

Table 4.2 : Description of Generator

Description	
No	G63801N
Size	SD 200XLC
Power	85 kW
Speed	1750 rpm
Duty type	S1
Ins Class	F
Armature	V:460, A:200
Enclosure	IP22
Excitation	V: 360V, I: 4.7A
Mass	48.2 Kg

The unit is a shunt-wound DC motor, having a field supply that is completely separate from the armature circuit. There is no tachogenerator fitted to this motor. At the rear of the motor is a force-ventilation cooling fan with a 415VAC supply rating of 4.2A.

4.2 Control Panel for the test rig

The test rig panel is detailed in this section, along with a full description of the controls and photographs of the rig. The front of the test rig panel is shown in Figure 4.3, with the control elements indicated:

Figure 4.3 Test rig panel exterior

A brief description of the control panel functions is given in Table 4.3 below:

Table 4.3 : Control panel functions [137].

Armature current	Indicates DC motor armature Amperes; Range: 0 to 200A max. This indication is taken from the DC motor current transformer output.
Field Current	Indicates DC motor field current; Range: 0 to 5.0A max. This output is fed from the buffered output of the DC field controller
Switch On/Off Speed Control (Local Control Keys)	Pushbuttons control AC Drive Start/Stop Red (Stop); Green (Start) This keypad is connected to the inverter drive by the use of a serial communications lead. The keypad normally resides on the drive front, but an optional remote panel-mount kit was chosen to mount the keypad on the test rig panel front.

Programming keys	These are used to access AC inverter drive parameters; Under normal operating conditions, the keypad is used to increase or decrease the motor set speed. If desired, an engineer mode can be selected to modify parameters such as speed loop tuning, ramp times, etc.
operator Screen	This screen lets the operator input the required number of speed values and load values to be run in sequence on the test rig. Once the number of steps has been entered, pressing the 'Enter' button will move to the 'Recipe' screens

4.2.1 Test Rig Panel Equipment

- AC integrator 690+ Series

The 690+ series is a single range of ac drives designed to meet the needs of most variable speed applications from simple single motor speed control through to the most complicated integrated multi-drive systems. At the heart of the 690+ is a 32-bit microprocessor based, motor control algorithm, to which can be added a host of control options that allow the user to tailor the drive to exact requirements. Three phase (380-500V) ratings are available from 0.37 to 355kW and single phase ratings (220-240V) from 0.37 to 2.2kW.

FULL TECHNICAL SPECIFICATION:

Full technical specification will be presented in APPENDIX A. Also, each screen will be shown and the functions on the screen identified.

4.3 Data Acquisition System

Data from the test rig will be fed to an external data monitoring system. Transducers, namely an accelerometer and angular speed encoder, have been fitted directly on the test rig. Each transducer produces a voltage output proportional to the amplitude of the measured parameter and each is connected to a data acquisition (DAQ) system by coaxial BNC cables to reduce signal noise.

The placement of transducers is presented in Figure 4.4

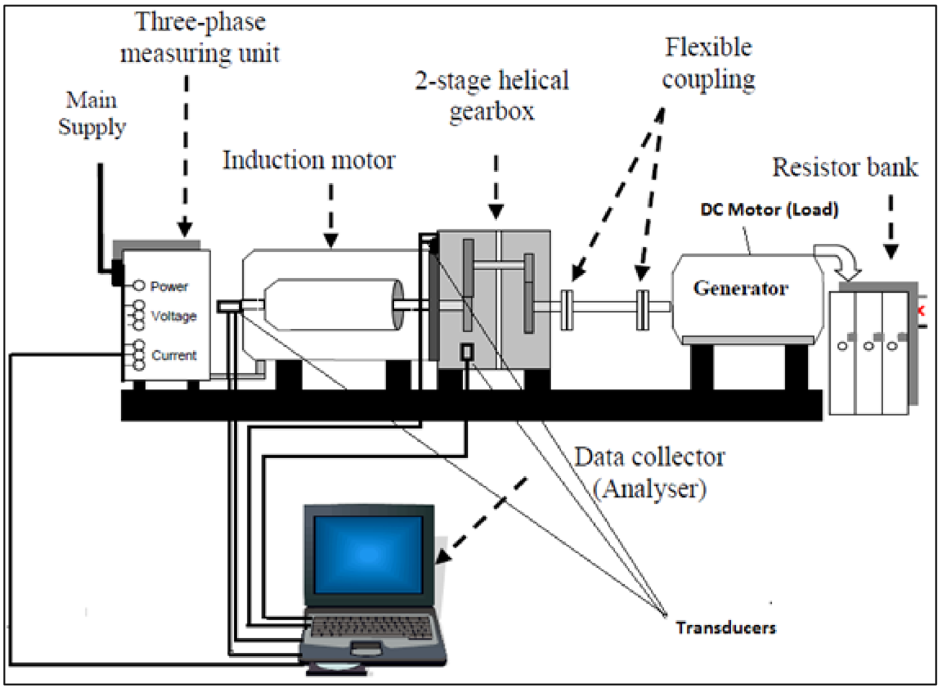


Figure 4.4 Setup for experimental gearbox test rig

Accelerometers - Dynamic excitation was measured via two accelerometers model PCB 336C04) which provided a 10 mV/g output over a frequency range from 1Hz to 20kHz (±10%) with one located directly on the side of the gearbox and the other located on the top of the induction motor flange (near gearbox). Each accelerometer was connected to a screw-threaded brass stud bonded to the casing with ceramic cement, a rigid connection which helped avoid over-heating of the accelerometers.

Shaft Encoder - an incremental optical encoder Type RI 32) was used to measure Instantaneous Angular Speed (IAS) over the range 10 Hz to 2 kHz. It was fitted to the end of the induction motor shaft which had 360 opaque segments equally spaced around its perimeter to form an encoder of sufficient accuracy for small changes in shaft speed to be recorded. No amplification of the measured IAS signal was required. The encoder was directly connected to the computer via the DQS system.

Devices for Current and Electrical Power Measurement

A digital photo and diagram of the three-phase current measurement unit are presented in Figure 4.5 and Figure 4.6 respectively. The motor current and voltage in each phase are measured using a PCB-mounted hall-effect current transformer (CT). A measured value for the current in each line is fed into the DAQ unit, which converts this into a voltage measurement, provides appropriate filtering and anti-aliasing, and feeds the signals to the data collection channel of a data collector / analyser. Thus, this unit can be used to measure the instantaneous current in each of the three phases, the instantaneous voltage of each of the three phases and the instantaneous electrical power supplied by each of the three phases.

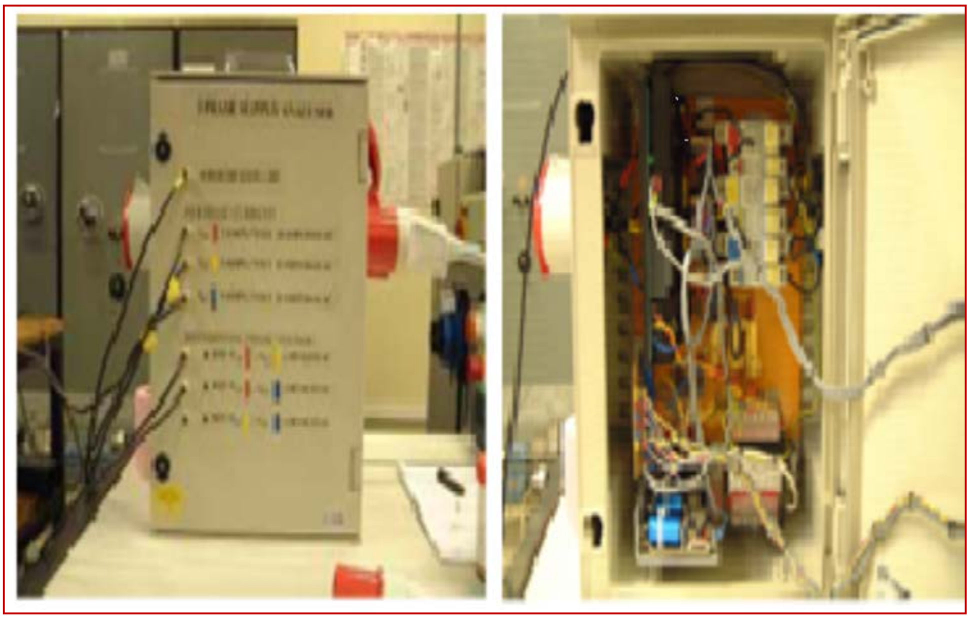
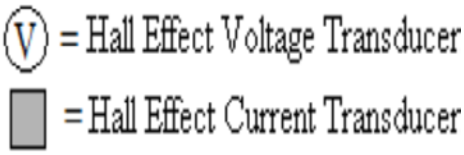


Figure 4.5 Three-phase current measuring unit

In Figure 4.6:

VL1L2, VL2L3 and VL1L3 are line to line voltages;

IL1, IL2 and IL3 are the three line currents.



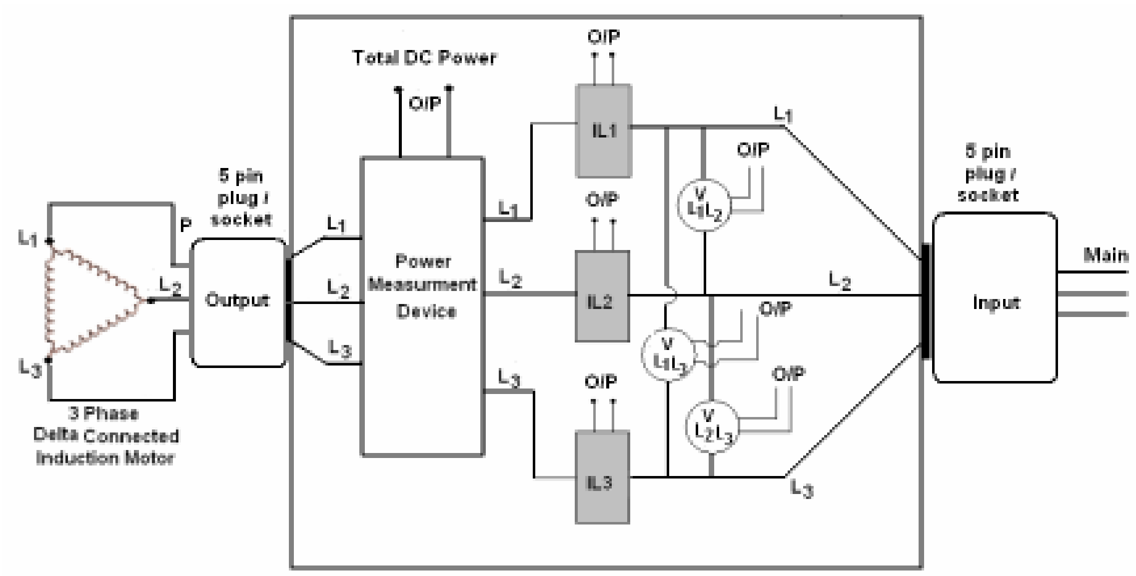


Figure 4.6 Diagram of three phase measurement unit

4.3.1 Data acquisition process

The data acquisition system is configured to take a maximum of 16 channels, of which a total of 11 will actually be used for this condition monitoring application. A PC card is connected to a spare PCI (Peripheral Card Interface) slot in the computer. A DAQ has two parts: hardware and software. The hardware consists of the data acquisition card and a host PC computer with control software and data storage space. The software controls the data collection process and has basic data analysis tools such as spectrum calculation for online data inspection. The data acquisition card used in this study is a National Instrumentation data acquisition card of PCI 6221. The sampling rate is 500 kHz for each channel with 16 bit data resolution and the input voltage range is ± 10V.

This configuration is shown in Figure 4.7:

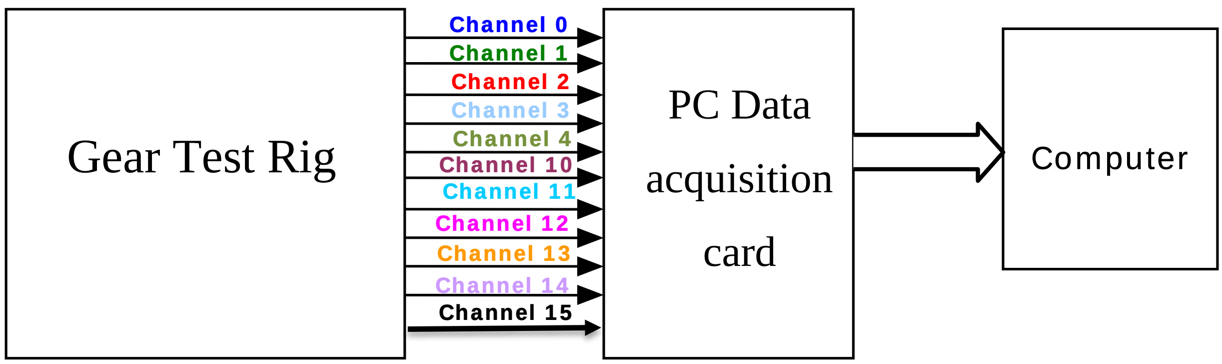


Figure 4.7 Diagram showing test rig signals

Channel 0 - signal from shaft encoder (1 pulse / revolution) to determine average speed calculation.

Channel 1- Signal from shaft encoder (100 pulses / revolution) for Instantaneous Angular Speed.

Channel 2 - Motor current.

Channel 3 - Vibration signal from gearbox.

Channel 4 - vibration signal from motor flange.

Channel 10 –DC Motor Armature current.

Channel 11 –Automated load setting; PLC > Field controller.

Channel 12 –speed feedback.

Channel 13 - Torque feedback

Channel 14 – motor current feedback.

Channel 15 –Automated speed setting; PLC > Inverter drive.

These eleven signals are measured from the test rig and sent to the data acquisition system which is connected with a software package allowing the display of virtual instruments on the computer screen. The software comprises of the data acquisition logic and the analysis software, as well as other programmes which are used to configure the logic or to move data from the data acquisition memory to the computer. A data acquisition control programme developed on Lab-windows was used in this research, and consisted of a main data inspection panel and a parameter set-up panel, as seen in Figures 4.8 and 4.9 respectively.

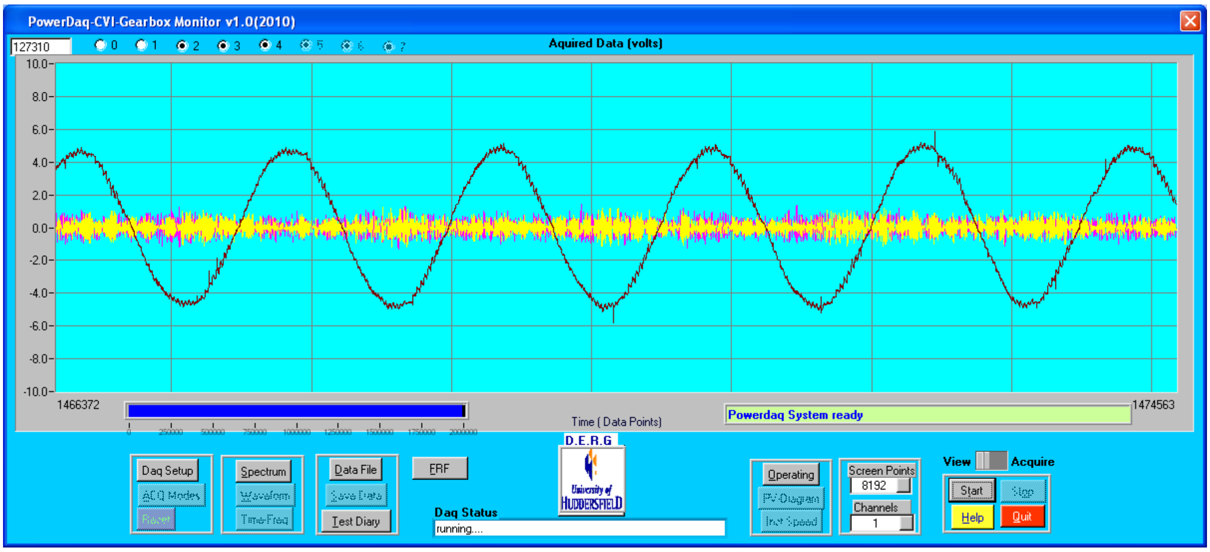


Figure 4.8 Screenshot of measured signals

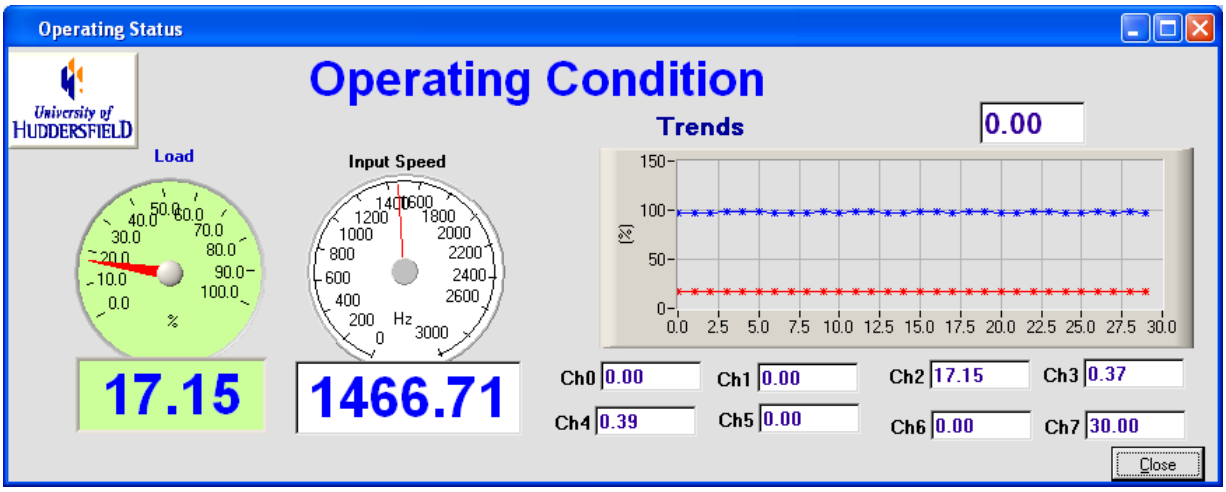


Figure 4.9 Screenshot of operating status

The software is based on a Windows operating system and has the ability to perform on-line data sampling. It required modifications such as inclusion of the channel number, sampling frequency, data length and filenames, all of which could be selected, recorded and stored on separate set-up page of the software package.

The accelerometer output is an analog voltage signal which is converted to a digital signal using the ADC. The ADC is used for further processing and analysis of the data through the programming of different algorithms using the Matlab software.

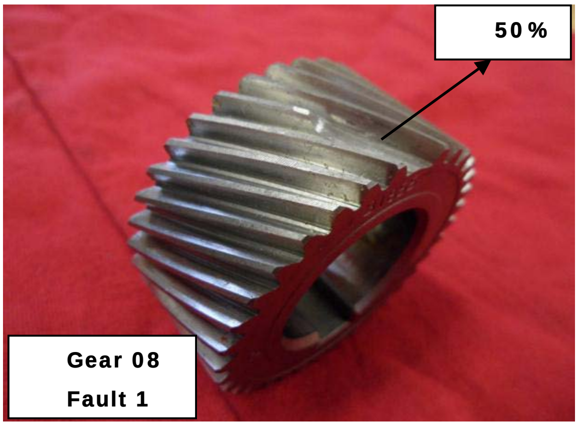
4.4 Gear Fault Simulation

In this research, two different severities of a local type fault were simulated. Fault simulation was carried out individually (one fault at a time) and the faults were artificially introduced to the pinion gear of the first stage in the gearbox shown in Figure 4.2. In an ideal situation, the faults should be introduced onto the same healthy pinion gear, with one tooth. However, due to time and machining limitations, the faults were introduced onto two identical pinion gears, by removal of a percentage of the tooth face width. The first pinion gear had 50% of one tooth removed and the second, 75% of one tooth was removed. Although the defects look very large they not influence the transmission significantly Because of a high overlap ratio the gearbox can still operate without noticeable signs of deterioration even when a full tooth has been removed.

In order to easily describe faults during this fault diagnosis study, the pinion gear faults are labelled throughout this thesis as follows: the health gear is referred to as the baseline, 50% referred to as Fault 1 and 75% broken tooth is Fault 2. These simulated faults are shown in Figure 4.10 respectively.

The data were collected for the three gear sets: Gear07, Gear08 and Gear09, which were all collected under the same gear operating conditions. Gear08 and Gear09 were induced with 50% and 75% tooth breakage respectively. Gear07 healthy gear is taken as the baseline for model development.

Operating parameters, load and speed settings: 0%, 44%, 60%, 72% and77% at 100% speed.



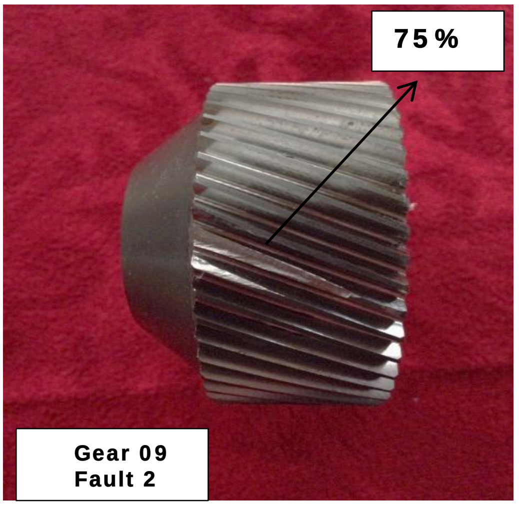


Figure 4.10 Simulated broken tooth (Gear08=50%, Gear09= 75%)

4.5 Gearbox Dataset

Gearbox data can be divided into two types: *static datasets* and *dynamic datasets*. As shown in Table 4.4, the static dataset contains mainly measurements from the controller and these were used to demonstrate the performance characteristics of the system. Additionally, this type of data can give a quick indication of system health. The dynamic datasets are often used for CM as they can produce more details of the health condition and hence allow diagnosis of faults.

Table 4.4 : Gearbox Datasets

Static datasets (control parameters)	Dynamic datasets
Armature current	Shaft speed
Load set	Angular speed
Speed feedback	motor current
Torque feedback	vibration signal from gearbox
Motor Current	vibration signal from motor flange
Speed Demand	

This research focused to use static dataset (control parameters) from embedded sensors and available in most industrial applications. Therefore the system does not require external sensors and accompanied sensor connection and this makes it easy and economical to be implemented in industrial environments.

In addition, control parameters based monitoring can also be implemented away from the monitored machines for remote monitoring.

4.6 Summary

In this chapter, a two stage helical reduction gearbox manufactured by David Brown Radicon Limited, was selected for this study project. A brief explanation of how the local fault was simulated and how the data was collected is given in this chapter. The test rig facility and data acquisition software were developed as detailed. A number of measurement transducers were used on the test rig to monitor the functioning of the gearbox for CM purposes.

CHAPTER 5: CONDITION MONITORING USING DATASETS FROM A GEARBOX RIG

This chapter presents a literature review of signal processing techniques which are used to monitor the condition of geared transmission systems based on vibration signals. Then discusses the dynamic and static datasets collected from the gearbox test rig. As the rig has a typical drive system, the datasets are considered representative for CM practices. Dynamic dataset were analysed to diagnose the condition of the gear: healthy and faulty, using conventional signal processing techniques such as time domain and frequency domain analysis.

The static data was also analyzed by comparison to evaluate the detection performances. This procedure of data collection and analysis allowed gaining a full understanding of CM datasets and paved the way for developing a more effective AI approach and efficient database.

5.1Conventional Methods for Monitoring Gearbox

5.1.1 Time-domain Analysis

Time domain analysis of vibration signals is one of the simplest and cheapest fault detection approaches. Conventional time-domain analysis attempts to use the amplitude and temporal information contained in the gear vibration time signal to detect gear faults. The amplitude of the signal can be used to signal that a fault is present and the periodicity of the vibration can then indicate a likely source for the fault [138]. Time domain approaches are appropriate when periodic vibration is observed and faults produce wideband frequencies due to periodic impulses [138]. Use of the waveform enables changes in the vibration signature caused by faults to be detected, but it is difficult to diagnose the source of faults.

Some mechanical systems generate high vibration levels throughout their operation. When these systems develop a progressive fault, the resulting vibration level is likely to increase consistently with time but the increase in vibration may be very small and difficult to identify. If the rate of development of the fault vibration is small, it may not be possible to clearly determine a fault symptom from variations in the waveform of the signal [139].

Mechanical systems are termed deterministic if their properties such as displacement, acceleration, etc. can be predicted over time. Mechanical systems such as a gearbox with a localised fault reveal characteristics which cannot be estimated over time. The characteristics of such systems, termed random or non-deterministic, cannot be accurately predicted, but they can be estimated by statistical parameters and these parameters can be used to predict fault progression [140].

Statistical indicators, which are commonly used for mechanical fault detection and based on the time-domain waveform include: the Root Mean Square (RMS), Peak Value (PV) , Kurtosis and Crest Factor (CF) [141, 142]. These indicators are also referred to as “condition indices”, [143]. The vibration signal from a gearbox is processed and a single value returned to indicate whether its condition is within normal operating parameters or not.

The condition index should increase as the fault increases; indicating the deteriorating condition of the gearbox. Sometimes this analysis can be performed by simple visual observation of the vibration time-domain waveform, but it is more likely that the time-domain signal will be processed to provide a statistical parameter (feature) which bears a known relation to the severity of the vibration.

5.1.1.1 Peak Value (PV)

Peak value is defined as the maximum vibration amplitude [143]:

$$PV = y_{max}(t) \tag{5.1}$$

Where y_{max} is maximum amplitude of the signal.

5.1.1.2 The Root Mean Square (RMS)

The RMS is the normalized second central moment of the signal (standard deviation*).* RMS of the vibration signal provides a measure of its overall energy and takes the time history of the vibration signal into account. RMS value of the amplitude of the acceleration from a given signal is expressed as [144]:

$$RMS_x = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(x(n) - \bar{x}\right)^2} \tag{5.2}$$

$$\bar{x} = \frac{1}{N}\sum_{n=1}^{N} x(n) \tag{5.3}$$

Where

N is the number of samples taken in the signal

x(n) is the amplitude of the signal for the nth sample

$\bar{x}$ is the mean value of the N amplitudes

From this definition it is clear that RMS is not sensitive to sudden short duration, isolated peaks in the signal and, thus is often not sensitive enough to detect incipient tooth failure. RMS becomes more useful as tooth failure progresses and is a measure of the overall vibration level of the system. It is therefore considered a very good descriptor of the overall condition of gearboxes and is sensitive to changes in operational conditions such as load and speed [145].

5.1.1.3 Kurtosis

Kurtosis is a measure of the “peakedness” of the signal, the higher the value of the kurtosis the sharper the peak and the longer the tails of the signal, the lower the kurtosis the more rounded the peak. Kurtosis is defined as:

$$kurtosis = \frac{\frac{1}{N}\sum_{n=1}^{N}\left(x(n)-\bar{x}\right)^4}{\left[\frac{1}{N}\sum_{i=1}^{N}\left(x(n)-\bar{x}\right)^2\right]^2} \tag{5.4}$$

The use of the fourth power makes Kurtosis very sensitive to the peakedness of the signal. Random noise following a Gaussian distribution has a kurtosis value equal to 3.0. A vibration signal collected from a normal gear usually shows uniform pattern, and the value of kurtosis tends to be 3.0 or lower. However, with a gear fault kurtosis increases, suggesting that the distribution of the vibration is no longer follow Gaussian. This is mainly due to the impulses (isolated peaks with high amplitude) generated by the affected gears. However, this method is often of little, or no, use since the incipient defects become severe before the kurtosis crosses a threshold level found with acceptable gears [146].

5.1.2 Frequency Domain Analysis

The spectral content of the measured signal is much more useful than vibration amplitude for determining gear condition. Therefore, instead of analyzing vibration directly in the time domain, this approach analyses the Fast Fourier Transformation (FFT) of the vibration signal. Using these techniques, it is possible to identify defects such as eccentricity, misalignment, or local tooth damage by increases of modulation sidebands in the spectrum. Local defect such as fatigue cracks and gear tooth breakages are often manifested in the vibration spectrum of a gear, by causing the amplitude of a particular frequency or sideband around the gear meshing frequency (and its harmonics) to change. These sidebands are located on both sides of the gear tooth meshing frequency and its harmonics, and are separated by integer multiples of the gear rotation frequency. Sidebands caused by either amplitude modulation or frequency modulation of the vibration signal often provide useful information. Indeed, Randall claims that the first three gear meshing harmonics and their sidebands provided enough information for successful gear fault identification [147]. Thus, tracking and recognizing the changes in amplitude of a particular frequency or eccentric sidebands in the signal can provide a good indicator of potential gear failure. However, in practice, the spacing of the side bands depends on periodic properties of the loading and on the transmission path, so it is very difficult to extract meaningful information directly from analysis of vibration spectra based on FFT. When the signal to noise ratio (S/N) is low and the vibration spectrum has a large number of frequency components due to the complexity of the system, it becomes almost impossible to distinguish the peaks from potential fault from peaks from other sources. This is the most difficult problem associated with the FFT based fault detection approach.

5.2 Conventional Methods for Monitoring Gearbox using dynamic data sets

To better understand gearbox CM using traditional diagnostic techniques, experimental work was conducted on the same gearbox test rig as had originally been designed and previously used to monitor the health of a two-stage helical gearbox using conventional techniques of vibration monitoring.

The goal of the experiment was to monitor the gear under healthy conditions and compare the results with those obtained when a realistic fault was introduced fault (breakage in one gear tooth) under similar operating conditions. Generally, many types of fault can be observed in gearbox operation, a broken tooth, a crack, scuffing, wear, etc. In this experiment, a broken tooth was simulated to the 1^{st} gear because it is a very common fault in gearboxes, and data was collected under different loads. This simulated fault is shown in Figure 5.1.

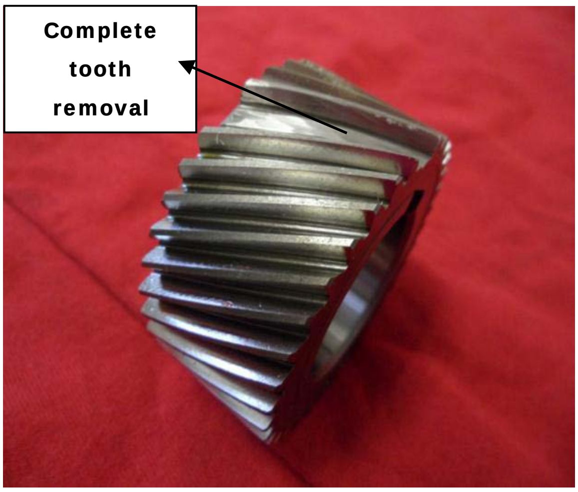


Figure 5.1 Simulated broken tooth

Conventional techniques used in this work include the waveform comparison in the time domain and spectrum analysis in the frequency domain. In addition, a direct comparison is made of the static data based CM.

5.2.1Detection in the Time domain

When a gearbox is operating under faulty conditions, it is expected that the vibration will be large and hence statistical parameters that describe the characteristics of signals will vary accordingly. In this section, the vibration waveforms are examined to confirm this hypothesis and three statistical parameters have been calculated. The peak value and root mean square (RMS) were calculated to reflect the strength of the signal amplitude, with peak value measuring predominantly local changes while RMS measured mostly overall changes in the system. In addition, the kurtosis was calculated to highlight local changes, and the peak factor, to provide a general measure of overall changes. Both kurtosis and peak value were calculated to reflect signal structures with dimensionless parameters to avoid the influence of operating parameters.

5.2.1.1 Vibration waveforms

Vibration waveforms for a healthy and faulty gear were collected from the transducer mounted on the gearbox casing with different current load operation conditions as shown in Figure 5.2. It can be seen that there are certain differences between the signal amplitudes due to the load variations for both gear conditions. Additionally, the waveform of the signals contains a massive amount of unknown information.

By comparing the two conditions it can be seen that all the waveform of the signals exhibit some distortion but there are no clear fault indications even under high load conditions.

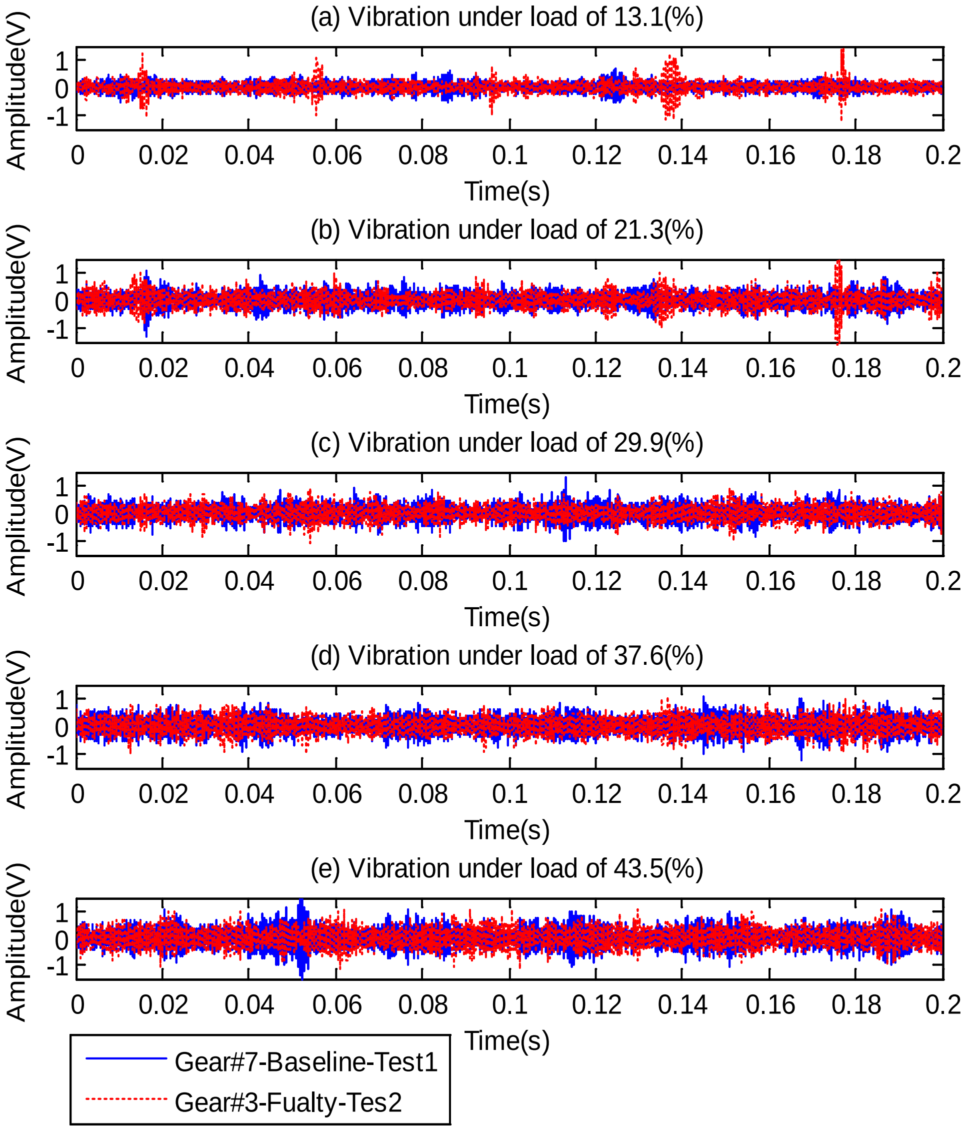


Figure 5.2 Vibration signals for healthy and faulty gears

For a more accurate understanding of the impact of the load variation on the faulty gear, the RMS, kurtosis and peak values were found for the vibration signals to give a more clear and reliable indication of the gear condition.

For any mechanical faults such as gears faults produce backlash forces in the system which appeared as distortion (change) in the original signal shape as a result that repeated impulse will be seen in the vibration signal of the gear every revelation. To understand the characteristics of the time signal which produced by such defects, number of the specific indicators may use in order to indicate the gear box condition and the fault symptoms. As the machine is operating under any defect, variable statistical properties will be expected, such as peak value, RMS, and Kurtosis are estimated to present more clear and reliable judgment of the gear condition.

Figure 5.3 shows the peak value, RMS and kurtosis values of the signal from the healthy and faulty gears measured by the transducer, located on the gearbox casing. It can be seen that these statistical parameters varied with load, but there is no immediate or clear pattern to the fluctuations.

In general these statistical parameters varied with different load, although there are fluctuations in these values from one load condition to the next. The peak values shows significant fluctuating during the load variation where the value of the peak value is not constant during the variable load for that it cannot gives good indication about the gear condition. On the other hand the RMS value exhibits slight increase in the vibration amplitude during faulty condition than healthy condition which it may be considered as a fault indication.

Looking to the Kurtosis value gives the best indication of the gear condition where it can be seen from the figure that there are considerable increase in the amplitude of the vibration signals due to load variation.

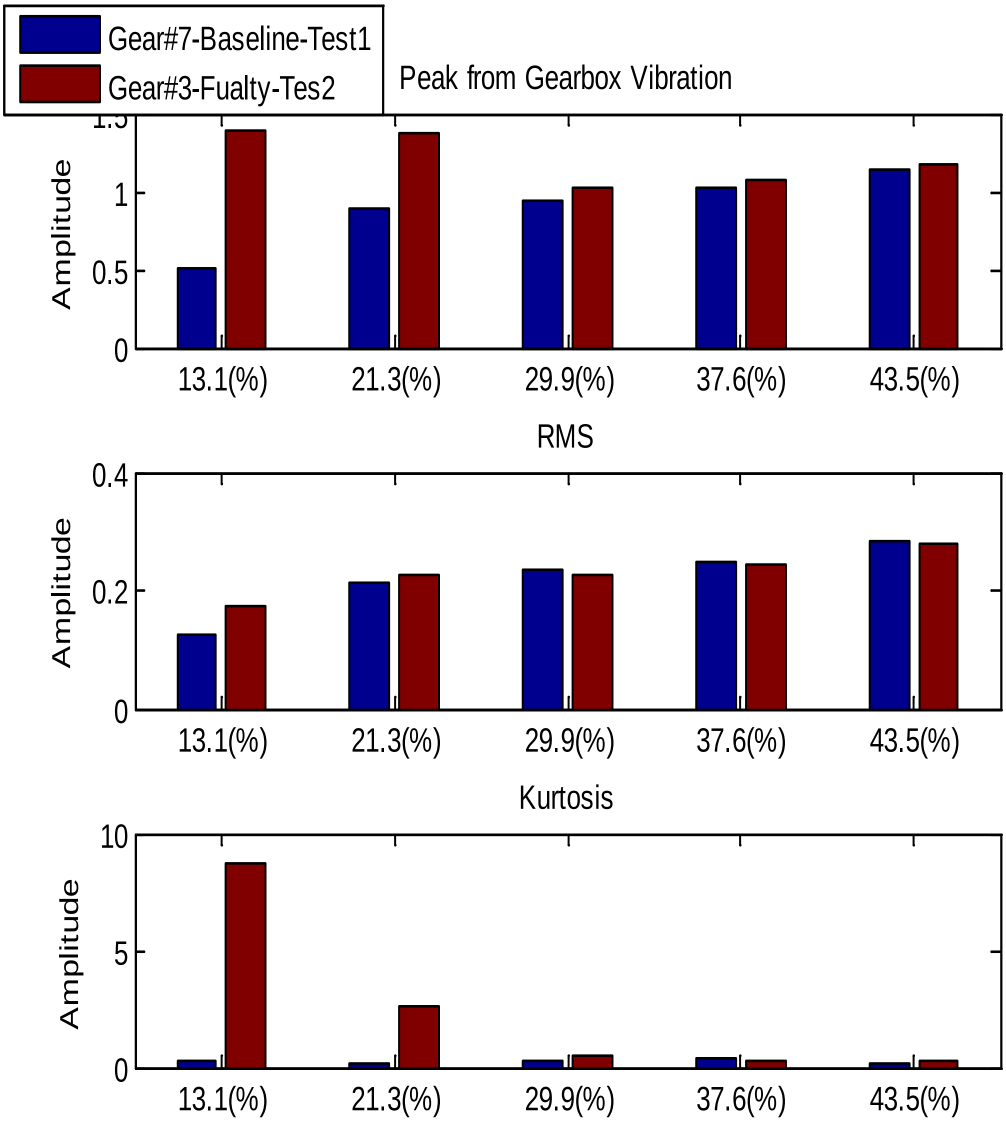


Figure 5.3 Peak, RMS and Kurtosis of vibration signal from gearbox

5.2.1.2 Motor Current Waveform

Figure 5.4 shows the time-domain of the stator current signal for the two cases: healthy and faulty conditions of the pinion gear. These waveforms show difference (distortion) from a pure sine wave but no clear symptoms of the fault appeared even under different loads.

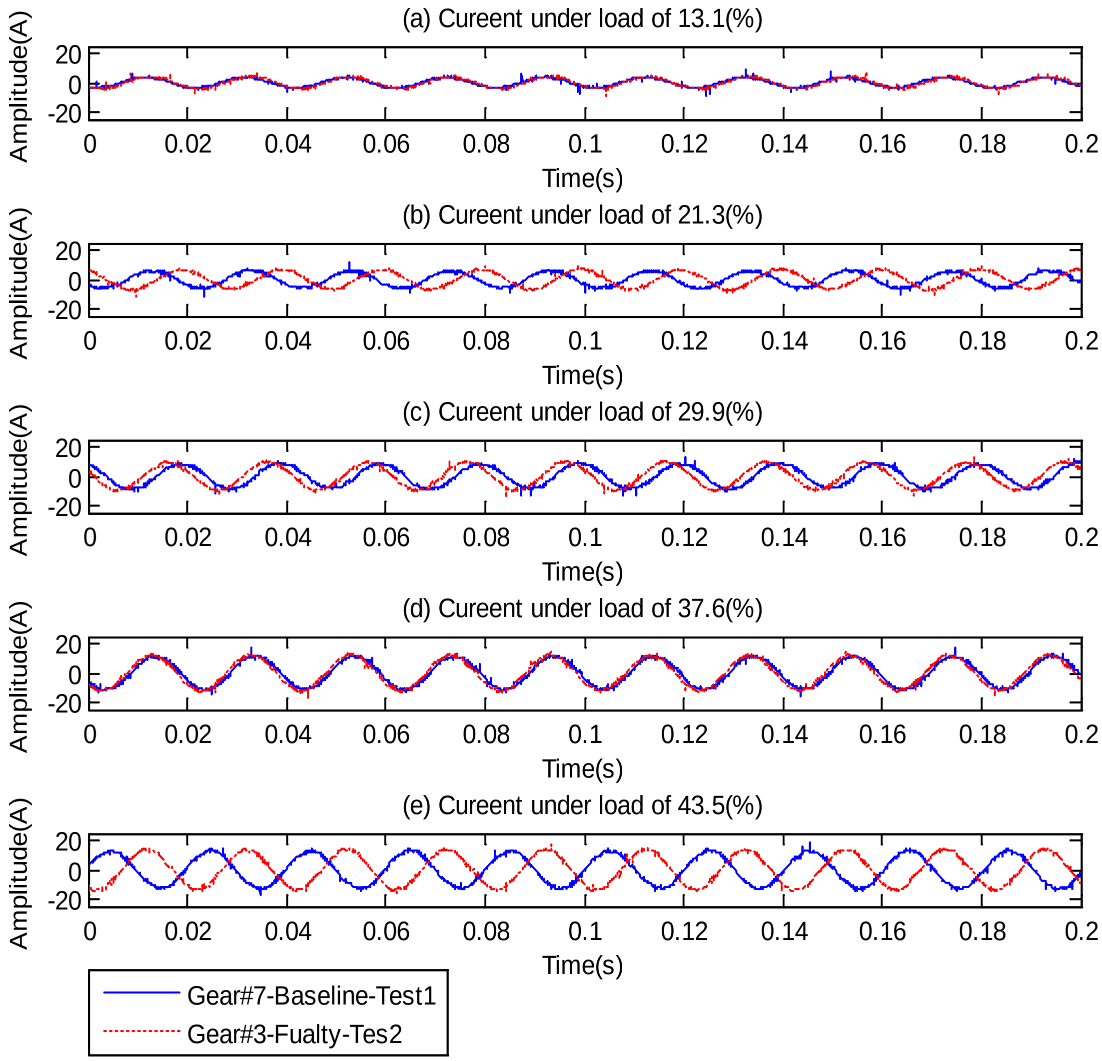


Figure 5.4 Stator current signals for healthy and faulty gears

Figure 5.5 shows the Peak, RMS and Kurtosis values of the motor current signals at different current load conditions for the healthy and a faulty gear. It can be seen that for all loads the Peak, RMS and Kurtosis for motor current are similar in both healthy and faulty conditions, mainly at small load. A slight difference in the RMS current value appears as the load increased but this difference is not sufficiently significant to be considered as a fault indicator.

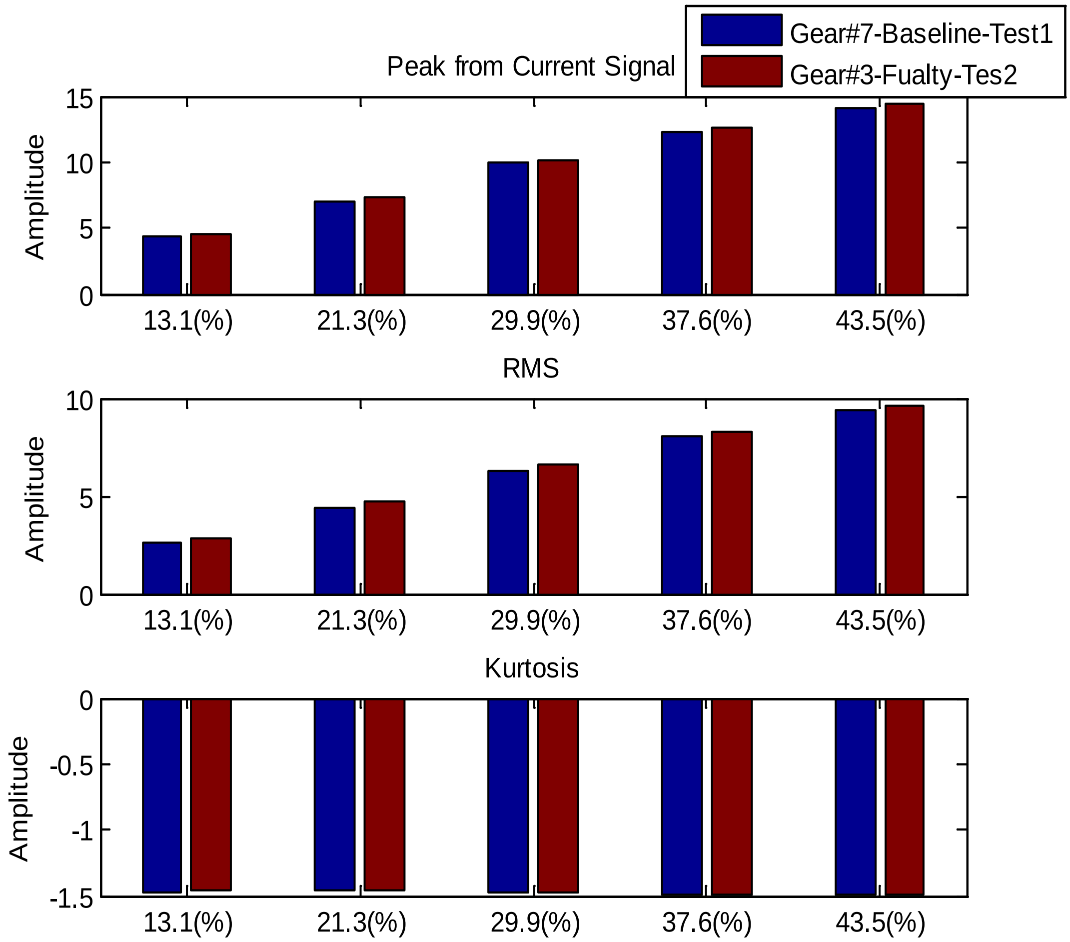


Figure 5.5 Peak, RMS and Kurtosis of stator current signals

5.2.2 Detection in the Frequency domain

5.2.2.1 Characteristic Frequencies

Figure 5.6 shows a schematic diagram of the two-stage gearbox under study. The essential frequencies of the vibrations and current signals of the gear box can be evaluated via Equations from (5.5) to (5.7). And the first, second and third values of the shaft rotational frequencies: f_{r1}, f_{r2}, f_{r3} can be determined as

$$f_{r1} = \frac{\text{Rotor mechanichal speed}}{60} \tag{5.5}$$

$$f_{r1} = \frac{1465}{60} \approx 24.42\ Hz$$

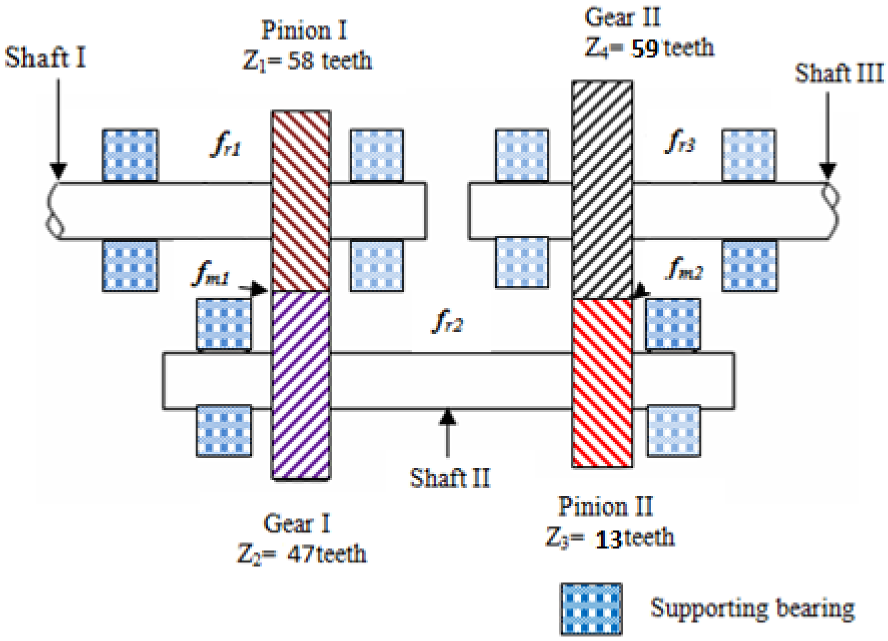


Figure 5.6 Fundamental frequencies of two stage gearbox

$$f_{r2} = \left(\frac{z_1}{z_2}\right).f_{r1} \tag{5.6}$$

$$f_{r2} = \left(\frac{58}{47}\right) 24.42 = 30.135Hz$$

$$f_{r3} = \left(\frac{Z_1}{Z_2}\right)\left(\frac{Z_3}{Z_4}\right) .f_r \tag{5.7}$$

$$f_{r3} = \left(\frac{58}{47}\right)\left(\frac{13}{59}\right) 24.42 \ = 6.64Hz$$

Where:

$(f_{r1,} f_{r2}, f_{r3}$) Are the three first values of the rotational speed in hertz, and

$\mathbf{Z_1}$ = number of teeth on the pinion gear at the first stage,

$\boldsymbol{Z_2}$ = number of teeth on the driven gear at the first stage,

$\boldsymbol{Z_3}$ = number of teeth on the pinion gear at second stage, and

$\boldsymbol{Z_4}$ = number of teeth of the driven gear at second stage

And the meshing frequencies for the first and second stage are

$$f_{m1} = f_{r1,}.Z_1 = 24.42 \times 58 = 1416.36Hz \tag{5.8}$$

$$f_{m2} = f_{r2,}.Z_3 = 30.135 \times 13 = 391.76Hz \tag{5.9}$$

Table 5.1 : Two- stage helical gearbox specification

Description	First stage (Input Shaft)	Second Stage (Output Shaft)
Number of teeth	58/47$[\frac{n_p}{n_g}]$	13/59$[\frac{N_p}{N_g}]$
Shaft speeds	$[W_{r1}]$ 24.42 (input) at full load	$[W_{r2}]$ 6.64 (output) at full load
Meshing frequency	$F_{mesh} = n_p.W_{r1}$ $= 1416.36Hz$	$f_{mesh} = N_g.W_{r1}$ $= 391.76Hz$
Contact ratio	1.45	1.469
Reduction ratio	$\frac{W_{r1}}{W_{r2}} = \left(\frac{n_p}{n_g}\right)\left(\frac{N_p}{N_g}\right) = 0.272$	

5.2.2.2 Vibration Spectrum

The frequency domain analysis for vibration signals of the healthy and faulty gear was carried out using the Fast Fourier Transform (FFT). The full spectrum of the vibration based on averaged healthy and faulty vibration signals are shown in Figure 5.7. It can be extracted from the figure that the dominant components in the spectrum are the transducer resonance responses. Furthermore, there are clear discrete components at low frequencies range. As a result, from analysis of the figures there are clear symptoms about the gear condition, can be extracted espsially at high load conditions and these symptoms refer to the presence of fault in the gear number one at first stage. The next investigation analysis is focused on the low frequency range. Particularly, to study and find the variation characteristics at the rotational and meshing frequencies those have calculated before (in section 5.1.2.1) and their harmonics.

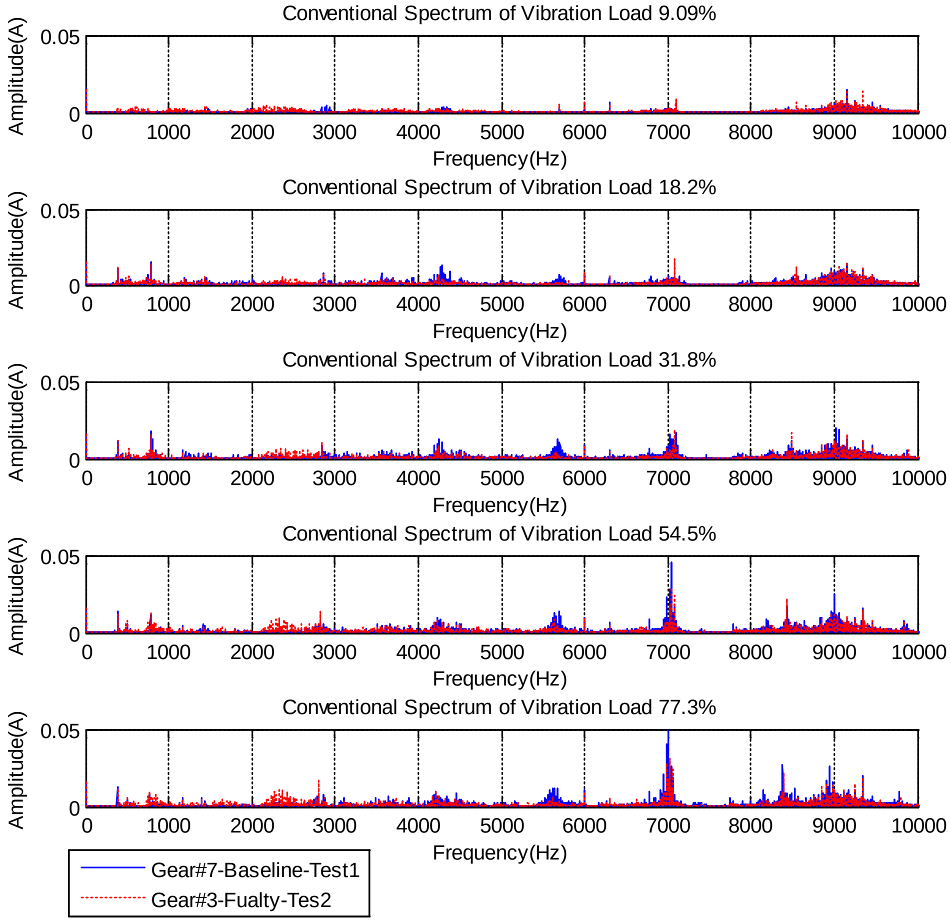


Figure 5.7 FFT spectral analysis of vibration signals from a healthy and faulty gearbox

5.2.2.3 Current Spectrum

It can be seen from Figure 5.8 that the current spectrum is rich with discrete frequency components (0 to 100Hz). At different load conditions, in gnarl all the graphs show slight increase in the harmonics amplitude at high load, and this increase in the amplitude could be an evident about occurrence of fault.

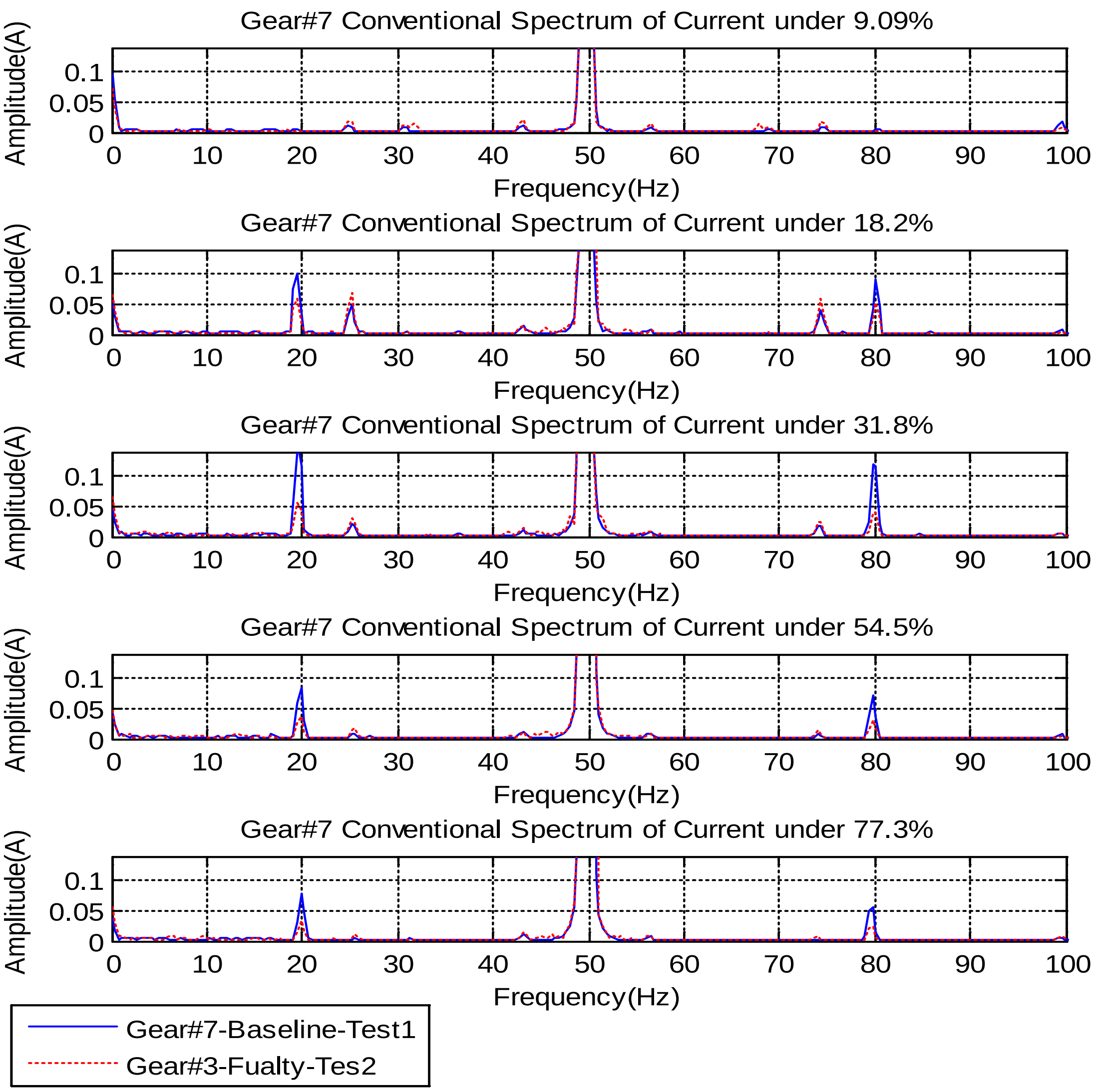


Figure 5.8 Spectral analysis of stator current signal measured for healthy and faulty conditions

5.3 Conventional Methods for Monitoring Gearbox using static datasets

The healthy gearbox for the following variables: DC motor armature current; load set; AC motor speed feedback; AC motor torque feedback; AC motor current; AC motor speed demand. The same variables are measured after the fault (introducing a break in one gear tooth from the gearbox primary drive set) was implemented in the gearbox and the results are shown in Figures 5.9, 5.10 and 5.11.

The commands included in the PLC program are set manually on the operator screen and their relevant details are shown in table 5.2.

Table 5.2 : Simulation data set for all Healthy and faulty gear sets

Step	Speed (%)	Load (%)	Time (s)
1	100	0	60
2	100	44	60
3	100	60	60
4	100	72	60
5	100	77	60

Figure 5.9 shows the load set, armature current and torque feedback conditions for a healthy and a faulty gear. It can be seen that the load set was similar in both healthy and faulty conditions. There was a slight difference in the armature current but this difference is not sufficiently significant to be considered as a fault indicator. Torque feedback gives the best indication of the presence of the fault, and it can be seen from the figure that there are increase in the Torque feedback signals.

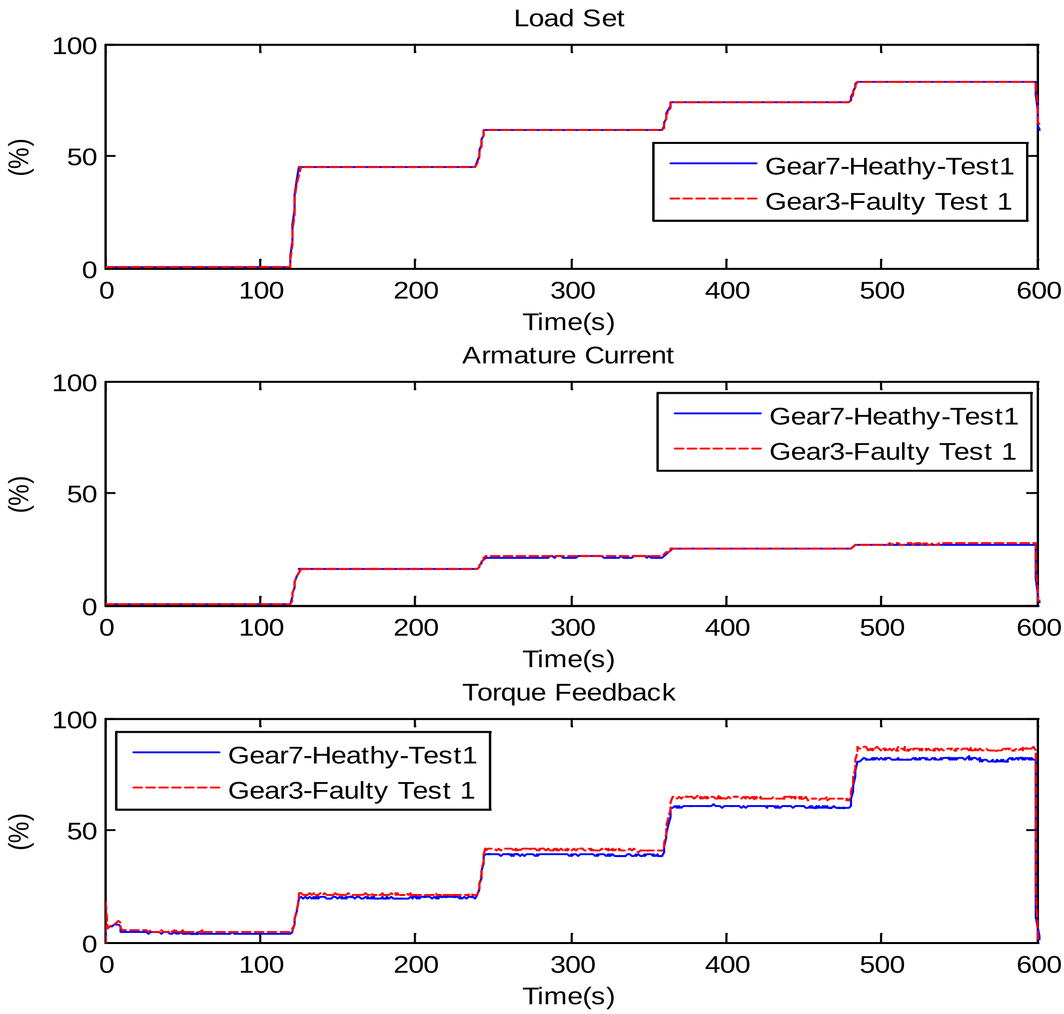


Figure 5.9 Lode set, Armature current and Torque feedback for healthy and faulty gear conditions

Figure 5.10 shows the Speed Feedback, Speed Demand and Motor Current conditions for a healthy and a faulty gear. By comparison of the two conditions it can be seen that there is a slight difference between the healthy and faulty condition for all measurements.

Figure 5.11 shows Motor Speed and Phase Current obtained from Dynamic Signals. It can be seen that there is a consistent slight difference between the healthy and faulty condition for all measurements.

Figures below give the two actual measured current signals and it is obvious that the values for the motor actual current for a faulty gearbox become greater than the actual motor current when a healthy gearbox is installed in the electrical drive. This was expected because the torque feedback is increasing and the controller has to produce higher demand values in order to compensate for a faulty mechanical transmission. The static data signals follow the same pattern therefore it is possible to use them instead of actual motor current for fault-detection purposes and more details about the usefulness of using these signals are presented in next Chapter .

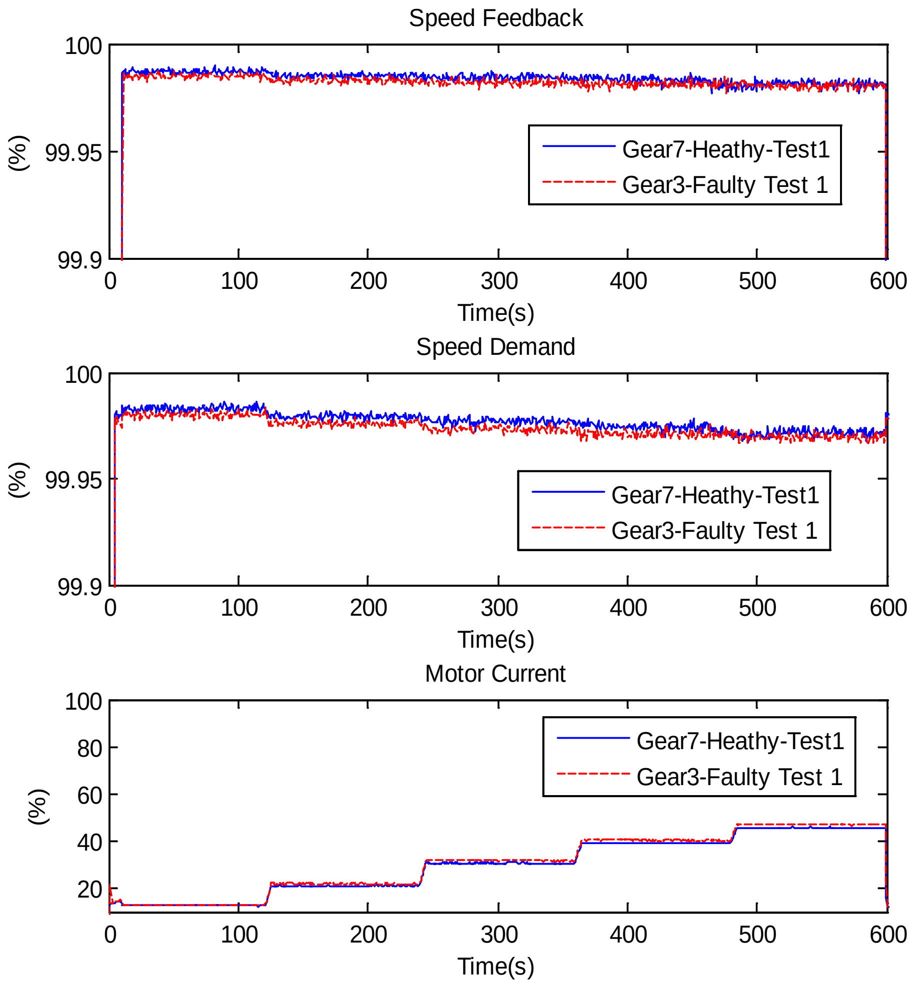


Figure 5.10 Speed Feedback, Speed Demand and Motor Current conditions for healthy and faulty gear

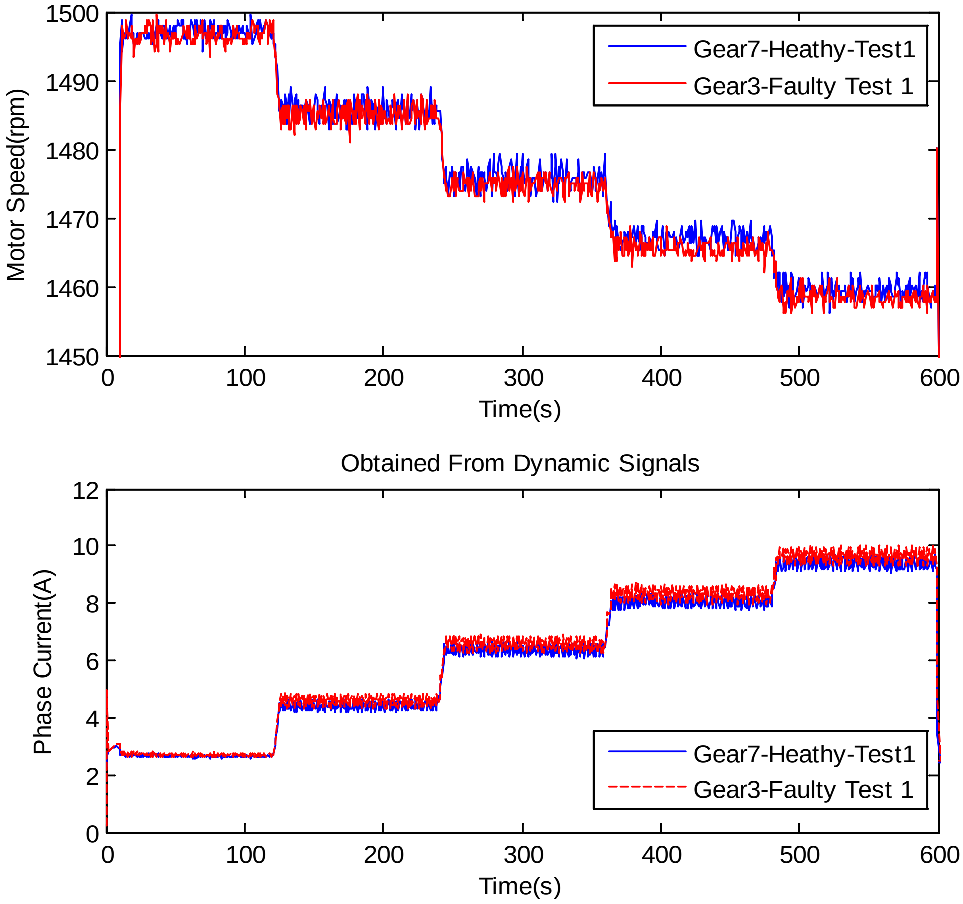


Figure 5.11 Motor Speed and Phase Current obtained from Dynamic Signal

5.3 Summary

The time domain analysis leads to popular statistical feature parameters such as peak value, RMS and kurtosis. The frequency domain analysis (standard Fourier transform) analysis produces spectral features including amplitudes at meshing frequencies, their harmonics and their associated sidebands. The set of these features is evaluated in the separation of faults under different conditions. This study demonstrates that conventional methods are not able to show the presence and progression of tooth breakage faults in gears and demonstrates the need for further development of analysis. The analysis of the dynamic datasets in conventional methods such as those waveforms in the time domain and spectrum in the frequency domain shows good detection and diagnosis results. However, the amplitude of the features is not sufficiently high for reliable diagnosis.

The primary study of the static data also shows certain detection information but not provide enough knowledge about the root of the faults.

AI technologies including artificial neural network (ANN), fuzzy logic and Adaptive Neuro-fuzzy inference system (ANFIS) are also developed rapidly due to the advances in computing technologies. It is important to apply these technologies to the CM data to achieve more accurate and efficient CM.

CHAPTER 6: MODEL BASED METHOD FOR GEARBOX FAULT DETECTION USING MOTOR OPERATING PARAMETERS AND GENERAL REGRESSION NEURAL NETWORK

This chapter examines the performance of a model based method by applying it to the detection and diagnosis of different faults in a gearbox dataset. The model is developed using General Regression Neural Network (GRNN) to capture the complicated connections between measured variables.

6.1 Introduction

A generalised regression neural network (GRNN) is a term first used by Specht [125]. It is a feed-forward type and a variant of the radial-basis function (RBF) type NN which, according to [127], can be designed in a fraction of the time it takes to train a standard feed-forward NN. It was also chosen for this work because it is one of the simplest NNs to use [126]. The GRNN uses supervised learning. To discover the generalisation capability, or accuracy, of the NN in predicting the output after training has taken place, it must be shown a testing dataset which contains only NN input data. This testing data is processed and a number of outputs, equal to the number of samples used for testing, are generated. The errors between the actual outputs from the training dataset and the predicted outputs based on the testing dataset are determined and used to indicate the accuracy of the NN prediction.

6.2 A General Regression Neural Network (GRNN)

The GRNN is well suited to interpolation. It is based on the estimation of a probability density function of a vector random variable, *X*, and a scalar random variable, *Y*. If the joint probability density function of these variables is both known then the conditional probability density function and the expected value can be computed. According to Specht [125], the estimated value of ***Y*** for a given ***X*** is presented in the following general regression equation:

$$E[\mathbf{Y} / \mathbf{X}] = \frac{\int_{-\infty}^{\infty} \mathbf{Y} f(X,Y)dy}{\int_{-\infty}^{\infty} f(X,Y)dy} \tag{6.1}$$

Where:

$E[\mathbf{Y} / \mathbf{X}]$ = conditional mean of *Y* on *X*

$f(X,Y)$ = known joint continuous probability density function

When it is unknown, the probability density function, *f(X,Y)*, is estimated from sample observations of *X* and *Y*. For a non-parametric estimate of *f(X,Y)*, the Parzen estimation

[148], $f'(X,Y)$, is used by the GRNN. It is defined by the following equation for the observed sample observations, X_i and Y_i of the vector X and scalar Y:

$$f'(X,Y) = \frac{1}{(2\pi)^{\frac{p+1}{2}} \sigma^{p+1}} \cdot \frac{1}{n} \sum_{i=1}^{n} f_X \, f_Y \tag{6.2}$$

Where:

$$f_X = \exp\left[-\frac{(\boldsymbol{X} - X_i)^T (\boldsymbol{X} - X_i)}{2\sigma^2} \right] \tag{6.3}$$

and

$$f_Y = \exp\left[-\frac{(\boldsymbol{Y} - Y_i)^2}{2\sigma^2} \right] \tag{6.4}$$

and

n = the number of sample observations

p = the dimension of the X vector

σ = the standard deviation (or smoothing parameter)

An estimate for the desired mean of ***Y*** at any given ***X*** is derived in Equation (6.5) by combining Equations (6.1) and (6.2) and performing the integration after first interchanging the integration and summation operations.

$$\hat{Y}(\boldsymbol{X}) = \frac{\sum_{i=1}^{n} Y_i \exp\left(-\frac{D_i^2}{2\sigma^2} \right)}{\sum_{i=1}^{n} \exp\left(-\frac{D_i^2}{2\sigma^2} \right)} \tag{6.5}$$

Where the scalar function D_i^2 is given by:

$$D_i^2 = (\boldsymbol{X} - X_i)^T (\boldsymbol{X} - X_i) \tag{6.6}$$

The main algorithm of the GRNN model is expressed by Equations (6.5) and (6.6). The estimate $\hat{Y}(X)$ is a weighted average of all the observed samples, Y_i, where each sample is weighted in an exponential manner according to the Euclidean distance, D_i, from each

X_i. This appropriate weighting is explained by the inversely proportional relationship between the expression $\exp\left(-\frac{D_i^{\,2}}{2\sigma^2}\right)$ and D_i. That is, as D_i increases, $\exp\left(-\frac{D_i^{\,2}}{2\sigma^2}\right)$ decreases and vice-versa. An optimum value must be obtained for the smoothing parameter, σ. σ Must be greater than 0, and will usually range between 0.01 and 1 with good results. Larger values of σ improve the smoothness of the regression surface. [150].

Figure 6.1 represents the neural network architecture of the GRNN algorithm of Equations (6.5) and (6.6). The Euclidean distance, D_i, is computed by the links between the input layer and the first hidden layer. Based on observed samples, X_i, and smoothing parameter, σ, the expression, $\exp\left(-\frac{D_i^{\,2}}{2\sigma^2}\right)$ is computed. A node in the second hidden layer takes the sum of the exponential values of all samples. Other nodes in this same layer, compute the products of the exponential values and the corresponding observed Y_i for each sample observation. The node in the third hidden layer computes the sum of all these product values (B), which is then supplied to the output node where the ratio between it and the previous sum (A) is calculated.

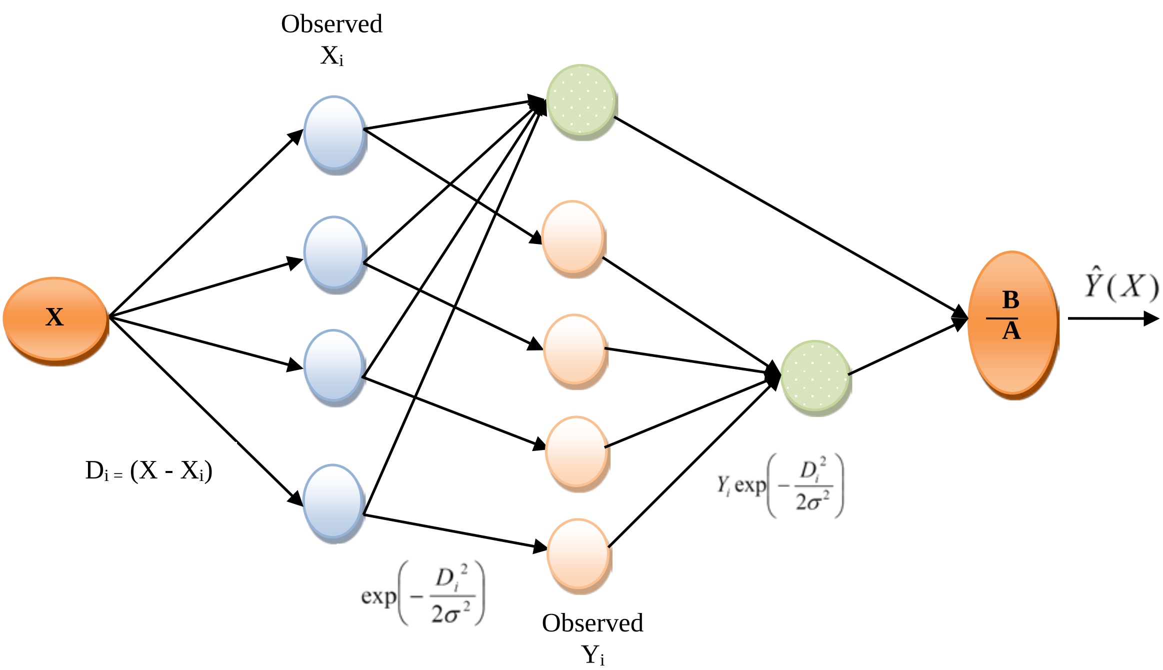


Figure 6.1 Architecture of General Regression Neural Network

The suitability of the GRNN, however, is attributed to several important features that make it convenient for online implementation. In the GRNN network only a single parameter is estimated. Unlike other networks, a once-through, non-iterative training process with a highly parallel structure is involved. Unlike many conventional regression analyses, the specification of the underlying regression function, bounds of the independent variables, initial convergence values and convergence criteria are not required beforehand. Additionally, the algorithm provides smooth transitions from one observed value to another even with sparse and noisy data in a multidimensional measurement space and can be used for any regression problem where an assumption of linearity is not justified. [149]

6.3 Data Characteristics

The data were collected for the three gear sets: Gear07, Gear08 and Gear09. The variables used were: DC motor armature current, load set, AC motor speed feedback, AC motor torque feedback, AC motor current and AC motor speed, see Table 6.1.

In addition, an additional temperature measurement is added to the system for more accurate detection.

Gear08 and Gear09 had tooth breakages of 50% and 75% respectively (see Section 4.5 and Figure 4.13). Gear07, a healthy gear was taken as the baseline for model development. For data collection, the full speed (1465 rpm) was used and the loads were sequentially varied: 0%, 44%, 60%, 72%, and 77% of the full load (100%). With each different load, the other parameters as shown in Table 6.1 were varied as shown in Figure 6.2. It can be seen that load related parameters have an increasing trend. This means that faults that cause load variation may be detected using these parameters.

Table 6.1 : Data plot signals and scaling factors

Value	Description	Scaling
Armature current	Measured current in DC motor armature from a C.T. mounted on the resistor bank.	0 – 100% = 0 to 200A
Load set	Load set by the test rig PLC and output to the DC motor field controller	0 – 100% = 0 to 4.0A Field current
Speed feedback	AC motor speed feedback indicated by the AC inverter	0 – 100% = 0 to 1470 RPM
Torque feedback	AC motor torque feedback indicated by the AC inverter	0 – 100% = 0 to 71.5 Nm (Full-load-torque)
Motor current	AC motor torque feedback indicated by the AC inverter	0 – 100% = 0 to 20.9 A
Speed demand	Speed output from the test rig PLC to the AC Inverter	0 – 100% = 0 to 1470 RPM
Temperature	Temperature of gearbox oil	0-100%=0 to 100 c^0

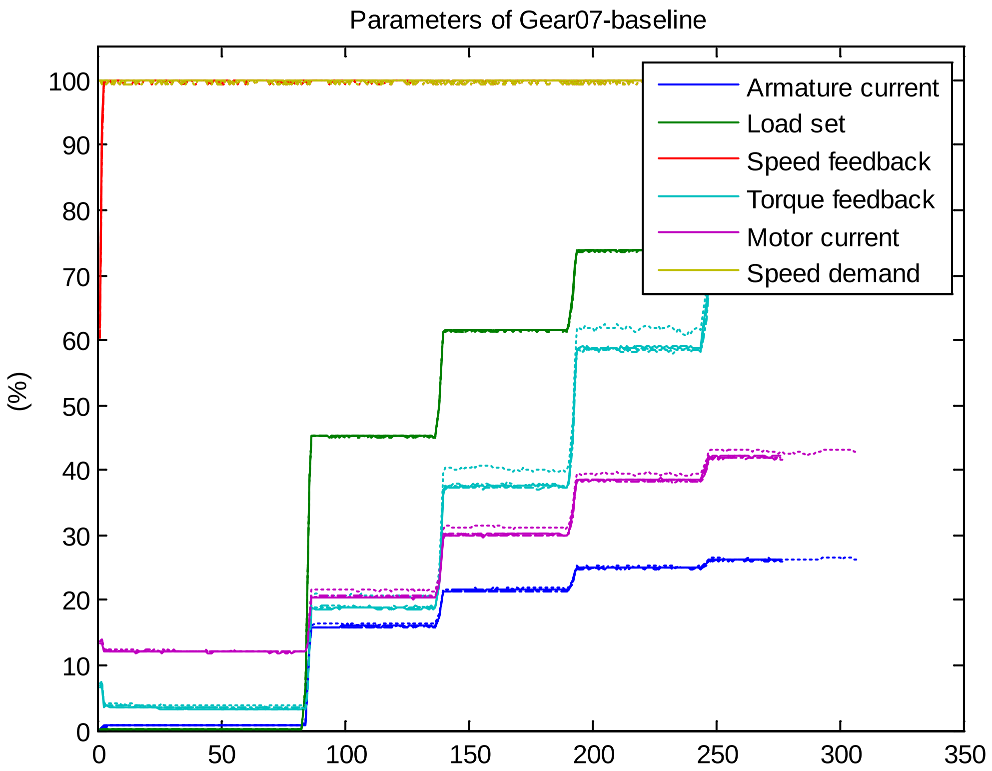


Figure 6.2 A typical data set obtained from control system

To fully evaluate the NN performance, it was considered sufficient to explore the use of only three of the parameters (Armature current (AC current), load set point and gearbox temperature). Figure 6.3 respectively shows eight data sets collected from eight independent tests on Gear07. It can be seen that each data set shows a gradual increase in the Armature current with increase in load and temperature of the gearbox. The rate of Armature current increase with load settings is very high and nonlinear, which indicates a correlation between Armature current and load setting that would not be easy to model simply.

In addition, the temperature has a noticeable effect on the current. Figure 6.3 shows a slight inverse influence on the current which decreases at higher temperatures. This reduction in the rate of change again indicates a more complicated model is required to describe the connections between electrical current, load settings and temperature influences.

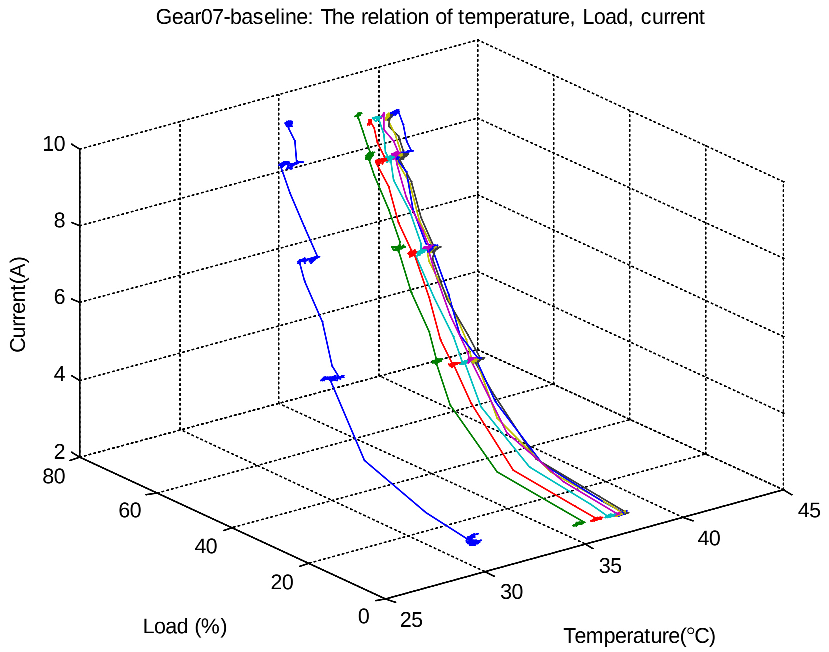


Figure 6.3 Data characteristics Gear 07: current, temperature and load

Figure 6.4 shows more details of the temperature influence. It can be seen that the current decreases with the increase in temperature at each load setting. It may be due to that the damping effect of lubrication decreases with temperature. Nevertheless, the correlation is nonlinear. As this temperature effect is very clear, it will certainly impact the model development. Fault detection should include this effect to obtain more accurate results.

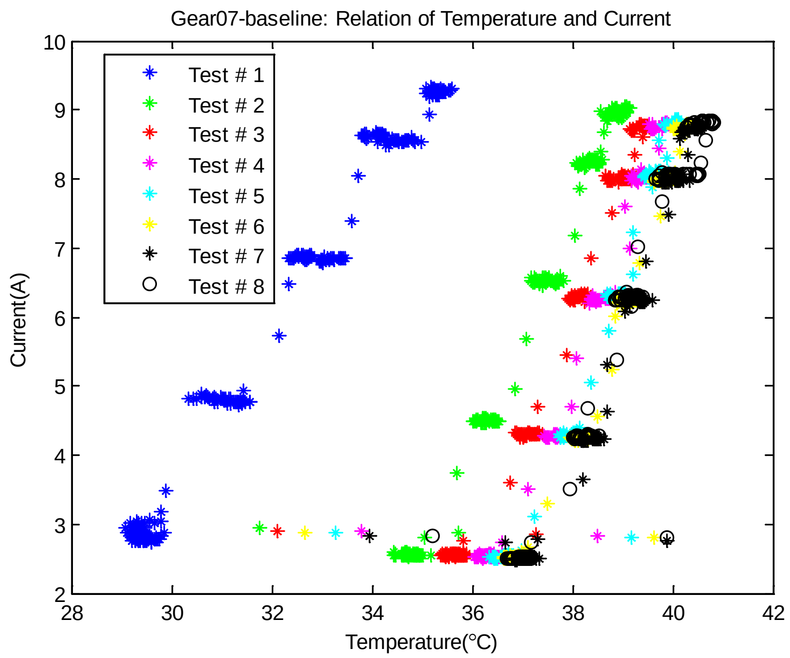


Figure 6.4 Data characteristics of current with temperature of gear in (Gear 07)

6.4 GRNN Model development for fault detection and diagnosis.

The GRNN model was developed using MATLAB software and the baseline datasets from Gear07. The model has two inputs: temperature and load set points and one output: AC current. To train the model, the datasets from Gear07 were used as the baseline for model development. In total, there were 2088 data samples from eight tests of different runs. The 2088 data points are divided into two equal subsets of 1044 points: one for model training and the other for model verification.

After several tuning cycles, it was found that for a GRNN spread parameter of 0.7, the network produced a balanced prediction in generalization and accuracy for the first subset of data. As shown in Figure 6.5, the measured values are all on the model surface which was used as the training data set.

On the other hand, the model has only very small output if there is not training set, which means that if there is deviation of the inputs the output will be small and the difference between measured output and predicted output will be large.

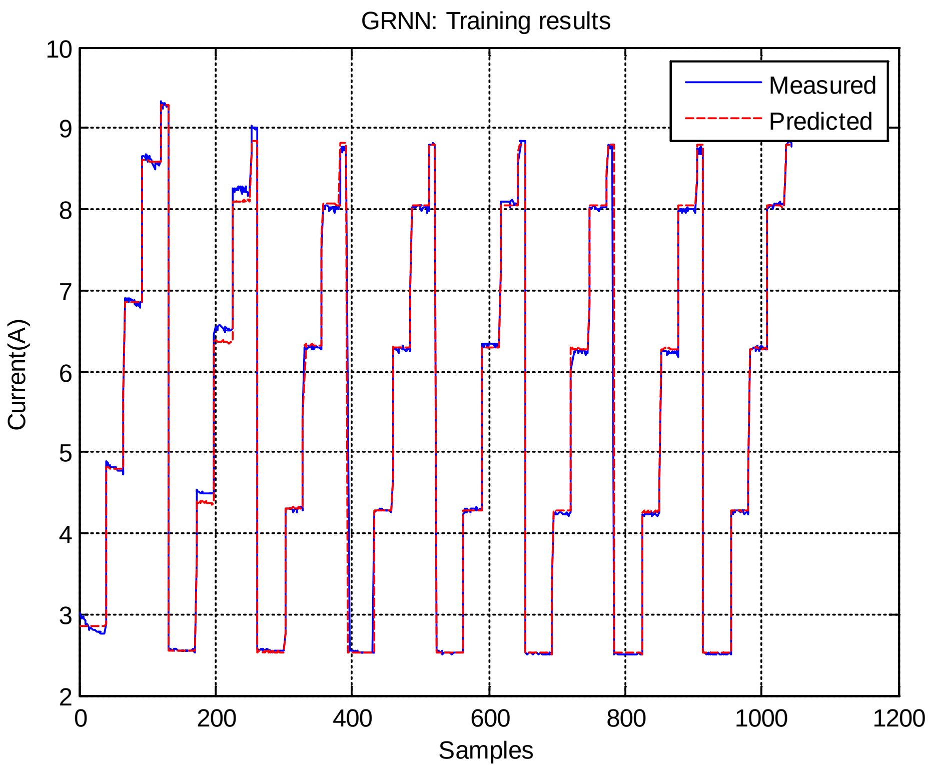


Figure 6.5 GRNN training result

6.5 Estimation of detection threshold

To confirm the models performance, the second dataset was used as the input and output of the models developed from the first data set. To measure the quality or accuracy of the model in fitting the second data set and detecting abnormalities in new datasets, a threshold was developed based on the first data set. This was achieved by a comparison between the actual current and the predicted current. In particular, a threshold (D_{th}) was defined as shown in Equation (6.9), equal to three times of the root mean squared value between the real measurement and the model prediction:

$$D_{th} = 3 * \mathrm{RMS} = 3\sqrt{\frac{1}{N}\sum_{i=1}^{N}(I_{mi} - I_{pi})^2} \quad (6.9)$$

Where:

N = The number of sample.

$\mathrm{I_{mi}}$ = The actual value determined from measurements.

$\mathrm{I_{pi}}$ = the predicted value using the NNs.

6.*5.1* GRNN evaluation

Figure 6.6 shows model verification results calculated using the second data set from Gear07. It can be seen that most of the errors are within the threshold (D_{th}), the mean and standard deviation (STD) of the GRNN model residuals are 0.0054 and 0.0653 respectively. However, the distances from the residual values to zero of GRNN are small, which means that the model fitted the data very well. There are a number of data points exceeding the threshold. These may be regarded as the outliers due to load transients when the temperature takes a short time to respond and there is a delay in current increase.

In general the model is sufficiently accurate for implementing fault detection for new data sets from other two gear sets.

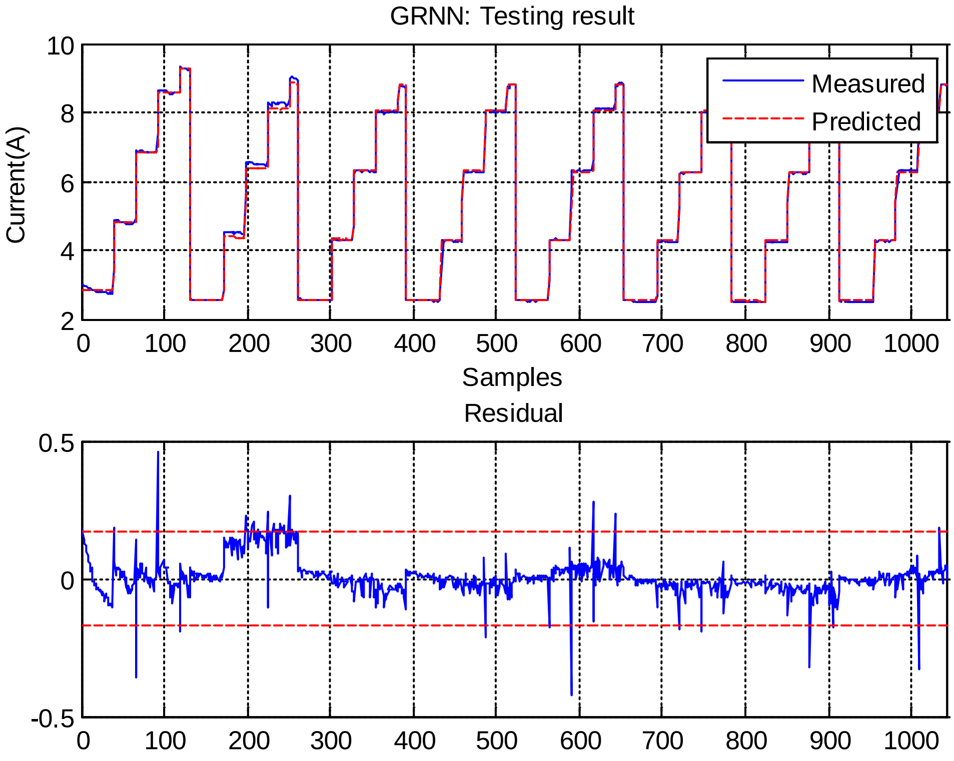


Figure 6.6 GRNN Model verification using second data set from Gear07

6.6 Fault Detection and discussion

6.6.1 Fault Detection on Gear08 using GRNN

Figure 6.7 presents measured and predicted currents for Gear08 with 50% tooth breakage. It can be seen that the predicted current is close to the measured, but there are many measurements which were significantly different from the predicted values.

In the lower part of Figure 6.7 the residual data is shown and it can be clearly seen that a significant number of data points exceed the threshold. Comparison with Figure 6.6 indicates there is a fault in Gear08. The maximum/minimum values of GRNN residual are of 0.4552/-0.3493 for the gear-08, which indicates that the residual range for this gear is of 0.8045. The mean and STD residual values of GRNN model residuals are 0.0550 and 0.1406 respectively, which indicates that the model is sensitivity to presence of a fault.

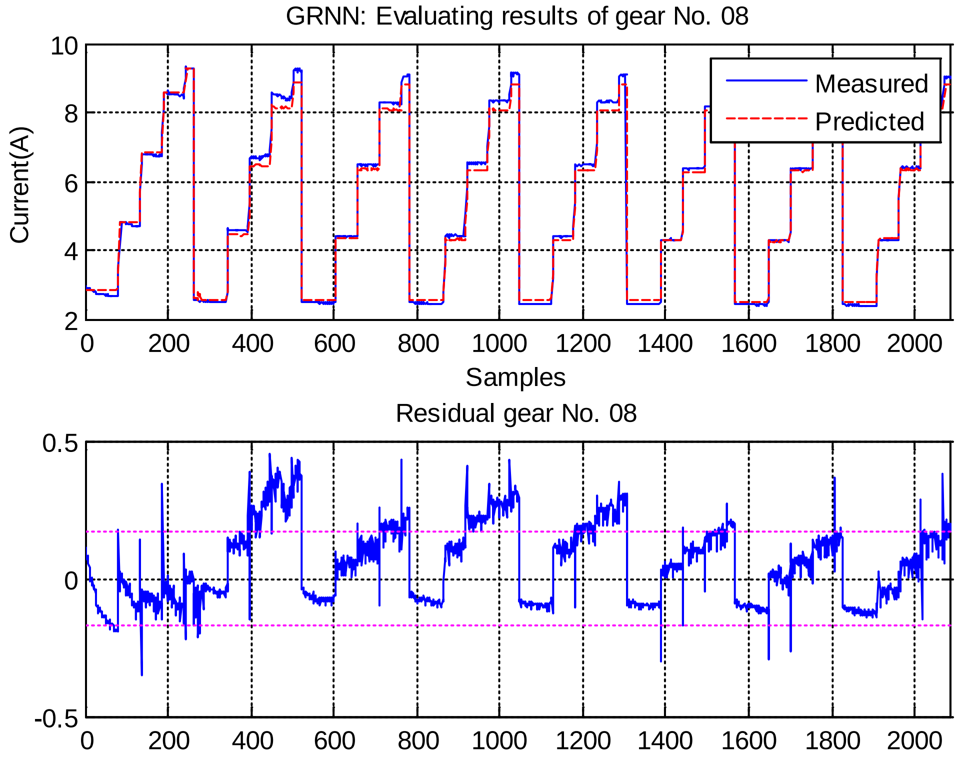


Figure 6.7 GRNN Evaluation of results for Gear08 – 50% tooth breakage

6.6.2 Fault Detection on Gear09 using GRNN

Figure 6.8 presents the measured and predicted Armature currents for Gear09 on which there was a 75% tooth breakage. It can be seen clearly that the predicted current has large differences from the measured one.

The lower part of Figure 6.8 presents only the residual data so that the details of the data points exceeding the threshold can be seen more clearly. Compared with Figure 6.6, many more successive data points exceed the thresholds, which indicate that there is a more severe fault in Gear09 than in Gear08.

The maximum/minimum values of GRNN residual are of 0.3923/-0.8203 for the gear-09, which indicates that the residual range for this gear is of 1.2126.

However, compared with (Gear08), the residual range for gear09 bigger than the residual range for gear08, which indicate that there is a more severe fault in Gear09 than in Gear08.

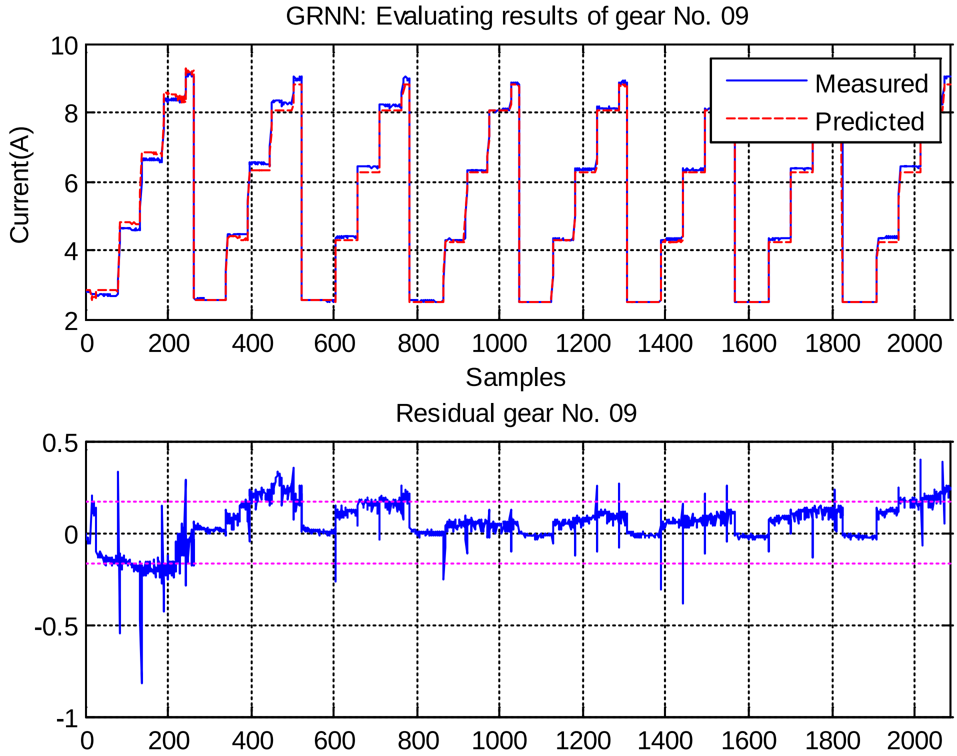


Figure 6.8 GRNN: Evaluating results of Gear 09 – 75% tooth breakage

6.7 Summary

This chapter has demonstrated that it is possible to use static data, mainly measurements from the Controller see section 4.4 chapter 4 for monitoring mechanical faults in gearbox transmission systems. Based on data characteristics and future integration requirements, the GRNN approach to gearbox fault detection and diagnosis has been demonstrated using static datasets obtained for motor operation. The model developed using baseline data, captures the nonlinear relationships between AC current, load setting and gearbox temperature.

The GRNN model was trained using the first half of data from Gear07 and verified using the second part of data from Gear07. The GRNN model was applied to generate residuals by comparing current measurements with the patters obtained from the training.

Once a fault has been introduced into the gear the output (current) will change and produce a difference ("error") between model prediction and measured value. Thus one can find whether Gear08 or Gear09 has the more severe fault by determining which has the higher residual values between model predictions and test measurements.

The simulation results show that the GRNN models are accurate and reliable estimators of complex gearbox processes, and it demonstrates the effectiveness of the proposed methods for detecting tooth faults in a two stage gearbox using motor operating parameters.

CHAPTER 7: GEARBOX FAULT DETECTION USING STATIC DATA AND BACK PROPAGATION NEURAL NETWORK

This chapter examines the performance of a back propagation neural networks (BPNN) model when applied to the detection and diagnosis of different faults in a gearbox. The model is developed using Neural Networks (NNs) to capture connections between measured variables.

7.1 Back Propagation Neural Network (BPNN)

The back propagation neural network (BPNN) is a popular NN and was chosen to serve as a comparison to the GRNN. Like the GRNN it is a multi-layer feed-forward network [150], but it uses the back propagation algorithm and the training speed of GRNN is faster than

BPNN. The back propagation technique has been applied to many pattern detection problems [152]. Generally it is called the Feed Forward Back propagation neural network, sees Figure 7.1, and contains input, hidden and output layers.

The architecture of the ANN can be changed to suit the needs of the application it is to be used with. Variables include the number of layers, the number of neurons in each layer (deciding on the number of neurons in each layer is a very important part of deciding on the overall network architecture. Using too few neurons in the hidden layers will result in under fitting and using too many neurons in the hidden layers can result in over fitting. Obviously, some compromise must be reached between too many and too few nodes in the hidden layers), the transfer function for each layer (used to calculate output from input), the learning function, the number of times the training process is repeated (epochs), and the error goal (the designated error value). Because each and every one of these parameters can be varied, it is obvious that to optimise a BPNN involves a much more intense series of tests.

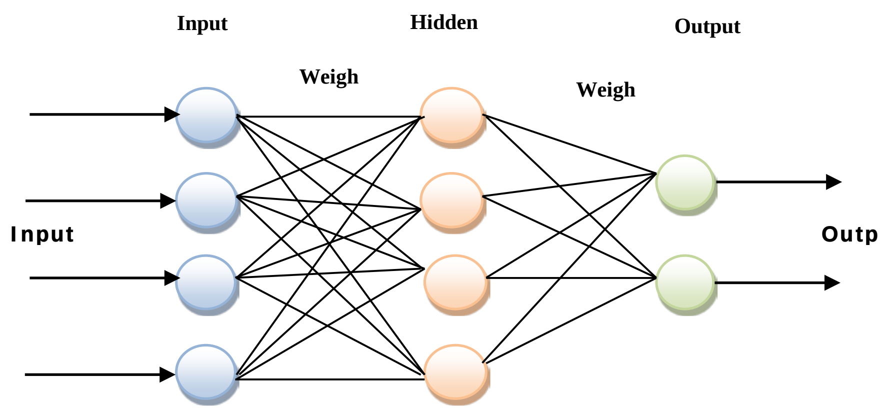


Figure 7.1 : Architecture of BPNN

7.2 Learning process of a BPNN

The learning process of a BPNN is seen in Figure 7.2. In the training stage, the training data is passed into the input layer. It is propagated to both the hidden and the output layer. In this stage, each node in the input, hidden and output layer calculates and adjusts the appropriate weight between nodes and generates the output value of the resulting sum. The actual output values are compared with the target output values. The error between these outputs will be calculated and propagated back to the hidden layer in order to update the weight of each node [152].

The standard back propagation algorithm for training the network is based on the minimization of an energy function representing the instantaneous error. In other words, it is desired to minimize a function defined as [152]:

$$E(m) = \frac{1}{2}\sum_{q=1}^{n}\left(d_q - y_q\right)^2 \qquad (7.1)$$

Where:

d_q represents the desired network output for the q_{th} input pattern, and

y_q is the actual output of the neural network.

Each weight is changed according to the rule (reference?):

$$\triangle w_{ij} = -k\frac{dE}{dw_{ij}} \qquad (7.2)$$

Where:

k is a constant of proportionality,

E is the error function and

w_{ij} represents the weights of the connection between neuron j and neuron i.

The weight adjustment process is repeated until the difference between the node output and actual output is within some acceptable tolerance.

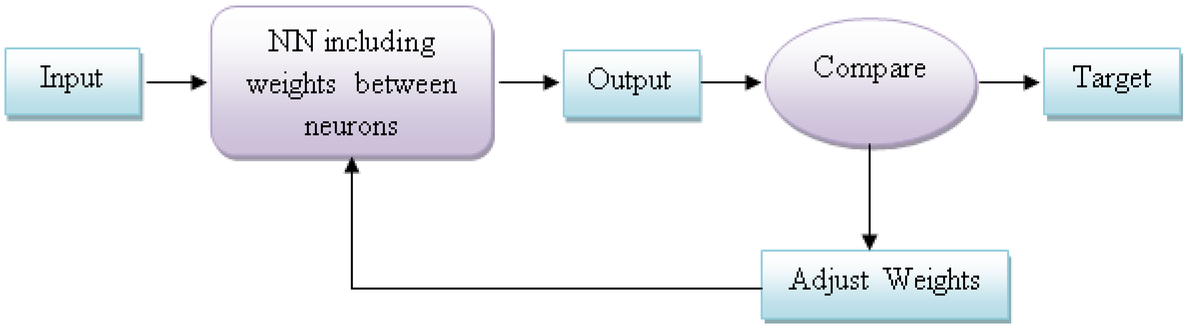


Figure 7.2 Learning process of the back propagation neural network

The back propagation training algorithm [153] can be summarized as follows: The input data sample is presented to the network and the network's output (from the output layer) is compared with the desired output and the error is calculated for each output neuron. Next a scaling factor called the local error is calculated for each neuron. This indicates how much, higher or lower, the actual output must be adjusted to match the desired output. The weights are modified to lower this local error. This process is repeated until the error falls within the acceptable value (pre-defined threshold) which would indicate that the NN has been trained successfully. If the maximum number of iterations is reached before the error falls within the acceptable value, the training was not successful.

7.2 Data Characteristics

Data are as described in chapter six, sections 6.3. (For more information and figures see Appendix B)

7.3 BPNN Model Development

The BPNN model was developed using MATLAB software based on the baseline datasets from Gear07. The model has two inputs: temperature and load set points and one output: AC current. To train the model, the datasets from Gear07 are used as the baseline for model development. As described in Chapter 6 there are, in total, 2088 data samples from eight tests of different runs and these are divided into two equal subsets of 1044 points: one for model training and the other for model verification.

Figure 7.3 presents a snapshot of the trained BPNN and it is to be noted that the number of iterations required for the training process was 20. It can be seen that the mean square error in fault detection achieved by the end of the training process was 0.000964 and that the number of validation check fails were six by the end of the training process.

Fig 7.4 shows the training performance plot of the neural network. It can be seen that the BPNN did achieve the desired Mean Square Error (MSE) goal by the end of the training process.

The result of the training process is presented in Figure 7.5. Obviously, the outputs of BPNN model are almost identical with the measured values, which indicate that BPNN model has been well trained.

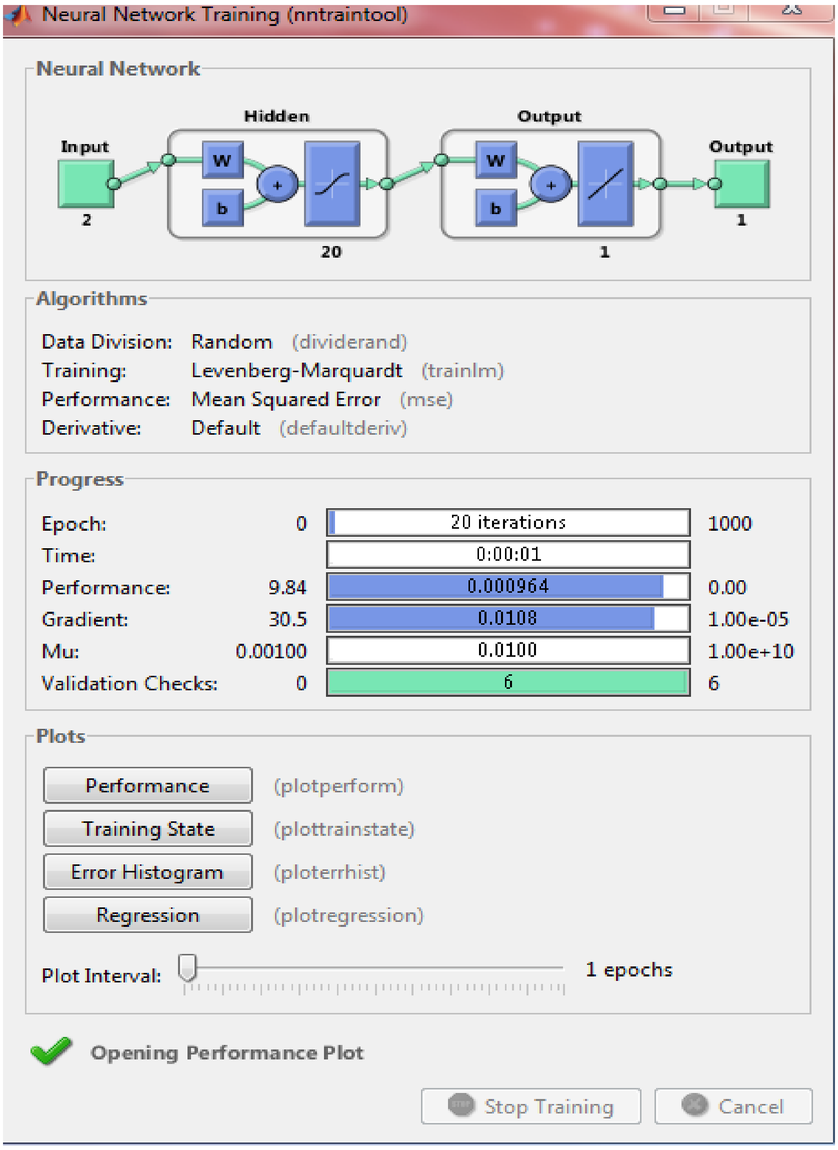


Figure 7.3 Overview of the BPNN

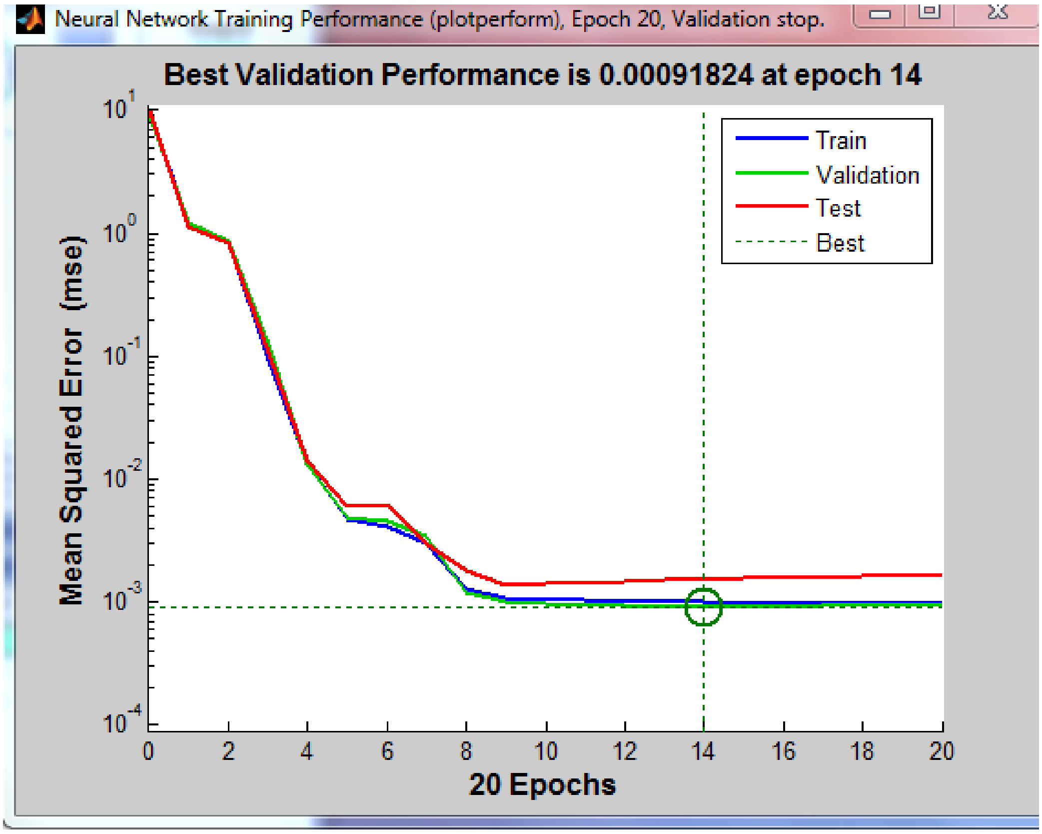


Figure 7.4 Mean-square error performance of the BPNN

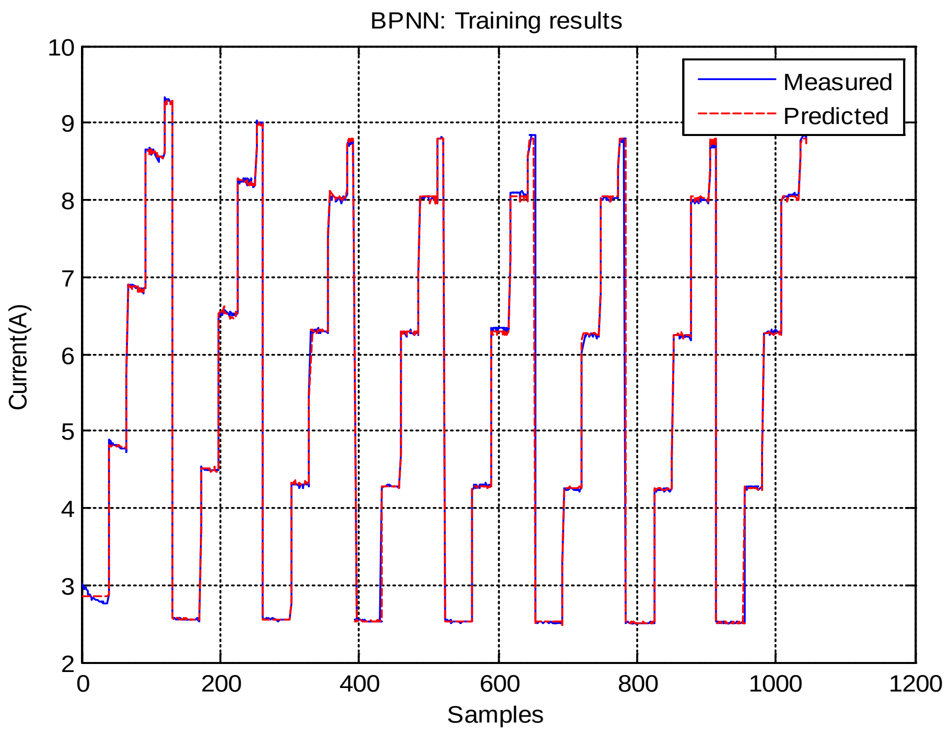


Figure 7.5 BPNN training result

The factor that is considered best for evaluating the performance of the network is the correlation coefficient of each of the various phases of training, validation and testing. Figure 7.6 shows the regression plots of the various phases: training, testing and validation. It can be seen that the best linear fit very closely matches the ideal case with an overall correlation coefficient of 0.9999.

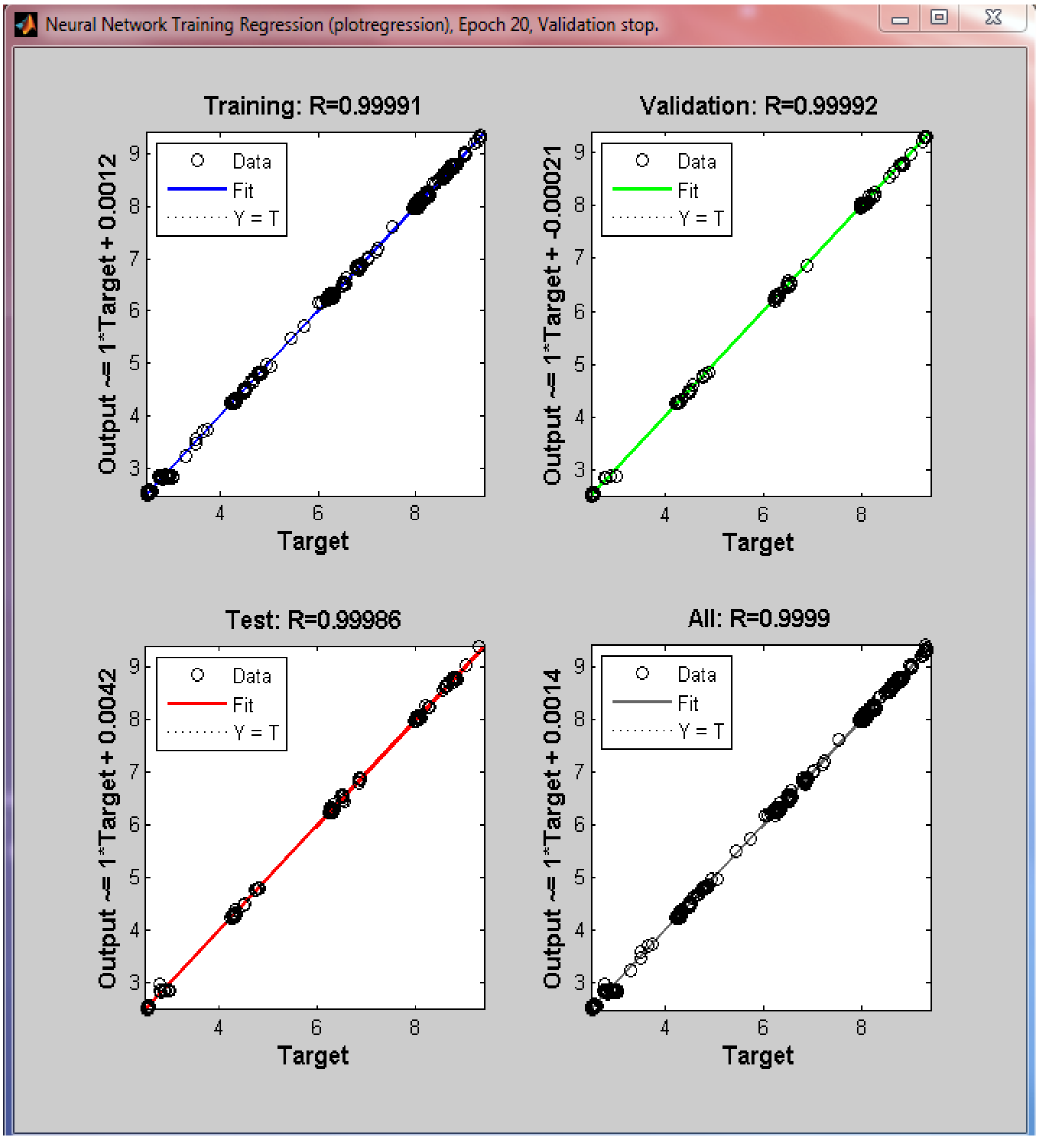


Figure 7.6 Regression plots of various phases of learning of the BPNN

7.4 Estimation of detection threshold

To confirm the models performance, the 2nd dataset is employed as the input and output of the models developed from the 1st set. To measure the quality of the models in fitting to the second data and to detect abnormalities from new datasets, a threshold is To confirm the models performance, the second dataset was used as input and output of the models developed from the first data set (for Gear07). As in Chapter 6, Section 6.5, the threshold (D_{th}) was defined as three times of the root mean square value of the differences between the measured real current and the model predicted current.

$$D_{th} = 3\sqrt{\frac{1}{N}\sum_{i=1}^{N}(I_{mi} - I_{pi})^2} \quad (7.3)$$

Where: the symbols have their previous meaning.

7.4.1 BPNN evaluation

For reliable detection, the second half of the dataset is used to calculate the interval. Figure 7.7 shows the model verification results which were calculated using the second part of the baseline data. The two horizontal dashed lines in the Figure are the upper and lower detection thresholds (D_{th}) respectively. It can be seen that most of the errors, obtained by subtraction of predicted and measured current values, are within the designated threshold, which indicates that the model fits the data well. However, there are several data points which exceed the threshold. Careful examination shows that these data points occur because of outliers arising during load transient periods when temperature measurements have delayed responses to current increases.

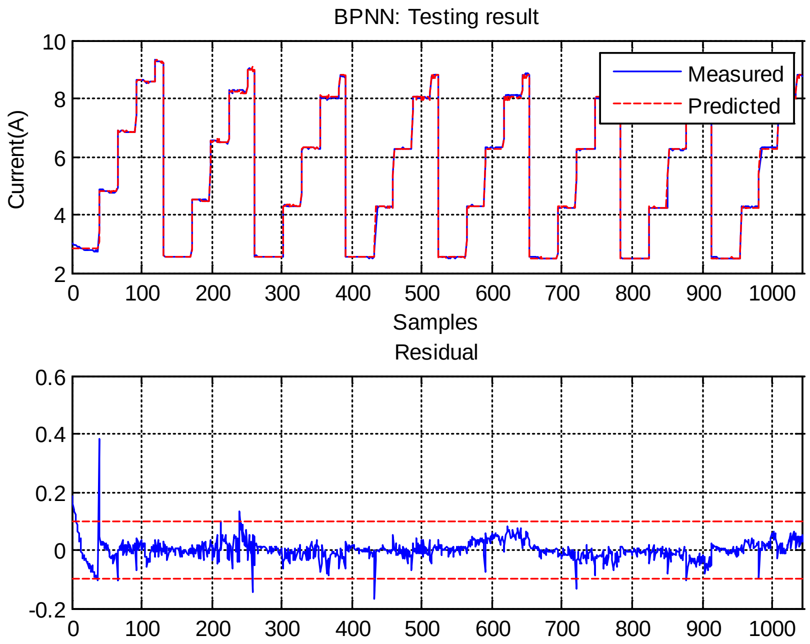


Figure 7.7 BPNN Model verification by 2nd part of data from Gear 07

7.5 Fault Detection and discussion

7.5.1 Fault Detection for Gear08 using BPNN

Figure 7.8 shows the model prediction against with measurement results for Gear 08 with 50% tooth breakage. It can be seen from the traces in the upper part of the Figure that there are significant differences between predicted and measured currents. The plot of the residual in the lower part of the figure shows clearly that many data points exceed the thresholds with many large differences between the two values. indicating there a fault in Gear08.

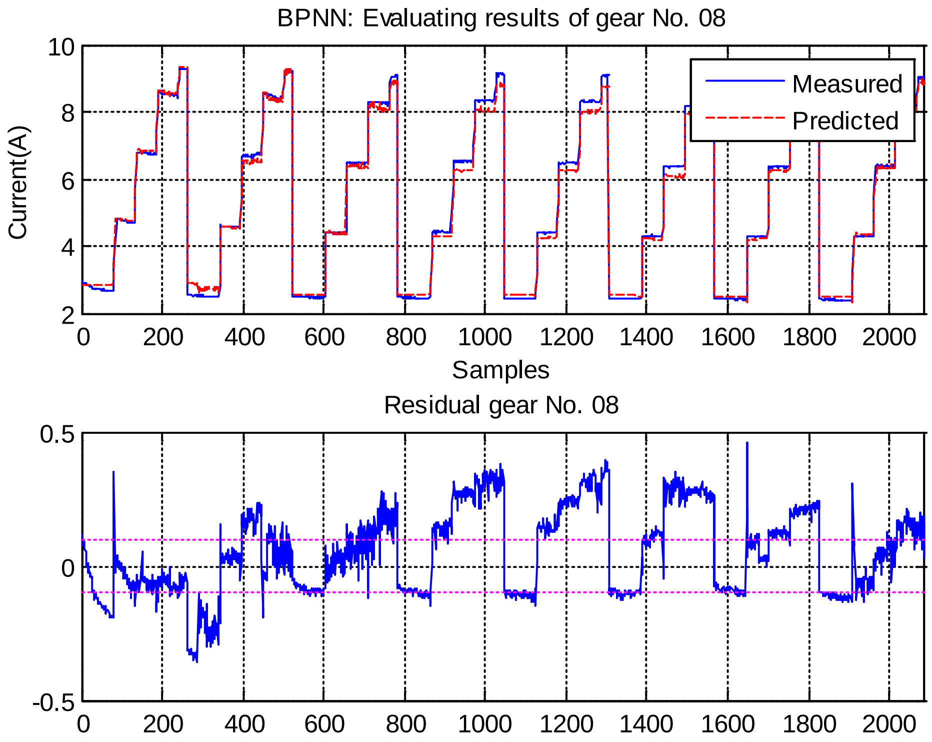


Figure 7.8 Evaluation of BPNN results for Gear08 – 50% tooth breakage

7.5.2 Fault Detection on Gear09 using BPNN

Figure 7.9 shows the model prediction against with measurement results for Gear 09 with 75% tooth breakage. Once again it can be seen from the traces in the upper part of the figure that there are significant differences between predicted and measured values. The plot of the residual in the lower part of the figure again shows clearly that many data points exceed the thresholds with many large differences between the two values, indicating there a fault in Gear09.

When comparing Figures 7.8 and 7.9 it can be seen that overall amplitudes of the errors are higher for Gear09 and show that this gear has a more severe fault than Gear08.

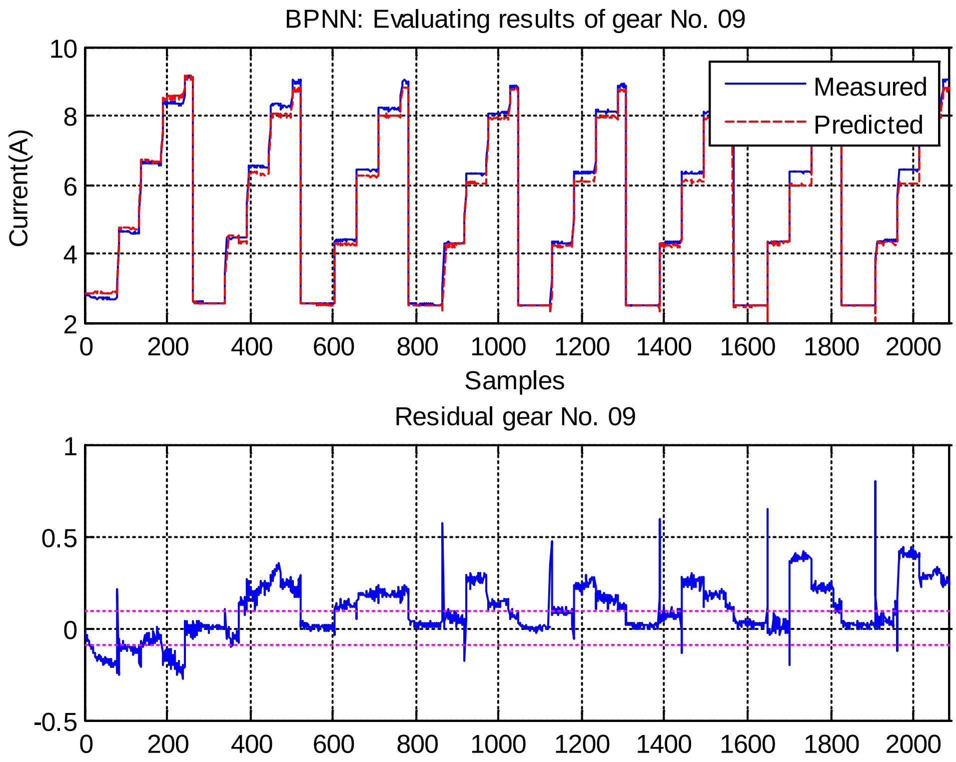


Figure 7.9 Evaluation of BPNN results for Gear09 – 75% tooth breakage

7.6 summary

This chapter has demonstrated that a BPNN can be used with the static dataset of motor operation, mainly measurements from the Controller as described in Section 4.4, to effectively detect a mechanical fault in a gearbox transmission system. In this case the fault was a broken tooth on a pinion gear. The model developed compares baseline data captured from one gear with measured data from a second gear to determine non-linear connections between AC current (armature current), load setting and gearbox temperature.

The simulation results show that the BPNN models are accurate and reliable estimators of complex gearbox processes, and it demonstrates the effectiveness of the proposed methods for detecting tooth faults in a two stage gearbox using motor operating parameters.

CHAPTER 8: GEARBOX FAULT DETECTION USING STATIC DATA AND AN ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

This chapter presents the results obtained from monitoring a faulty gearbox using an adaptive neuro-fuzzy inference system (ANFIS) to capture the nonlinear connections between the electrical motor current and control parameters such as load settings and temperatures. The predicted values generated by ANFIS model are then compared with the measured values to indicate the abnormal condition in gearbox.

8.1 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS had gained popularity over other techniques due to its knowledge extraction abilities, domain partitioning, rule structuring and capacity of modification [154]. The ANN has the capability of motor monitoring and fault detection cheaply and reliably. However, it does not provide heuristic reasoning about the fault detection process. On the other hand, fuzzy logic can easily provide heuristic reasoning, while finding the provision of exact solutions difficult. By merging the positive features of ANN and fuzzy logic, a simple non-invasive fault detection technique has been developed [155]. By using a hybrid, supervised learning algorithm, ANFIS can construct an input-output map. The supervised learning (gradient descent) algorithm is used to train the weights to minimize the errors.

An ANFIS, as its name implies, is a network structure consisting of nodes and directional links through which the nodes are connected. Moreover, part or all of the nodes are adaptive, which means the outputs of the ANFIS structure depends on the weights connected to the nodes, and the gradient descent learning rule specifies how these parameters should be changed to minimize a prescribed error measure.

8.2 ANFIS Architecture

ANFIS architecture consists of five layers in which the first and the fourth layers are adaptive nodes and the remaining layers are fixed nodes. The adaptive nodes are associated with their respective parameters, get duly updated with each subsequent iteration while the fixed nodes are devoid of any parameters [156], [157], [158]. This system contains two inputs, x and y and one output f which is associated with the following rules:

Rule 1: If (x is A_1) and (y is B_1) then ($f_1 = p_1x + q_1y + r_1$)

Rule 2: If (x is A_2) and (y is B_2) then ($f_2 = p_2x + q_2y + r_2$)

Where:

x and y are the inputs,

A_i, B_i and f_i are fuzzy sets and systems output respectively, and

p_i, q_i and r_i are the design parameters that are determined during the training process.

The ANFIS architecture to implement these two rules is shown in Figure 8.1, in which a circle indicates a fixed node, and a square indicates an adaptive node.

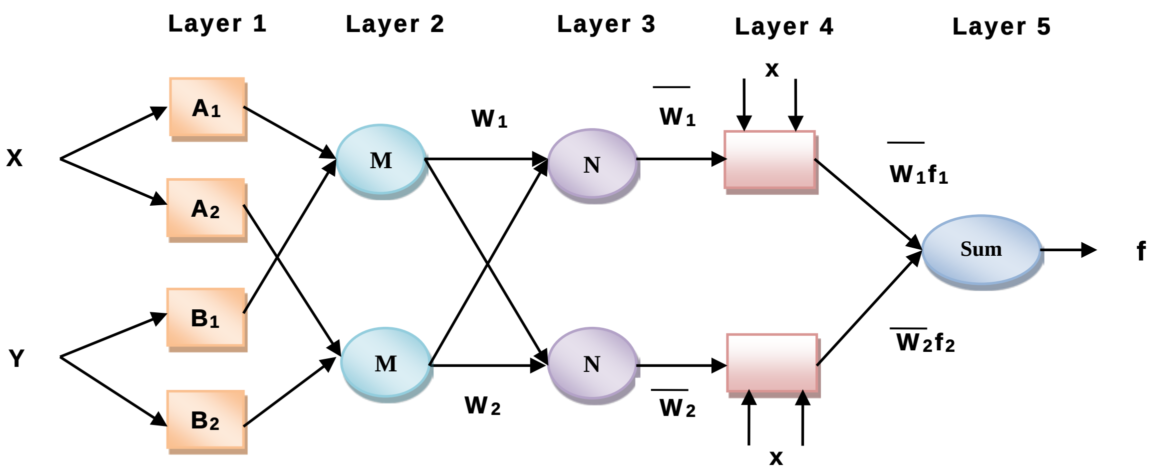


Figure 8.1 Architecture of ANFIS

Layer 1 - fuzzification layer: every node in this layer is an adaptive node. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by:

$$O_i^1 = \mu_{Ai}(x); i = 1,2 \tag{8.1}$$

$$O_i^1 = \mu_{Bi-2}(y); i = 3,4 \tag{8.2}$$

Where:

x and y are the inputs to node i,

A is a linguistic label (small, large) (what is B?), and

$\mu_{Ai}(x)$, $\mu_{Bi-2}(y)$ can adopt any fuzzy membership function.

Usually we choose $\mu_{Ai}(x)$ to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as:

$$\mu_{Ai}(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \tag{8.3}$$

Here (a_i, b_i and c_i) are the parameters of the membership function and are referred to as premise parameters.

Layer 2 - rule layer: consists of fixed nodes (labelled, M in Figure 8.1) whose output is the product of all the incoming signals. The outputs of this layer can be represented as:

$$O_i^2 = w_i = \mu_{Ai}(x).\mu_{Bi}(y); i = 1,2 \tag{8.4}$$

Layer 3 - normalization layer: consists of fixed nodes (labelled, n in Figure 8.1). The outputs of this layer can be represented as:

$$O_i^3 = \bar{w}_i = \frac{w_i}{(w_1 + w_2)} \tag{8.5}$$

Layer 4 - defuzzification layer: every node in this layer is an adaptive node with the output of each node the product of the normalized firing strength and a first order polynomial.

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \tag{8.6}$$

Where:

$\bar{w}_i$ Output of the layer 3, and

pi, qi and ri are parameter set.

Layer 5 - summation neuron: a fixed node which computes the overall output as the summation of all incoming signals.

$$O_i^5 = \sum_i \bar{w}_i f_i = \sum_i w_i f_i / \sum_i w_i \tag{8.7}$$

8.2.1 Learning algorithm for ANFIS

As stated above, both the premise (non-linear) and consequent (linear) parameters of the ANFIS should be tuned, utilizing the so-called learning process, to optimally represent the actual mathematical relationship between the input space and output space.

Normally, as a first step, an approximate fuzzy model is first used by the system and then improved through an iterative adaptive learning process. ANFIS takes this initial fuzzy model and tunes it by means of a hybrid technique combining gradient descent back propagation and mean least-squares optimization algorithms (see Figure 8.2). For each epoch, an error measure, usually defined as the sum of the square of the difference between actual and desired output, is reduced.

Training stops when either the predefined epoch number or error rate is obtained. There are two passes in the hybrid learning procedure for ANFIS. In the forward pass of the hybrid learning algorithm, functional signals go forward till layer 4 and the consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backward and the premise parameters are updated using gradient descent [135].

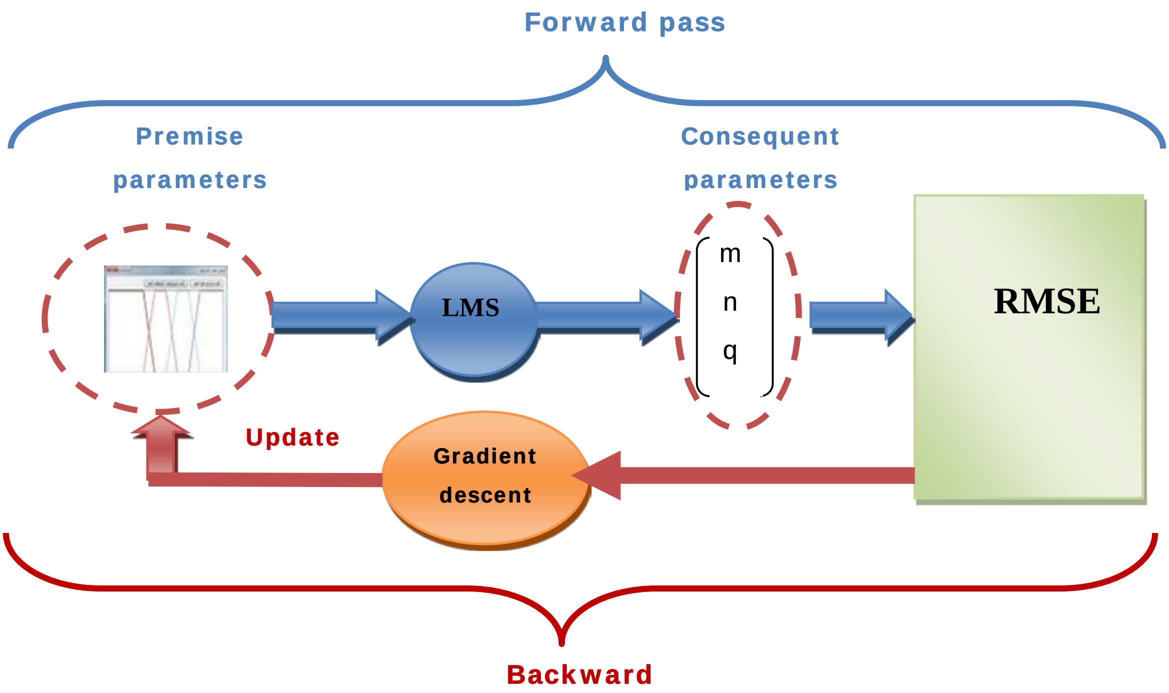


Figure 8.2 ANFIS learning using hybrid technique

8.3 Data Characteristics

Data are as described in Chapter 6, Section 6.3. (For more information and figures see Appendix B)

8.4 Model Development

As with GRNN and BPNN the ANFIS model was developed using the baseline datasets from Gear07. The model has two inputs: temperature and load set points and one output: AC current. For each input, a bell shape is chosen for each membership function (MF) and the number of MFs is 2. To train the ANFIS model, the same 2088 data samples from Gear07 as used previously were again divided into two equal subsets: one for ANFIS model training and the other for model verification. The convergence of root mean squared error (RMSE) was used to evaluate the learning process. When the rate of decrease of the RMSE was no longer significant, the learning process was terminated.

Through the learning process, the parameters of the MFs are automatically adjusted in order that the outputs of the ANFIS model match the actual values in the training data. In this study, after executing 300 epochs, all RMSEs of the outputs reached the convergent stage, see Figure 8.3.

The initial shapes of the MFs and their changes after learning are show in Figure 8.4. It can be seen that the degree of membership changed significantly to match the outputs of the model with the measured values in the training set.

The result of the training process is presented in Figure 8.5. Obviously, the outputs of ANFIS model are very close to the measured values, which indicate that ANFIS model has been well trained.

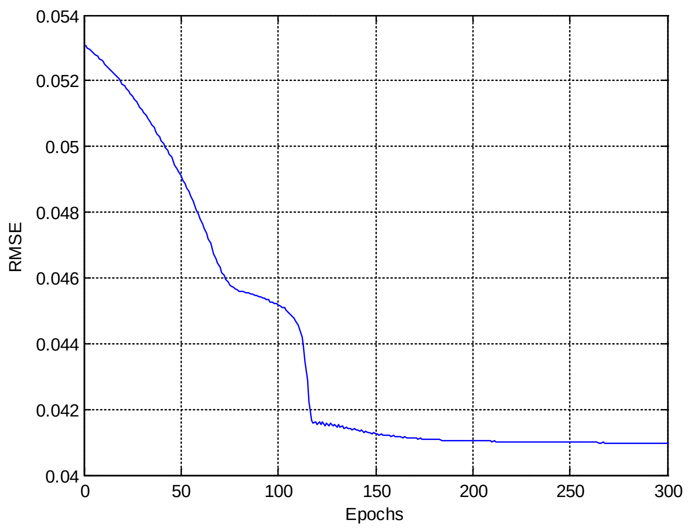


Figure 8.3 The network RMSE convergence curve

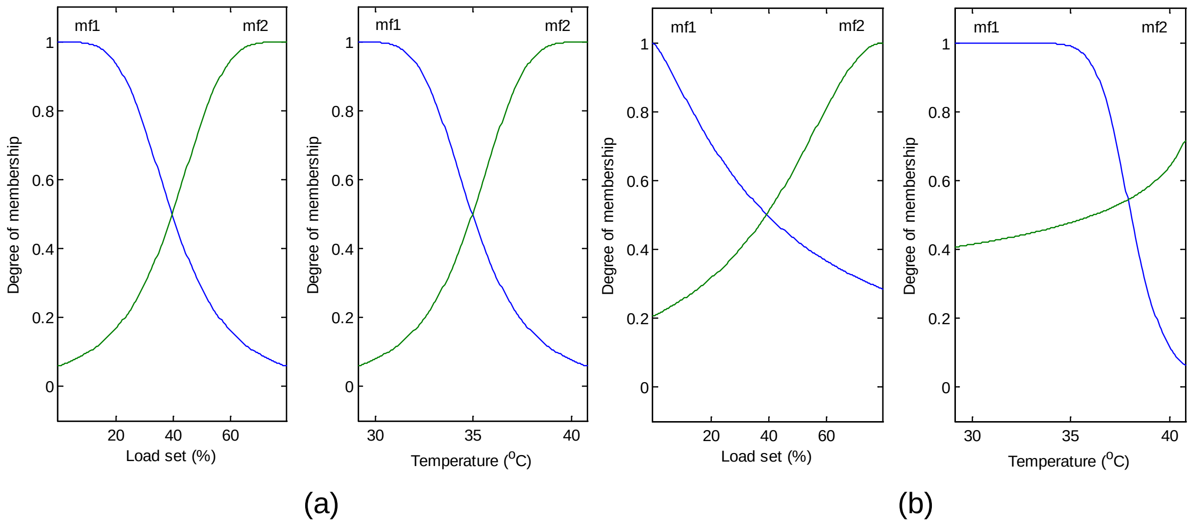


Figure 8.4 Bell shaped MFs a) Initial, b) Final

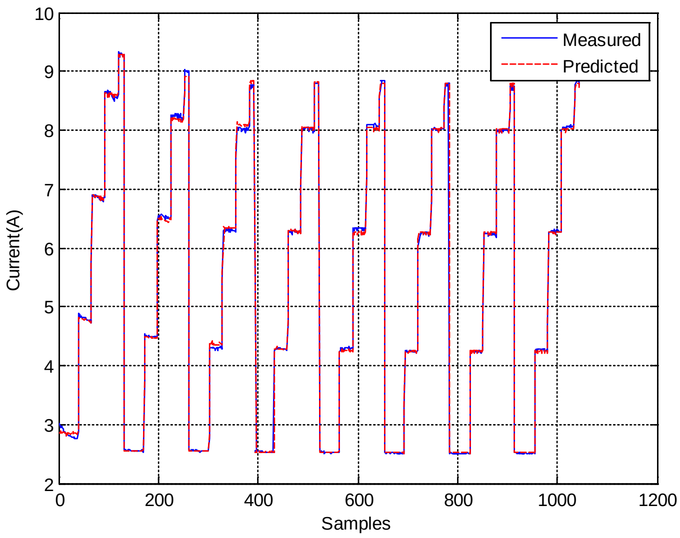


Figure 8.5 Training results

8.5 Model evaluation and detection threshold.

To confirm the model performance, the second dataset from Gear07 was used as the input and output of the model developed from the first set, see Section 6.5. Again, as previously, to measure the quality of the model in fitting the second data and to detect abnormalities from new datasets, the root mean square error (RMSE) was used, where:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(I_{mi} - I_{pi})^2} \tag{8.8}$$

Again, the threshold (D_{th}) was used as a criterion for accepting the test results, where: three times of RMS.

Figure 8.6 shows model verification results which are calculated using the model using the second part of data from Gear07.

In Figure 8.6 (b), the two horizontal dashed lines are the upper and lower detection thresholds respectively. It can be seen that most of the errors obtained by a subtraction between predicted and measured values, are well within the threshold, which indicates that the model fits the measured data well. On the other hand it also indicates that the data reflecting the process is healthy.

However, some data points do exceed the threshold. The same explanation is proposed for this as previously, outliers arise from load transients when there are changes in current and the temperature takes a little while to reach equilibrium. The model is sufficiently accurate to use for fault detection using new data from other two gear sets.

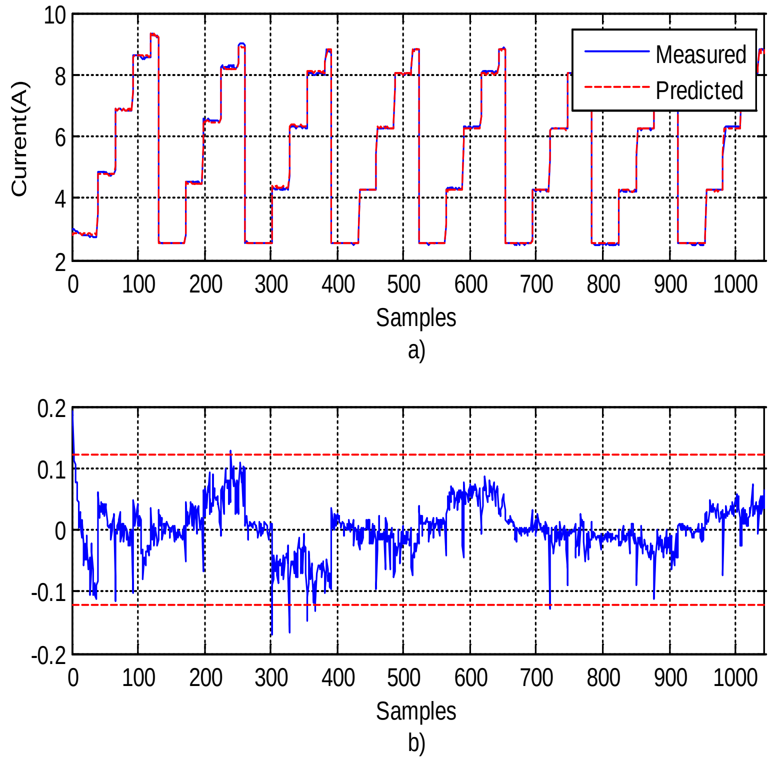


Figure 8.6 The test result for ANFIS model, a) Measured and predicted results, b) Residual

8.6 Fault Detection and Discussions

8.6.1 Fault detection on Gear08

Figure 8.7 (a) presents the measured current for Gear08 with 50% tooth breakage and predicted current for a relatively healthy gear. It can be seen in the upper panel of the figure that the trace for the predicted current has significant differences from the trace for the measured current. The lower panel, Figure 8.7 (b) shows the residual data which shows the differences between the two currents more clearly. It can be seen that the value of Dth exceeds the prescribed threshold on a number of occasions from which the observer can conclude there is a fault in Gear08 over and above any fault present in Gear07.

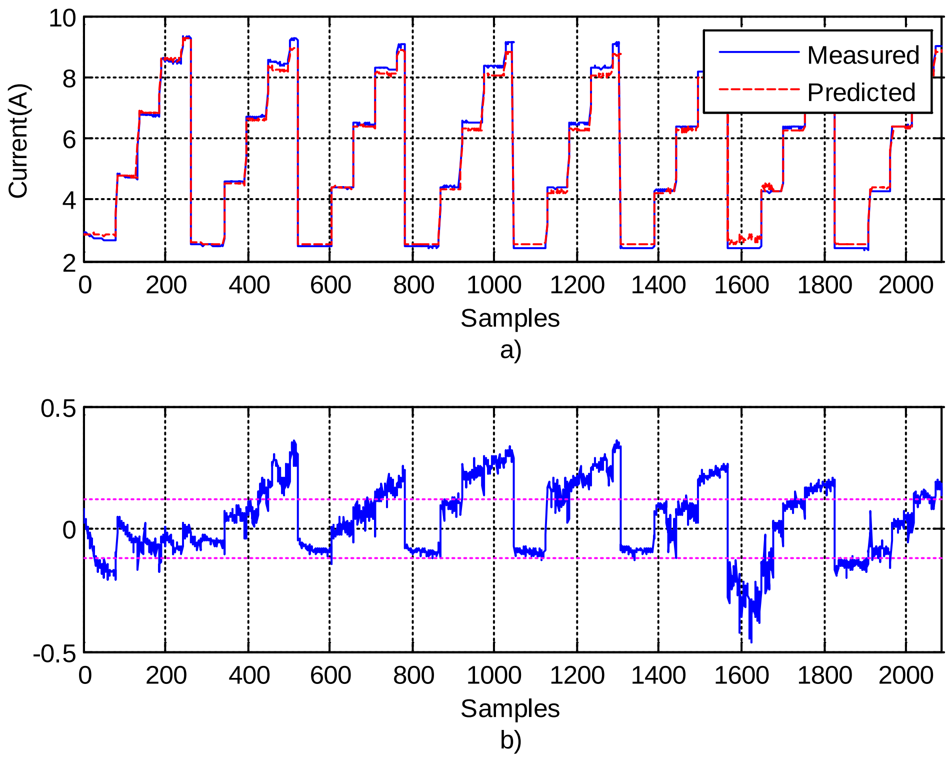


Figure 8.7 a) Measured and predicted current of Gear08 – 50% tooth breakage, b) The residual

8.6.2 Fault detection on Gear09.

The ANFIS model was used for fault detection with Gear09 with 75% tooth breakage and Figure 8.8 (a) shows the measured and predicted currents. It can be seen clearly that the predicted and measured currents have large differences. The plot of residual values presented in Figure 8.8 (b) shows many points which exceed the prescribed threshold.

Comparisons of the residuals show that the overall amplitudes of the errors for Gear09 are much higher, and demonstrate that this gear has a more severe fault than Gear08.

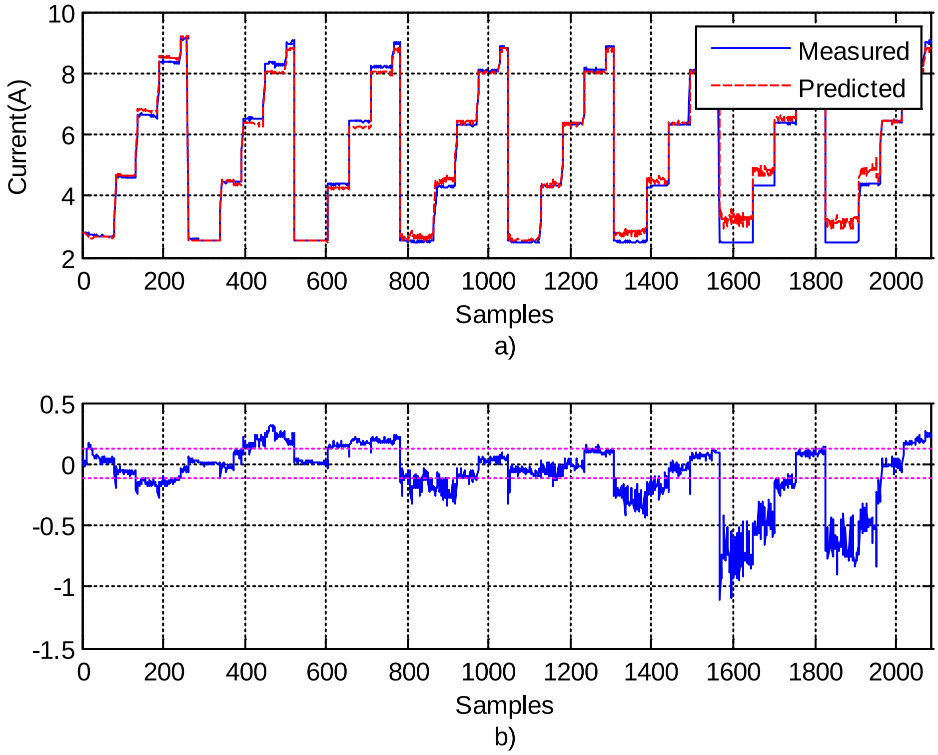


Figure 8.8 a) Measured and predicted currents of Gear09 - 75% tooth breakage, b) The residual

8.7 Comparisons of three methods

In order to appraise the efficacy of three proposed models so that the best for industrial applications of fault diagnosis can be discerned, a comparative study was performed. This section reports the results in three parts: the accuracy of the detection results, the detection performance and the time consumed in the training process.

8.7.1 Comparison of training time

The training time for gear-07 of GRNN, BPNN, and ANFIS is shown in Figure 8.9 and Table 8.1. For the networks to converge using the same training set and chosen parameters, it can be seen that GRNN achieved the shortest training time of 0.2028s, whilst BPNN and ANFIS took, respectively, 3.51s and 4.0092s. The parameters as mentioned in Chapter 7 and 8 are 20 nodes (number of iterations required for the training process), 3 network layers, and 1000 epochs for the BPNN model; 2 membership functions and 300 epochs for the ANFIS model. The training time of these models will increase significantly if these parameters increase. On the other hand, the training time also increases if the models are trained using a large training set. Obviously, shorter training times are of considerable importance from the application point of view. From the results in this study, GRNN is a superior to BPNN and ANFIS in training time.

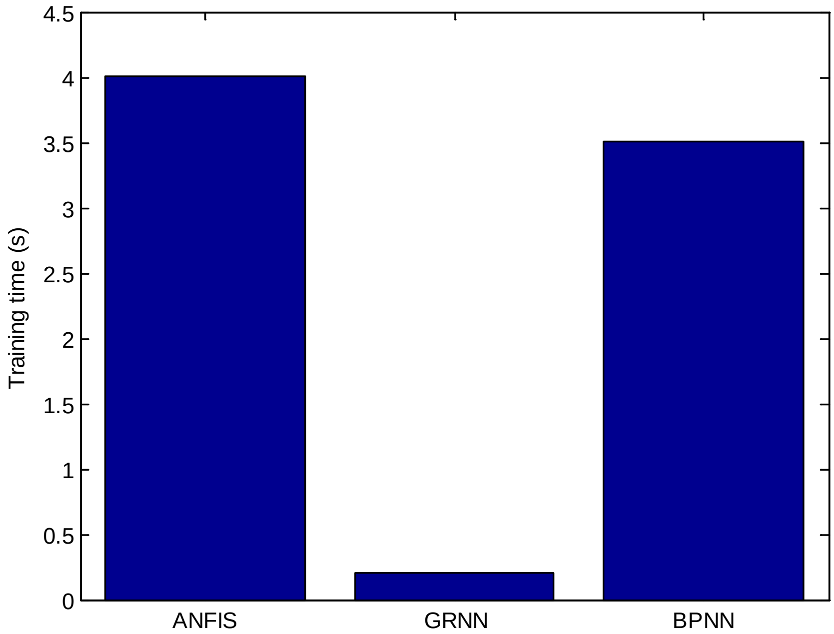


Figure 8.9 The training time of the three models

Table 8.1 : The training time

Method	Training time **(s)**	Difference (s)
GRNN	0.2028	0
BPNN	3.5100	3.3072
ANFIS	4.0092	3.8064

8.7.2 Comparison of the model accuracy

The GRNN is the fastest learning model. However, it is necessary to examine the accuracy of the models and their residuals used for fault detection. Figure 8.10 shows the residuals of different models for the gear-07. It can be seen that all the prediction points in the residual plots are distributed around the horizontal axis and there is no trend in the residuals. In other words, the zero line divides the residuals into two roughly symmetrical parts indicating that the models describe the test data well.

As shown in Fig. 8.10, the residual values of ANFIS are very close to the zero in comparison with those of GRNN and BPNN. In case of BPNN, several residual points fall far from the line through zero. This also occurs in GRNN residual. However, the distances from the residual values to zero of GRNN are smaller than those of BPNN. Additionally, the residual variation of GRNN and BPNN is larger than that of ANFIS.

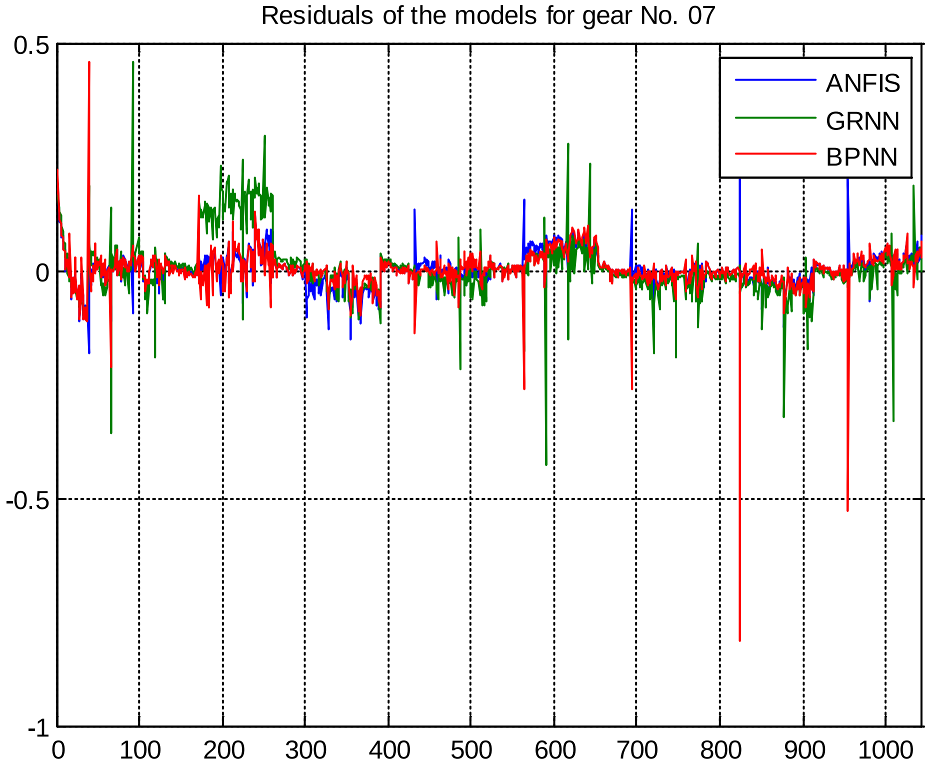


Figure 8.10 The residuals of the models for gear-07

The comparative study further carries out by investigating the mean and standard deviation (STD) of the model residuals which are shown in Table 8.2. The best model gives minimum results of mean and STD for gear-07. Hence, the mean and STD residual values of ANFIS model are smallest which indicates that ANFIS model can give the highest accuracy.

Table 8.2 : The mean and STD of residuals for different models

Gear No	Mean			STD		
	GRNN	BPNN	ANFIS	GRNN	BPNN	ANFIS
G07baseline	0.0054	-9.6203e-005	0.0017	0.0653	0.0515	0.0388

8.7.3 Comparison of the model detection performance.

To examine the models residuals used for fault detection. The residuals of ANFIS, GRNN, and BPNN are depicted in Figure 8.11 for gear-08 (50% tooth fracture) .It can be seen that, the residual values of ANFIS are very small in comparison with those of GRNN and BPNN. In case of BPNN, several residual points fall far from the line through zero, especially for the first 500 data points. This also occurs in GRNN residual. However, the distances from the residual values to zero of GRNN are smaller than those of BPNN. Additionally, the residual variation of GRNN and BPNN is larger than that of ANFIS, which indicates that BPNN model can give the highest performance.

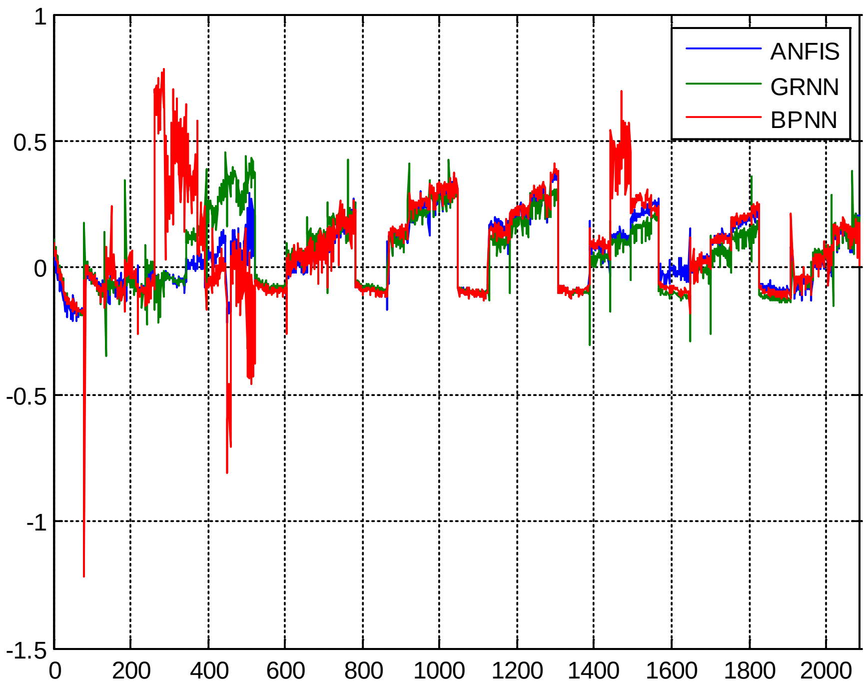


Figure 8.11 The residuals of the models for gear-08

Similarly, the residuals of ANFIS, GRNN, and BPNN are depicted in Figure 8.12 for gear-09 (75% tooth fracture) It can be observed that the magnitudes of both BPNN and GRNN residuals are much bigger than those of ANFIS. From the figure it can also be seen that the magnitude of the residuals for the BPNN are generally more than those for the GRNN. These can be confirmed by examining the residual ranges of the models presented in Table 8.3. From this table, the maximum/minimum values of BPNN residual are of 0.7867/-1.2209 for the gear-08 and 1.6305/-1.5430 for the gear-09, which indicates that the residual ranges for these gears are of 2.0076 and 3.1735. These values are significant big compared to the residual ranges of GRNN (0.8045 for the gear-08 and 1.2126 for the gear-09) and ANFIS (0.6208 and 1.0478 for the gear-08 and gear-09, respectively).

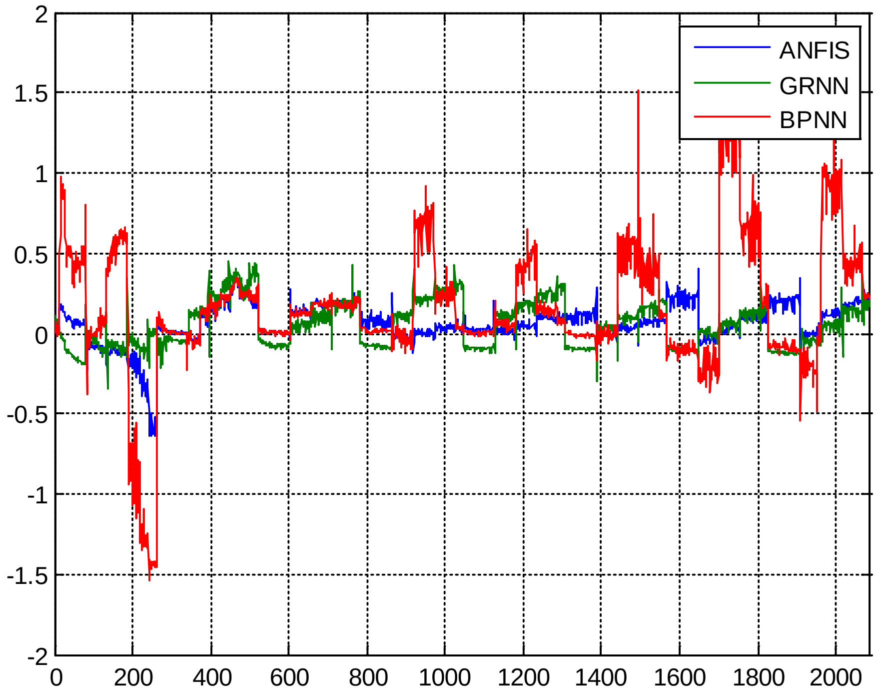


Figure 8.12 the residuals of models for gear-09

Table 8.3 : The residual ranges of the models

Gear No	GRNN		BPNN		ANFIS	
	Min	Max	Min	Max	Min	Max
G08/50%	-0.3493	0.4552	-1.2209	0.7867	-0.2298	0.3910
G09/75%	-0.8203	0.3923	-1.5430	1.6305	-0.6431	0.4047

The comparative study further carries out by investigating the mean and standard deviation (STD) of the model residuals which are shown in Table 8.4. For all the gear data, the mean and STD residual values of BPNN model are biggest. Largest the mean and STD residual values for gears 08 and 09 means that model is most sensitive to changes in the level of fault in the gear, which indicates that BPNN model can give the highest sensitivity to the presence of a fault.

Table 8.4 : The residual mean and STD of the models

Gear No	Mean (residual)			STD (residual)		
	GRNN	BPNN	ANFIS	GRNN	BPNN	ANFIS
G08/50%	0.0550	0.0766	0.0471	0.1406	0.1912	0.1303
G09/75%	0.0485	0.1581	0.0614	0.1103	0.4096	0.1254

Examining the accuracy in the testing processes, it is concluded that ANFIS is the best model if the training time is not an important matter. However, GRNN is an acceptable alternative model if a short training time is required.

Examining the models residuals used for fault detection in the testing processes, it is concluded that BPNN is the best model give the highest sensitivity to the presence of a fault.

8.8 Summary

This chapter has demonstrated that an Adaptive Neuro-Fuzzy Inference System can be used with the static dataset of motor operation, mainly measurements from the Controller as described in Section 4.5, to effectively detect a mechanical fault in a gearbox transmission system. In this case the fault was a broken tooth on a pinion gear. The model developed compares baseline data captured from one gear with measured data from a second gear to determine non-linear connections between AC current (armature current), load setting and gearbox temperature.

Preliminary test results show that the ANFIS based method is an accurate estimator of complex gearbox processes and allows the detection of differences both from a given baseline and between different gear signals. It has been demonstrated that the proposed method is capable of detecting tooth faults in a two stage gearbox using motor operating parameters.

In comparison between the proposed techniques, the BPNN model provided better fault detection performance; ANFIS is the best model gives the highest accuracy and GRNN is a superior to BPNN and ANFIS in training time.

CHAPTER 9: CONCLUSION AND FUTURE WORK

This chapter summarises the achievements of the research and explains how the objectives were met. It includes a summary of the author's contribution to knowledge and the novel aspects of the research work. The key results of the research work on the condition monitoring of the helical gearbox using AI with the aid of operator parameters are drawn together. Finally, the chapter ends by recommending areas for future work.

9.1 Summaries and Conclusions

This study developed gearbox monitoring methods by using the operating parameters (static data) obtained from machine control processes rather than traditionally used parameters such as vibration and acoustic measurements. It proposes a novel scheme for monitoring rotating machinery using so-called static data available in most industrial applications including armature current, load set, speed feedback, torque feedback, motor current, and speed demand. These parameters have been explored based on a gearbox test system in this research programme. This research programme developed and evaluated this scheme using a gearbox transmission system. The test rig had a number of operating parameters including armature current, load set, speed feedback, torque feedback, motor current, and speed demand that could be accessed. By examining these parameters, AI techniques, including general regression neural networks (GRNN), back propagation neural networks (BPNN), and ANFIS were developed to describe the inter-relations between the parameters and to implement a model based detection strategy. Then the model based method is used to detect a number of faults introduced into the test rig. This thesis presented extensive simulation results to demonstrate the effectiveness of the proposed methods.

9.2 Review of the Objectives and Achievements

The main achievements of this research work are described below and correlated with the original objectives set out in Chapter One.

Objective 1: To present, discuss machine condition monitoring and its applications to a gearbox.

Achievement 1: The concept of condition monitoring for machinery has been defined and discussed in Chapter one in Section 1.1 and Chapter two in Section 2.1 in terms of fault detection and diagnosis, the importance of timely maintenance to minimise overall product cost and increased process profitability. Chapter one summarized maintenance strategies and why use operating parameters obtained from machine control processes rather than the traditional measurements, the aim and objectives also providing the structure for the research.

Objective 2: To describe the test rig facility and fault simulation of a two stage helical gear transmission, including gear types and their operation, their failure modes and causes.

Achievement 2: The fundamentals of a two stage helical gear transmission have been dealt with comprehensively. A brief explanation of how the local fault was simulated and how the data was collected is given in Chapter four. In Section 2.3 describes gears types and their operation, and Section 2.4 explains gear failure modes. Causes of gearbox failures were also reviewed in Section 2.4.1.

Objective 3: To review different techniques being used for fault detection and diagnosis in gearbox condition monitoring, using vibration signal and various artificial intelligence based methods.

Achievement 3: The time domain, frequency domain, spectrum and wavelet analysis are the most common CM techniques for gearbox faults detection and diagnosis, and have been introduced and reviewed in Section 2.2.1. Model-based methods and artificial intelligence based methods were also reviewed in Sections 2.2.3 and 2.2.4 respectively.

Objective 4: To develops experimental procedures for CM of a two stage helical gear transmission system primarily focusing on a faulty gear (pinion) in the first stage gear transmission system.

Achievement 4: The test rig facility and data acquisition software were developed as detailed in Chapter four. A two stage helical reduction gearbox manufactured by David Brown Radicon Limited, shown in Figure 4.1, was selected for this study project.

A number of measurement transducers were used on the test rig to monitor the functioning of the gearbox for CM purposes. A brief explanation is given of how the local fault was simulated and how the data was collected. The rig was used to investigate the static data and dynamic data as described in Chapter five. As the rig has a typical drive system, the datasets are considered representative for CM practices. Dynamic datasets were analysed to diagnose the condition of the gear: healthy and faulty, using conventional signal processing techniques such as time domain and frequency domain analysis.

The static data was also analyzed by comparison to evaluate its detection performance. This procedure of data collection and analysis allowed the researcher to gain a full understanding of CM datasets and paved the way for developing a more effective AI approach and efficient database. Also, the test rig was used to provide experimental data to test the performance of a model based approach by applying it to the detection and diagnosis of different faults in a gearbox dataset as it developed, using AI techniques (Chapters six, seven and eight).

Objectives 5 and 6: To examine the performance of a model based condition monitoring approach by using only operating parameters for fault detection in a two stage gearbox, and develop it by applying different AI techniques.

Achievements 5 and 6: The research confirms that it is possible to use static data, which contains mainly measurements from the controller, for monitoring mechanical faults in gearbox transmission systems. Based on data characteristics and future integration requirements, the GRNN, BPNN and ANFIS approaches to gearbox fault detection and diagnosis have been presented for use with the static dataset of motor operation.

The models were developed using comparison between baseline data and data captured from the nonlinear connections between AC current, load setting and gearbox temperature. GRNN, BPNN and ANFIS models were trained using the first half of the data gathered from gear 07 (baseline) and the model was verified using the second half of the data. The models were designed to generate residuals by comparing current measurements with previous trained patterns. Once a fault has been introduced into the gear the output (current) will change and produce a difference (“error”) between the model prediction and measured value. Thus one can determine whether gears 08 and 09 have more severe faults by finding whether residual values are greater than between model predictions and test measurements.

The simulation results show that the three models are accurate and reliable estimators of complex gearbox processes, and demonstrate the effectiveness of the proposed method for detecting tooth faults in a two stage gearbox using only motor operating parameters.

Objective 7: To carry out a comparative study of three methods (GRNN, BPNN.ANFIS) to appraise the accuracy of the models and their residuals used for fault detection.

Achievement 7: The comparative study examined the mean and standard deviations of the residuals obtained from gear-07 as described in Chapter 8 for examining the accuracy in the testing processes, it is concluded that ANFIS is the best model if the training time is not an important matter. Examining the models residuals used for fault detection in the testing processes, the comparative study examined the mean and standard deviations of the residuals obtained from gear 08 and gear 09 as described in Chapter 8. For all the gear data, the mean and STD residual values of BPNN model were the most which indicates that the BPNN model can give the highest sensitivity to the presence of a fault. However, GRNN has the advantage of a shorter training time and acceptable accuracy.

9.3 Contributions to Knowledge

- **First contribution:** This thesis develops gearbox monitoring methods using the operating parameters obtained from machine control processes rather than traditional measurements such as vibration and acoustics.
- **Second contribution:** This research examines the performance of a model based condition monitoring approach by using just operating parameters for fault detection in a two stage gearbox.
- **Third contribution**: a model has been developed using ANFIS, GRNN and BPNN for motor current prediction which determines the difference between predicted and measured values by direct comparison for fault detection.
- **Fourth contribution:** The author has suggested a novel scheme for machine fault detection which utilizes control parameters from embedded sensors and available in most industrial applications. An underpinning technique has been developed and

successfully tested. It has the potential to achieve cost effective monitoring system because it is available in most systems.

9.4 Suggestions for Further Work

This work can be extended by developing and applying more artificial intelligence (AI) techniques for fault detection and diagnosis in more complicated datasets.

- Collect more data from the rig with other faults including shaft misalignment, cracked shaft, other types of gear breakages, etc.
- Combine the static data with feature data sets from dynamic data.
- Evaluate and develop data compression and optimisation techniques such as PCA.
- Evaluate and develop SVM techniques.
- Evaluate and develop hybrid techniques from neural networks, SVM and fuzzy analysis.
- Evaluate and develop feature selection and classification techniques for dealing with sensor less drives where more control parameters can be obtained.

APPENDIX (A): FULL TECHNICAL SPECIFICATION AND OPERATOR SCREENS (DESIGN BY MARK LANE (2011)

FULL TECHNICAL SPECIFICATION:

Power Supply – 220-240VAC (±10%) single or three phase; 380- 460VAC (±10%) three phase; (500V option available); Ambient – Constant torque ratings – 0-45°C (40°C with IP40 cover); Quadratic torque ratings – 0-40°C (35°C with IP40 cover) Derate from above temperatures to 50°C. Max Altitude up to 1000m ASL, derate 1% per 100m above 1000m; Overload – Constant torque ratings – 150% for 60 seconds, 180% for 1 second; Quadratic torque ratings – 115% for 10 seconds; Output Frequency – 0-480Hz Switching Frequency – Frame B 3,6 or 9kHz; Frame C, D, E and F 3 or 6kHz (all with audibly silent switching pattern) Dynamic Braking – Frame B and C standard; Frame D,E and F optional.

The function diagram for the 690+ AC Vector drive as used in this test rig is given in Figure A.1:

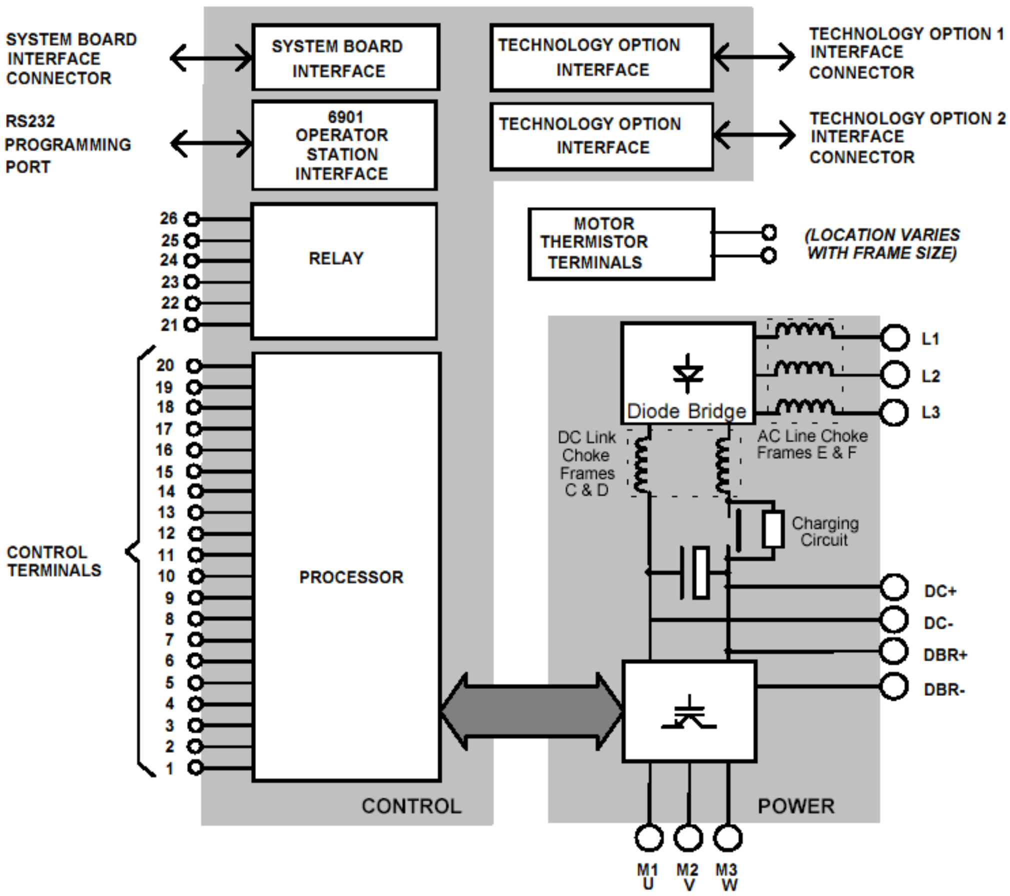


Figure A.1 Functional Block Diagram – 690 + Inverter, Frame C [3]

The drive processor uses an advanced 32-bit microprocessor-based motor control model and operates as a 6-pulse PWM unit with a 3 kHz switching frequency as standard.

- **Power Supplies: Switched Mode**

Manufacturer: Allen-Bradley

The 1606-XLP Compact Power Supply was chosen due to its compact size as panel space is at a premium in the test rig enclosure. These devices are equipped with many of the same features and certifications as the XL devices, and support low-power applications. This power supply provides a cost-effective way to save space while delivering safe and reliable power.

Advantages

– Rated outputs between 15…100 W (0.6…4.2 A at 24V DC).

– Multiple output voltages available.

– Multiple single and three-phase inputs available for global applications.

– Smaller, cost-effective solution for low power applications.

- **Allen Bradley 140M-C2E-B63 Starter Motor Protector:**

This is a 3-pole, 575 Volt Max. Motor protector with an adjustable current range of 4-6.3A. It is used to protect the DC motor cooling fan motor against stalling and over current conditions. There is an auxiliary contact fitted to this device that will stop the test rig from operating should the cooling fan trip. This will protect against damage to the DC motor caused by thermal effects.

The specification of this device is detailed below:

- Isolator Module for Motor Protection Circuit Breakers.
- Isolates the load for highest safety of equipment and staff.
- Prevents unauthorized reconnection of power.
- Padlock capability.
- Ideal for preventive maintenance / plant shut downs.
- Permits testing of circuit breakers and auxiliaries while disconnected.

- **Motor Starter, Allen Bradley 100-C09*10**

This is the motor starter (referred to also as a contactor) used to operate the DC motor 3-phase cooling fan. Features of this unit are:

- AC and DC coil control.
- Common accessories with other 100-C contactors.
- IP2X finger protection.
- Provisions for adding two conductors per terminal.
- Meets IEC, CE, UL, and CSA standard requirements.

- **Route co Transformer**

The transformer rating is calculated according to the load requirements of the equipment contained in the control panel. A transformer is required to bring the line-to-line voltage of 415VAC down to 110VAC for use by components such as the 24VDC power supply and DC motor cooling fan contactor.

- **DC Motor armature current transformer**

In order to give indication to the operator of the rig how much armature current the DC motor is dissipating into the resistor bank, a current transformer will be fitted into one leg of the DC motor armature connections. This will convert the 0 – 200A current into a 0-10VDC signal that can be fed into an indicator on the panel. The specification of the current transformer was chosen so that the range can be changed by altering jumpers on the unit to give more resolution if the full range of measured current is not used.

TECHNICAL SPECIFICATION:

Manufacturer: LEM

Type: DC Current transformer

Part #:DK200-B10

Power supply: 24VDC

Output signal: 0 – 10VDC

Jumper range: Normal - 100A

Mid -150A

High -200A

The setting was left on HIGH, to utilise the full range of the current transformer and to match the panel meter scaling that will indicate 200A with a 10V supply input. If better resolution is required at a later date, then a new panel meter with a lower scaling will need to be ordered instead.

- **DC Motor protection**

Because the DC motor is acting as a generator, circuit protection in the armature circuit must be provided. This is to protect against severe damage both to the DC motor and potentially personnel working close by should the resistor bank short-circuit or develop a fault. The type of fuse chosen for this purpose is a high-speed semiconductor fuse that has a fast-acting rupture time. These are commonly used in DC drive applications to protect the semiconductor devices in the drive, but their use here will ensure a fast disconnection of fault current with a potential clearing current of 22kA at 700V (the clearing current will be much higher for our lower-voltage motor) so we can be sure of safe and reliable fault disconnection.

Type: FWP-200A

Description: Fuse link DC 200A

Manufacturer: Cooper Buss mann

Fuse carrier: BH1133.

PLC Hardware components [137]

Design by Mark Lane (2011)

PLC Inputs

The PLC inputs are defined as follows in Table A.1:

Table A.1 : PLC External Inputs

Type:	Description	Function / Scaling
Analogue	Speed feedback from AC inverter	0 – 10V = 0 to 100% calibrated speed
Analogue	DC Motor field controller feedback	0 – 10V = 0 to 4.7A Field current
Analogue	Current feedback from AC inverter	0 – 10V = 0 to 100% calibrated speed
Analogue	DC Motor armature current feedback from current transformer	0 – 10V = 0 to 207A (maximum armature current)
Digital	DC Field controller health	1 – Controller healthy
Digital	AC Inverter health	1 – Inverter healthy
Digital	AC Inverter at zero speed	1 – Motor at zero speed

PLC Outputs

The PLC outputs are defined as follows in Table A.2:

Table A.2 : PLC External Outputs

Type:	Description	Function / Scaling
Analogue	Speed set point to AC inverter	Control speed of AC motor according to the program demands 0 – 10V = 0 to 100% calibrated speed
Analogue	Load set point to DC field controller	Vary the AC motor load demand according to the program demands 0 – 10V = 0 to 100% calibrated load
Digital	AC drive start	0 – Stop AC Drive 1 – Start AC Drive

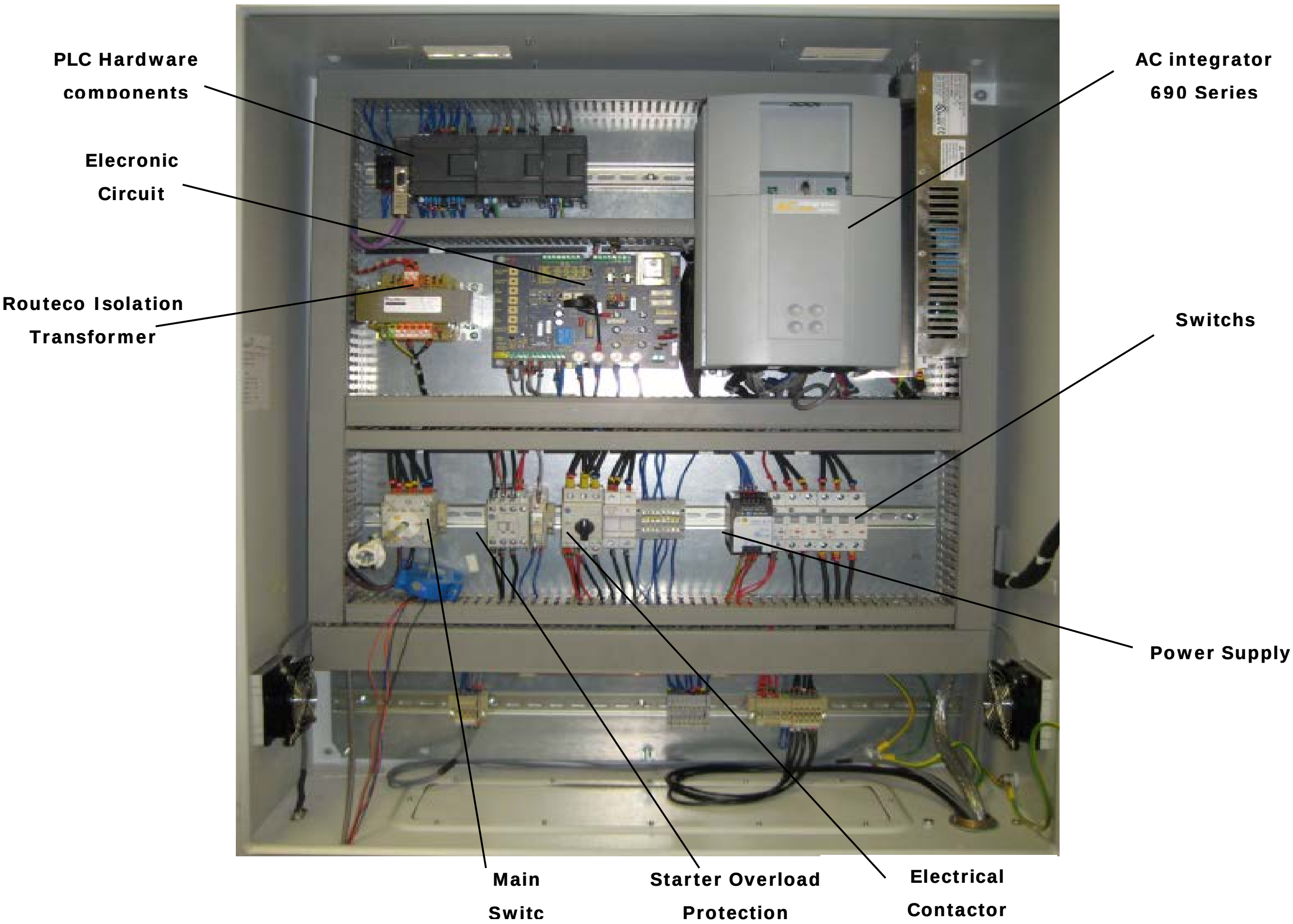


Figure A.2 Test rig control panel interior

Operator screens (Design by Mark Lane (2011) [137].

The operator screens have been written on a Siemens TP177A unit that interfaces to the S7-200 PLC via. a PPI connection (Point-to-Point Interface) that handles all of the data transfer between screen and PLC. The operation of the protocol is invisible to the programmer – the transfer of data values to and from the PLC is performed automatically and no communications routine is required.

Main operator screen

This screen is the main screen used to operate the test rig once all of the parameters have been set-up. Auto or Manual running modes can be selected from this screen. Automatic mode runs the test rig according to data set up in the ‘Recipe Screens’. The speed and load set points are run from one value to another automatically and an option is provided to ‘Repeat’ the test rig operation continuously. Manual mode allows a set speed and load to be run on the test rig for general operation.

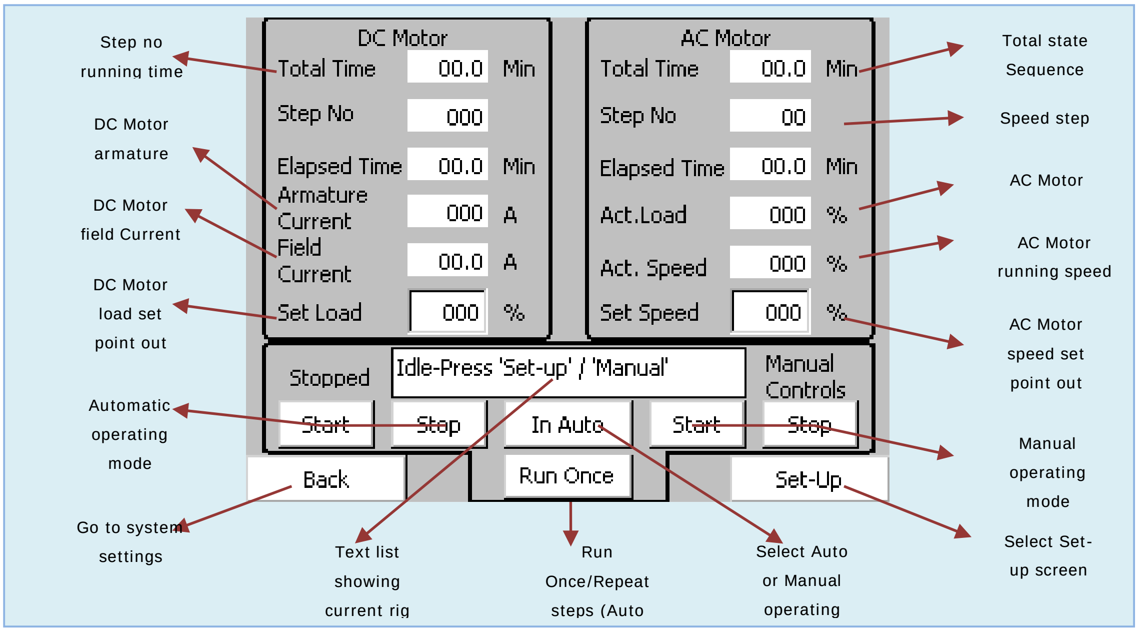


Figure A.3 Main Operator Screen

This screen can be left at any time that the test rig is running without affecting operation. All the DC motor status information is on the left of the screen. The load of the DC motor can be set here if the test rig is in manual mode, otherwise the load setting that is being sent to the DC motor from the auto sequence is shown. Other useful information is the total time that has been set for the load test to run and what step sequence is currently in operation.

The AC motor information is on the right of the screen. AC motor speed can be set here in manual mode and the actual motor speed and load percentage value can be viewed as well. At the bottom middle of the screen is a text list showing the test rig status. If the test rig is not responding to user input, it is useful to check this to see which user step the test rig is waiting for if it cannot be operated for whatever reason.

Selecting Auto or Manual mode is performed by pressing the toggle button in the middle-bottom of the screen. By default, the test rig always starts-up in Automatic mode.

Automatic mode – Single Cycle:

'Start' and 'Stop' pushbuttons for this mode are at the bottom-left of the screen. The 'Start' pushbutton will only be shown once the number of steps required has been entered, all of the sequence step data has been filled in and the 'Finish' key pressed on this page. The test rig can be stopped at any time by pressing 'Stop'. The automatic mode can either operate as a single-step (runs through all steps and speeds then stops) or continuously where after the last step has finished, the test rig will start again from step 1 without stopping.

To switch modes, use the toggle button to select "Run Once" or "Repeat".

Manual mode:

Manual mode operation keys are at the bottom-right of the screen. These are only shown if the test rig is in manual mode. "Start" and "Stop" buttons control the test rig.

The speed and load set point displays on the screen now change to input values so the operator can manually alter the values. A ramp time of 10 seconds is automatically applied to these set point values to protect the drive and load against sudden load or speed changes.

Set-up Screen

This screen lets the operator input the required number of speed values and load values to be run in sequence on the test rig. Once the number of steps has been entered, pressing the ‘Enter’ button will move to the ‘Recipe’ screens.

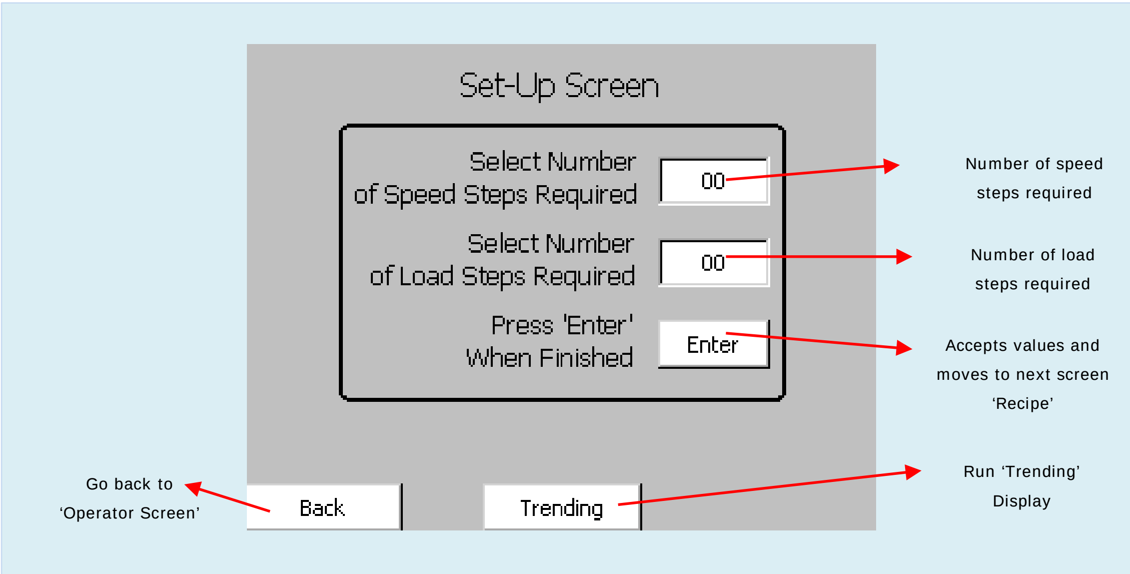


Figure A.4 (Set-up) Screen

To allow trending of values to assist with diagnostics, a trend screen is included on the display. Press the ‘Trending’ button to open the trend screen.

Recipe Screen

This screen is repeated 4 times for entry of up to 20 recipe steps for each of the load and speed sequences. Only the number of steps that were entered on the previous page will be shown, if the number of steps is lower than the step numbers shown on-screen, then blanks will be displayed on-screen. Once recipe entry is complete, pressing ‘Finish’ will return to the main Operator Screen.

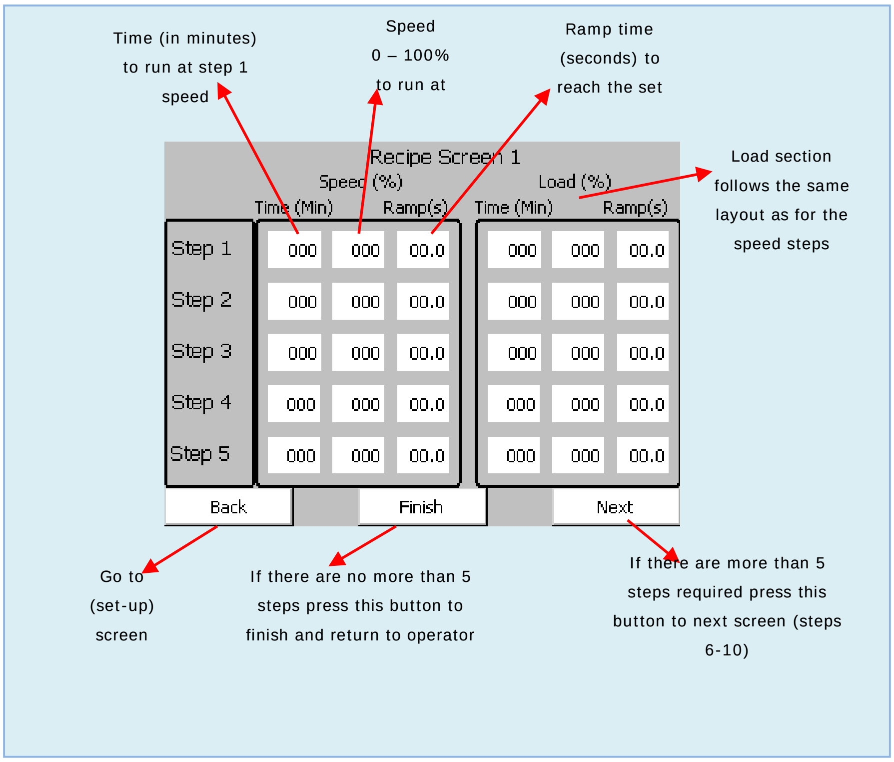


Figure A.5 (Recipe Screen 1)

<u>Trend screen</u>

The trend screen is configured to show the following values in a continuous display with an update rate of 1 second. The trend screen is shown below:

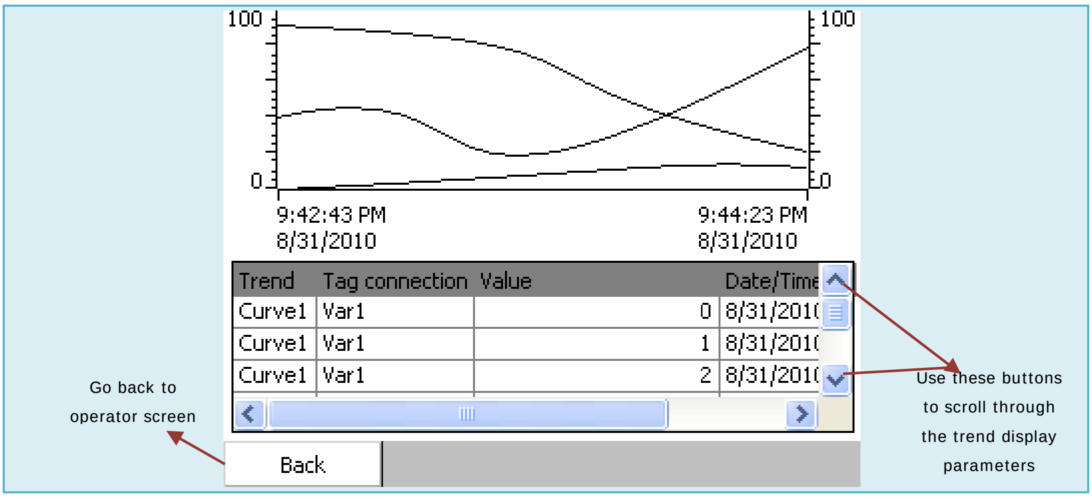
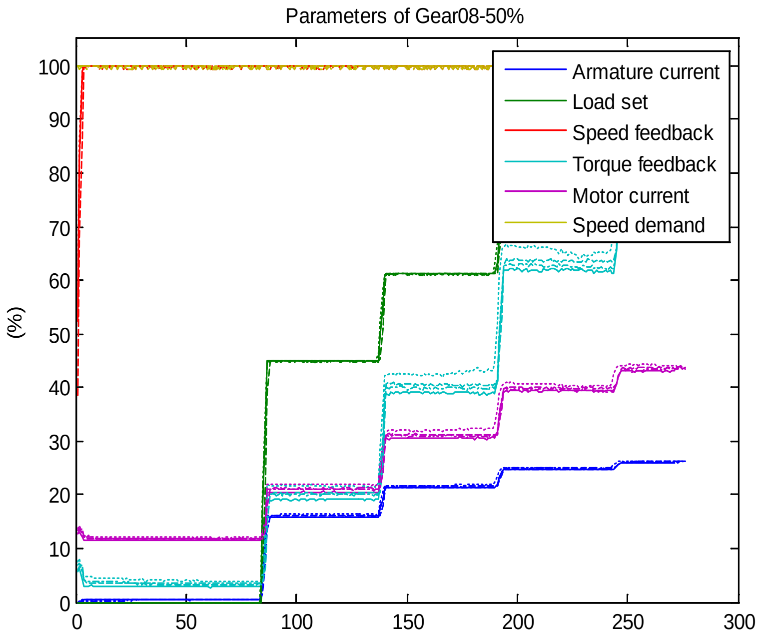
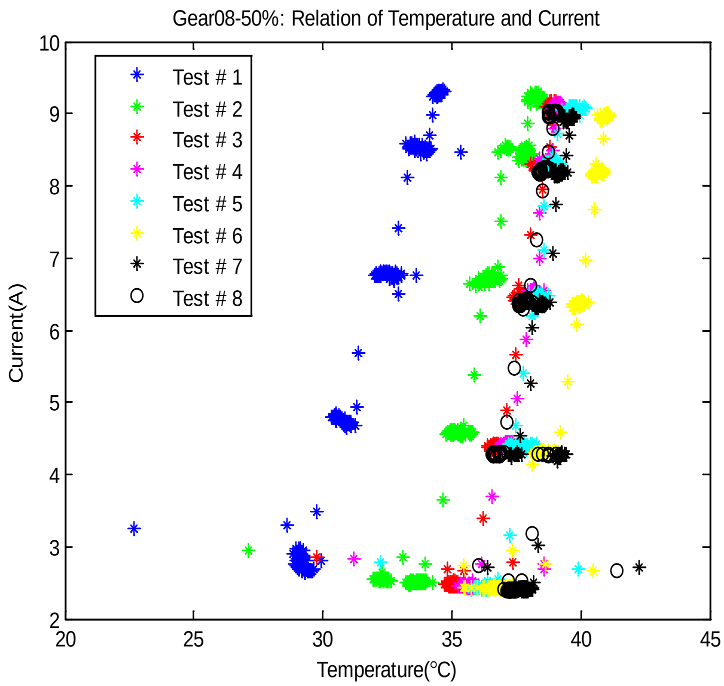


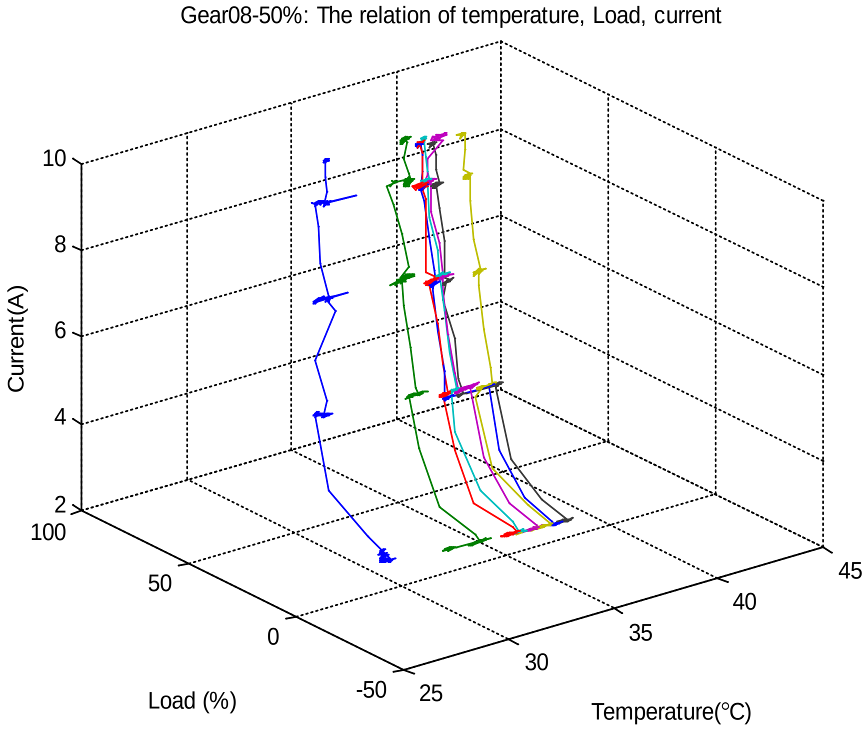
Figure A.6 Trending Display Screen

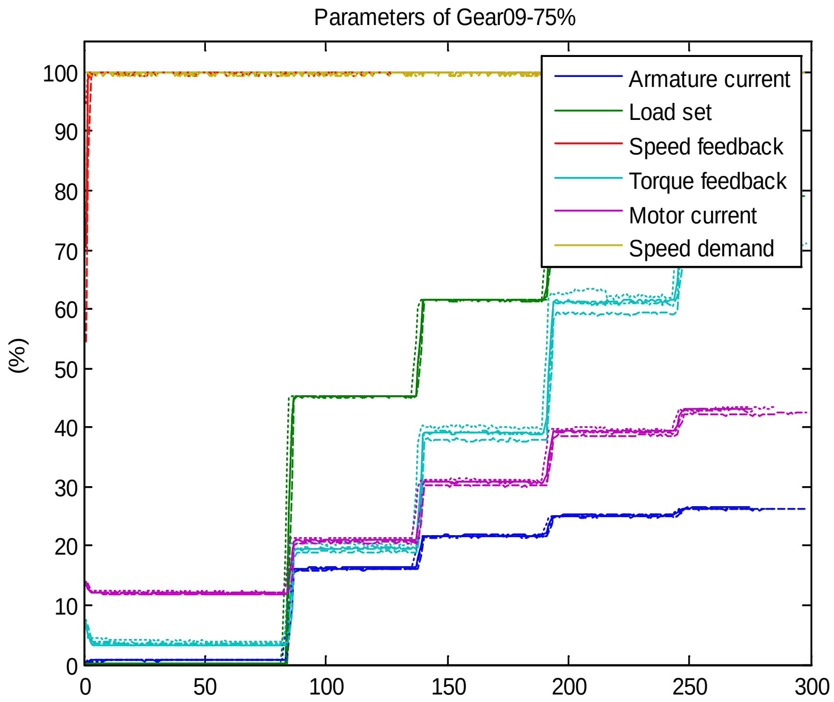
This display is not intended to be used for accurate measurements, but as a general indication of test rig operation.

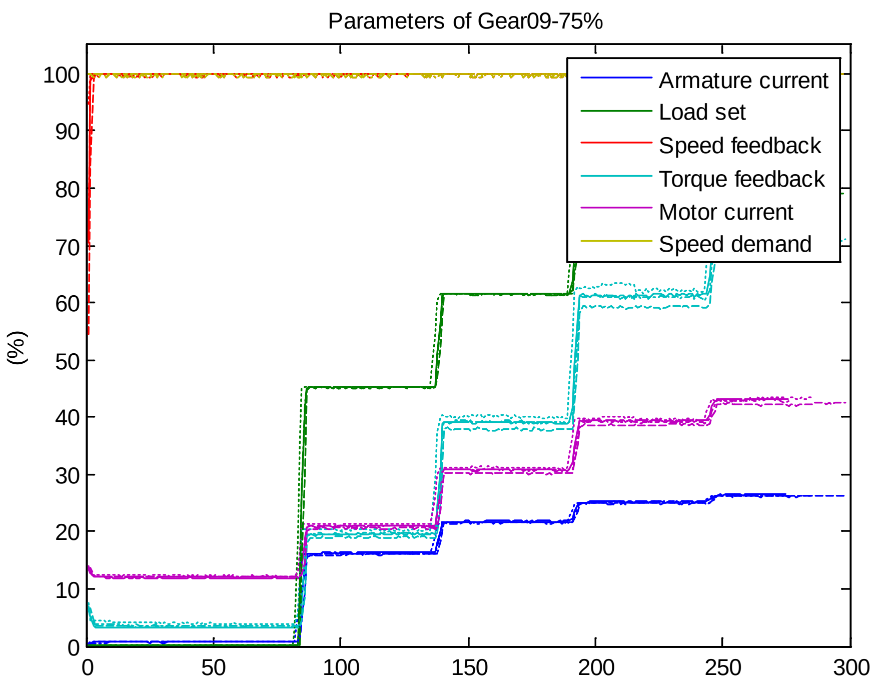
APPENDIX (B): DATA CHARACTERISTICS OF GEAR 08 AND GEAR 09

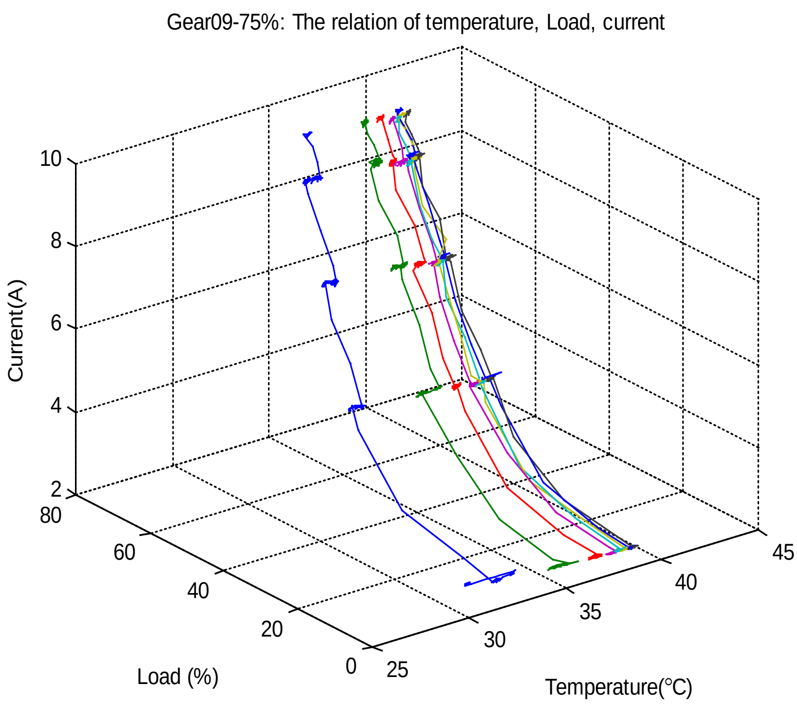





Gear08-50%: The relation of temperature, Load, current
Current(A)
10
8
6
4
2
100
50
0
-50
Load (%)
25
30
35
40
45
Temperature(°C)


Parameters of Gear09-75%
(%)
100
90
80
70
60
50
40
30
20
10
0
0
50
100
150
200
250
300
Armature current
Load set
Speed feedback
Torque feedback
Motor current
Speed demand


Parameters of Gear09-75%
Armature current
Load set
Speed feedback
Torque feedback
Motor current
Speed demand
(%)
0
10
20
30
40
50
60
70
80
90
100
0
50
100
150
200
250
300


Gear09-75%: The relation of temperature, Load, current
Current(A)
2
4
6
8
10
Load (%)
0
20
40
60
80
Temperature(°C)
25
30
35
40
45

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