Computational Intelligence for Fault Diagnosis in Gearbox Systems

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To my beloved mother with great gratitude for her lifelong sacrifice for the whole family. Undoubtedly, without her prayers, endless love and encouragements this thesis would have been impossible. Thank you mom for every beautiful thing you did to make our life beautiful.

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Abstract

Employing an efficient condition monitoring system in industrial applications is an important factor in improving the quality of production and increasing the operational life of machines by revealing machine faults at the earlier stage. Damage in gearbox system is one of the most catastrophic failures in machineries. Any defects related to a gearbox will influence the performance of an entire mechanical system. A reliable and efficient fault diagnosis system is required to reduce the maintenance cost and downtime, thereby preventing machinery performance degradation and failure. Many condition monitoring and fault diagnosis systems are investigated in the literature for gearbox fault detection and diagnosis. However, there are still many challenges to tackle mainly due to the complex nature of gearbox structure, limited access to the component to be monitored and the low signal-to-noise ratio experienced especially when operating machineries under fault conditions.

The aim of this research is to develop a systematic methodology for the design of condition monitoring systems for gearbox faults by investigating sensor selection, sensor location, and sensory features to be able to diagnose a fault accurately. Therefore, the goal is to select reliable techniques at each stage in order to improve the reliability

of the fault diagnosis system. Different sets of experiments based on gearbox conditions are conducted using several sensors including vibration, acoustic emission, speed, and torque. Measured signals are analysed using conventional and advanced signal processing and data analysis methods including time, frequency and time/frequency domains such as Fast Fourier Transform (FFT), Short Time Fourier Transform (STFT), and Wavelet analysis (WT). Several statistical and mathematical techniques have been proposed as features extraction methods to reduce the dimensionality and select appropriate information. For this research, a single stage gearbox system with two main type of faults (pitting and broken teeth) with various degrees of damage in helical gear are used to evaluate the proposed approach. This research investigated the relationship between sensor location and detecting the fault in gearbox system. A methodology has been proposed for locating indirect monitoring sensors such as acoustic emission and vibration on gearbox to obtain high quality information regarding the behaviour of machine condition. The methodology is designed to evaluate the optimum sensor positioning for detecting faults in the gearbox system.

A novel gearbox monitoring approach named an Automated Sensor and Signal Processing Selection for Gearbox system (ASPSG) has been applied to select the most reliable and sensitive sensors, features and signal processing methods based on optimal sensor location. The ASPSG approach is based on simplifying complex sensory signals into a group of Sensory Characteristic Features (SCFs) and

evaluating the sensitivity of these SCFs in detecting gearbox faults. The aim of this approach is to enhance the performance of monitoring system of gearbox fault detection and to reduce the number of sensors required in the overall system and reduce the cost. To implement the suggested ASPSG approach two strategies are proposed: automated system based on Taguchi's orthogonal arrays and stepwise system using (Linear Regression (LR), Fuzzy Rule Based System (FRBS) and Principal Component Analysis (PCA), techniques). To evaluate both strategies, four different classification models are employed using supervised and unsupervised neural networks. Both strategies have been implemented to prove the capability of the suggested approach. A cost reduction is performed based on removing the least utilised sensors without losing the performance of the condition monitoring system. The results show that the ASPSG approach can provide a systematic design methodology for condition monitoring systems for gearboxes and that it is capable of detecting faults in a gearbox system with less cost and reduced number of experiments. Consequently, the findings of this research prove that the sensor location could have significant effect on the design of the condition monitoring system and its performance.

Publications

The following publications have been published as a direct result of this thesis:

- Hasan Alkhadafe, Ahmad Lotfi, Amin AL-Habaibeh, Daizhong Su, "An Investigation into Loose Bearing Prediction and Diagnosis on Gearbox System Performance Measurement" the 24th International Congress on Condition monitoring engineering management (COMDEM 2011), in 1st June 2011, PP. 977-807.

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- Hasan Alkhadafe, Amin Al-Habaibeh, Daihzong Su and Ahmad Lotfi, "Intelligent Selection of Sensors and Signal Processing Methods for Condition Monitoring of Gear Systems", Journal of Computers & Industrial Engineering (Under review)

- Hasan Alkhadafe, Amin Al-Habaibeh, Daihzong Su and Ahmad Lotfi, "Condition Monitoring Of Helical Gears Using Automated Sensor And Signal Processing Selection Method", Journal of Measurement (Under review)

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Nomenclature

Roman Symbols

AE	Acoustic Emission
ANN	Artificial Neural Network
ASPSG	Automated Sensor and Signal Processing Selection for Gearbox
PCA	Principal Component Analysis
CBM	Condition Based Monitoring
CF	Crest Factor
RMS	Root Mean Square
IOP	Initial Optimisation Procedure
PSO	Particle Swarm Optimization
WT	Wavelet Transforms
FT	Fourier Transform
WVD	Wigner-Ville Distribution

STFT	Short-Time Fourier Transform
DoE	Design of Experiment
STD	Standard Deviation
PV	Peak Value
FFT	Fast Fourier Transform
SK	Spectral Kurtosis
OAs	Orthogonal Arrays
LR	Linear Regression
FIS	Fuzzy Inference System
CI	Computational Intelligence
KNN	K-Nearest Neighbour algorithm
NN	Nearest Neighbour
FFNN	Feed Forward Neural Network
BP	Back Propagation
RB	Radial Basis
CNN	Competitive Neural Network
LVQ	Learning Vector Quantization
GCM	Gearbox Condition Monitoring system

Chapter 1

Introduction

1.1 Introduction

Condition monitoring and fault detection systems are becoming essential for a wide range of industrial sectors, in order to detect faults and to avoid machine performance degradation, breakdown, and failure (Zhan and Makis, 2006). The information gained from monitoring is also used to establish a maintenance plan based on early caution or detection of machine faults. This procedure is considered to be of great value for mechanical applications such as aircrafts, wind turbines, and power plants, where an unexpected disruption could have serious economic and environmental consequences (Mehrjou et al., 2011).

Gearbox systems are an essential part of machinery and they play significant role in a number of industrial applications, for example in production machines and power plants. Gearbox systems are designed to work for a sustained period of time without any unscheduled stops or failures. An unexpected failure has the potential to cause a chain of problems to the entire machinery, which results in high maintenance costs due to the decrease in production rates and unexpected and unscheduled maintenance. To guarantee the efficient working of machinery, a reliable condition monitoring system is required to detect faults at an earlier stage than the complete shutdown. Bartelmus and Zimroz (2009) stated that the failures in gearboxes are mainly caused by faults with gears (60% of gearbox defects and 24% failures), which are a result of unsuccessful maintenance. For this reason, gearbox system condition monitoring and fault diagnosis is essential in order to reduce the occurrence of failure and ensure that the machines are working effectively.

If the gearbox is operating ineffectively it becomes easy to develop defects with areas such as the shaft, bearing and gears. Bearing defects in gearbox systems have been researched extensively (Yang et al., 2005) and (Barszcz and JabLonski, 2011). Vibration analysis has been the method for machinery maintenance in rotating parts such as gearbox systems. Vibration signals are measured from a gearbox; in order to analyse the condition of the system and identify defects without interfering with its operation. The most common technique utilised for testing machine vibration is called Spectral Analysis. (Zhan, 2005). Vibration measurement is frequently applied for fault diagnosis in rotating machines. It carries useful information about mechanical parts, such as signals from a combination of frequency components (Zhan and Makis, 2006). The maximum of these frequencies are associated with rotational movements of machines. Energy of vibration is changed when a part of the machine becomes loose or broken. To analyse the vibration signals, a number of methods are used such as time domain, frequency domain or even time-frequency domain (Ebersbach, 2006).

Nowadays, Acoustic Emission (AE) technology has received great attention for monitoring rotating machines. AE is an efficient method for discovering initial damage in a more advanced way compared with oil debris measurement and vibration measurement. However, a majority of research that has used AE in gearbox diagnosis have been conducted on bearings and spur gears with low speed (Mba and Rao, 2006). This study proposes to further investigate gearbox condition monitoring system, by applying both AE and vibration measurement technologies on helical gear damage.

The key steps involved in the diagnosis of machinery fault are pattern recognition, feature selection and classification. These involve classifying characteristic features such as vibration signals and acoustic emission into different categories. There exist a number of methods for data analysis that have been used in engineering industries to detect faults from vibration features, such as aural, tactile, and visual inspection. These are basic condition monitoring methods for fault diagnosis, and can involve sensory enhancement devices (such as microphones or stroboscopes) to aid monitoring (Stevens et al., 1996). However, these approaches are not always reliable when the extracted features are contaminated by noise, specifically when data is collected in a noisy environment. It is difficult for an expert to deal with the contradicting symptoms if multiple features are measured. Therefore, new analytical tools are required, that can adequately deal with time and frequency, such as statistical and computational intelligent techniques.

1.2 Problem Definition

Nowadays, smart condition monitoring, diagnosis and prognosis technologies are essential in most industries, especially in industries where mechanical equipment such as gearbox systems are used. These technologies help to achieve optimum service availability, to maintain the safety of equipment and to reduce maintenance budget. The gearbox is the most essential part of a mechanical system. The failures in gearboxes are critical in relation to failure rates and mean downtime of machinery (Ahmad and Kamaruddin, 2012). Fault diagnoses in gearbox systems are a challenging task due to the complexity of their structure and the rotating parts generating vibrations. Therefore, an unexpected failure can potentially cause a major economic loss. The challenge of processing vibration signals is the issue of the low ratio of signal-to-noise. Background noise interferes with the measured signals. In a majority of cases, sensors have to be installed remotely due to limited access, which can potentially increase the risk of collecting an overwhelming amount of data. A high volume of data will contain a certain amount of redundant information. In order to differentiate between the noise and operating conditions, advanced methods of data extraction would be required.

1.3 Overview of the Research

Rotating machinery that has moving parts produces vibration signals and noise. The setting up and operating of each machine emits individual vibration signals (Tian et al., 2003). Therefore, an alteration in the vibration signal results in a change in the machines condition. This signal can be used to detect a fault before it turns critical. This is the main idea behind the condition monitoring system for diagnosing faults. The information gained from the signal is used to detect defects at earlier stage (Tian et al., 2003; Wang et al., 2007). The condition monitoring process is split into three major stages. Firstly, a relevant physical quantity is measured. Secondly, the captured signal is processed and features of the machines condition are extracted. The obtained features are taken from the reference values in order to detect and/or predict the defect. Lastly, the information obtained from the previous steps is used for predictive maintenance and decision-making. Furthermore, the method of condition monitoring systems can be used to detect other types of defects. The signals obtained from the machines often interfere with other signals, as well as noise. Thus, the challenge for condition monitoring is to identify the signal content that is associated with the condition of the monitored component (D'Elia, 2008).

Vibration analysis is a powerful technique used for monitoring the condition of rotating machinery. Vibration analysis is based on techniques such as time-domain and frequency-domain. These methods have limitations in that they are only convenient for stationary vibration signals. However, a majority of rotating machinery has non-stationary vibration signals. Time-frequency analysis and wavelet transformer analysis is used to overcome these difficulties. A wide range of research has been conducted into condition monitoring of gearbox systems. In reality, the gearbox system is operated systematically by changing the operating conditions of load and speed, but the different types of faults have not been investigated in detail. A large body of research has explored gearbox condition monitoring at fixed loads or fixed speeds, with sensors often mounted on the gearbox casing. Meanwhile, other research has not specified detail about the conditions of load, speed, or position (Price, 2001).

The location of sensors plays an important role in designing an effective condition monitoring system. Previous research has used different types of direct and indirect sensors (Papadimitriou and Au, 2000). These are located separately from components in the gearbox, and comprise of vibration and acoustic emission sensors. However, research that investigates the most effective placement of sensors is still relatively new. A significant amount of research has attempted to develop a condition monitoring for predicting early faults in the gearbox system. Different types of sensors have been used, as well as different methods of signal processing and feature extraction, but there still exists the issue of extracting the correct sensory data and signal processing in order to adequately predict the gearbox faults. In order to determine the problems of current practice of condition monitoring systems, it is important to characterise the structure of such systems. These must provide information for:

1. The selection of suitable sensory signals.

2. The selection of suitable signal processing methods.

3. The extraction of useful features from suitable signal processing methods.

4. The improvement of a classification system strategy.

1.4 Research Aim and Objectives

Gearbox plays an important role to transmit power. Its health state is very critical for maintaining the normal operational of whole industrial application. However, the problems associated with the gearbox could potentially affect the performance of the entire system. Also, the condition monitoring of gearbox system is very difficult because of its complex structure.

The aim of this research is to investigate advanced computational techniques for diagnosing and predicting faults in gearbox systems. The developed system should provide high performance while reducing the cost of sensors and number of experiments. It will complete this by exploring different systems for monitoring the condition of the gearbox, and will identify the most effective techniques for predicting rotating mechanical systems. This research proposes to use sensory data including vibration, acoustic emission, speed and torque. The objectives of research project are as follows:

- To identify appropriate sensors, which are used effectively, to collect useful information about the status of gearbox.

- To determine the most appropriate features extraction and signal processing techniques that can be used to analyse the sensory signal and simplify the incorporated information into a form suitable for classification model.
- To investigate different type of defects such as pitting and broken tooth on helical gear individually, and distinguish the differences between them in terms of characteristics of defect signature.
- To explore the relationship between sensor location and fault detection in order to obtain high quality information about the behaviour of the gearbox. This will be done by in indirect sensors such as acoustic emission and vibration sensors.
- To develop systematic approach (ASPSG) to select the most appropriate sensory data and associated featrures that are sensitive to the faults in order to reduce cost and development time.

1.5 Major Contribution of The Thesis

- This study attempts to use the acoustic emission and vibration signals captured from several locations, with varying speed and load conditions, to explore the stages of fault development in gearbox system. The impact of collected vibration signals at different locations following the path of gearbox structure are examined and compared with other vibration signals. The effect of pitting and broken tooth faults are investigated at different stages; for pitting defect at (25%, 50%, 75% and 90%) and for broken tooth at (25%, 50% , 75% and 100% full tooth missing). Sensory signals are investigated by collecting all signals at different shaft speeds, from 100, 200, 350, 500 and 750 RPM and at different loads ranging from 2, 4, 6 and 8 Nm.

- A new approach is proposed to investigate the optimum sensors positioning in order to enhance the gearbox condition monitoring system. New research is established to investigate the relationship between sensor location and detecting the fault in a gearbox system. A new methodology is also proposed for locating indirect monitoring sensors such as acoustic emission and vibration on the gearbox in order to obtain effective information regarding the behaviour of the machine. Experiments are designed to evaluate the optimum sensors position for detecting faults in the gearbox system.

- Novel proposed approach ASPSG for gearbox system is introduced. The ASPSG is applied in this research to collect the most suitable sensory data, reliable features and signal processing methods in order to minimise cost and time. Sensory characteristic features are calculated and used to measure sensitivity, but can also be related to healthy and unhealthy conditions in gearbox systems using a wide range of signal analysis.

- Two procedures are proposed to develop the ASPSG approach, which will ensure a high quality of information from sensory signals, in order to develop a reliable condition monitoring for gearbox fault diagnoses systems. The first procedure of ASPSG, is based on a holistic approach that uses a Taguchi technique based on an orthogonal array. The holistic approach provides a general picture of sensitivity for each sensor, relying on changing values of speed and load. Four types of neural networks are used to evaluate this procedure. The second procedure of ASPSG, is based on a stepwise method that uses three techniques: Linear Regression (LR), Fuzzy Rule Based System (FRBS) and Principal Component Analysis (PCA). Nine experiments are conducted based on varying degrees of parameters of the gearbox (speed and load). The stepwise procedure is used to measure sensor sensitivity in order to examine the relationship between sensor sensitivity with speed and load.

1.6 Thesis Outline

The report is organized into nine chapters as following:

Chapter 1: This chapter provides an introduction into the work. The background of this study is provided, followed by a summary of current problems in gearbox condition monitoring systems. The specific aims and objectives are also outlined.

Chapter 2: This chapter provides a literature review and background of the research, starting with a summary about maintenance strategies. It also gives a brief explanation of condition monitoring methods that have been developed and/or that are used in industry. It explains the problems with current monitoring methods in order to gain an understanding of the current research on gearbox condition monitoring systems. It provides an overview of gear, followed by details about gear failure modes.

Chapter 3: The overall methodology of this research is presented by describing the ASPSG approach and its technicalities. This chapter outlines the key steps of the proposed methodology and examines the assumptions. The chapter also provides a description of the framework for the subsequent chapters.

Chapter 4: This chapter provides a detailed description of the experimental set-up that is used to conduct the investigation. It also describes the tools and the specification for the components that are used such as sensors, related hardware and the data acquisition system. The chapter concludes by describing the fault simulation.

Chapter 5: This chapter presents a new methodology for sensor location optimisation. It provides a description of how locating indirect monitoring sensors such as acoustic emission and vibration on gearbox can improve the quality of information regarding the behaviour of the machine. The methodology evaluates the optimum sensor position for detecting faults in the gearbox system. This chapter also investigates the relationship between sensor location and detecting the fault in the gearbox system.

Chapter 6: This chapter provides a description of the implemented ASPSG approach and the way it can be used to systematically develop a condition monitoring system for multi-sensors. The ASPSG approach is based on a holistic procedure using Taguchi method in order to detect gradual gear damage. This approach is explained in details, and expanded in order to demonstrate how to use the association matrix to evaluate the combination of signal processing methods and statistical techniques that can be used as independent features for condition monitoring design. The neural networks technique is also used to evaluate the design process.

Chapter 7: This chapter introduces stepwise procedure of ASPSG approach. It includes a description of how the ASPSG approach based on stepwise can be used to detect gearbox fault by using several sensors. The ASPSG approach is also expanded in this chapter to show how to construct the Associated Matrix (ASM) using three techniques which are LR, FIS and PCA. This chapter shows how the ASM matrix can be applied to evaluate sensory characteristic features and signal processing methods. The chapter provides also some suggestions on how the ASPSG approach can be used to improve the condition monitoring design to optimise cost and performance.

Chapter 8: Conclusion and recommendations for future work for this research are given.

Chapter 2

Literature Review

2.1 Introduction

The rapid developments in condition monitoring technologies are receiving much attention from industrial societies in order to improve productivity, quality and reduce the cost of maintenance. Condition monitoring can be defined as process of observing a state of parameters for the purpose of tracking important changes that could cause a fault (Ran and Penman, 2008). It is a process of assessing machine degradation in terms of physical defect, such as pitting, cracking in tooth gear and increase in resistance or performance degradation from deviation of the systems operation. A condition monitoring system should allow a maintenance program to be arranged precisely on time in order to caution the failure before it happens. Machinery parts can be observed by using appropriate monitoring system equipment so that any abnormal condition of these parts can be identified by measuring parameters such as vibration, temperature and sound (Randall, 2011b). This chapter will present a review of condition monitoring systems.

2.2 Maintenance and Condition Monitoring System

Since the industrial revolution, machine maintenance has gained importance due to the cost of equipment, machinery and infrastructure. Dhillon (2006) stated that the USA industry consumes annually hundreds billion of dollars on plant maintenance and reform. The majority of this huge amount of money has been spent on treating frequent and catastrophic failures in machines. Even though frequent failures may be small, concealed and take place more regularly. They are sometimes more costly than catastrophic failures. However, the catastrophic failures are much rarer occurrences. Both kinds of defect can stop production, lower product quality, increase cost, and increase risk to machine operators. Periodic maintenance can decrease downtime by reducing failures occurrence and increase productivity. The most utilised methods of managing maintenance are reactive, preventive and predictive maintenance. In the past, industrial plant used two types of maintenance to repair faults: a reactive, which takes place when the fault occurs and a preventive, which is based on a scheduled timetable. Recently, and as a result of the evolution in technology the possibility for the development of cost-effective instrumentation and technologies for predictive maintenance is allowing the identification of machine problems by measuring the condition of the machine and predicting maintenance requirements (Morris and Pardue, 2006).

2.2.1 The Significance of Maintenance

Maintenance is a group of technical and administrative procedures and tasks associated with each other, which aims to maintain the machine, or return it to the state that it can perform its required functions. Maintenance management aims to reduce the overall maintenance cost and improve the availability of the machines(Ahmad and Kamaruddin, 2012). In the industrial community, maintenance budgets are an essential element that need to be considered. Therefore, much recent research has performed to improve the relationship between good quality production and less maintenance cost.

The increasing request of the maintenance budget which is considered as the total operating cost of production is responsible for about 15% to 40% of the cost of manufactured goods (Pedregal and Carnero, 2009). Furthermore, the maintenance cost, in particular with regards to spare parts, is required to avoid a series of catastrophic faults that may occur on machines to keep them in good working order for longer periods of time (Li et al., 2011). In general, growing machine faults are a direct result of the reduction of product quality which increases machine downtime which could lead to an increase in the maintenance cost. Moreover, these defects may lead to immobilising the entire machine which can be expensive and increase the maintenance costs. Therefore, the applications of Condition Based Maintenance (CBM) are advanced maintenance strategies that are based on performance parameter monitoring and subsequent actions. Maintenance decisions depend entirely on one of the monitoring techniques such as thermal monitoring, oil debris monitoring, vibration monitoring and acoustic emission monitoring which are applied to identify and diagnose the defect. All these monitoring methods have been reported as a robust tool in the machine condition monitoring by a number of studies which applied these methods (Sartain et al., 2008; Diwakar et al., 2012). Signal processing methods and intelligent computing techniques are applied to perform machine fault detections and to prevent any consequential failures which will reduce the maintenance cost. By maximising condition monitoring information, CBM is expected to reduce the operation and maintenance costs of machinery (Zhang and Vachtsevanos, 2007a).

2.2.2 Maintenance Strategies and Condition Monitoring

Over the last decade the maintenance of equipment and machinery has received great attention by the industrial companies in terms of non-stop production and preservation of assets. The main target of a maintenance unit is to maintain machinery and plant tools in a working condition to avoid failure and continue their operation. However, the major problems of machine faults are the high cost of maintenance and unexpected downtimes. Therefore, industrial societies are seeking to develop a program of predictive maintenance (Randall, 2011a). Maintenance strategies can be structured into three major aspects which are introduced in the following sections:

- **Breakdown Maintenance** is a traditional maintenance strategy. In this type of maintenance, the machine is allowed to work until a failure occurs or its performance keeps degrading to the point where equipment must be replaced. Also, there is no predetermined action to prevent failure. Failure is a random event and it may be unexpected, and could also become catastrophic. The traditional maintenance is the most expensive maintenance procedure because it has the greatest rate of lost production and needs a large amount of spare parts inventory to reduce downtime. This type of maintenance method can only be used if the cost of replacing the machine or part is very low, and the failure does not affect the rest of the plant tools (Staszewski and Tomlinson, 1994b).

- **Planned Maintenance** or scheduled maintenance is to shut down the machine after a specific interval of operation based on the statistical analysis of previous maintenance information. In this case, the machine is partially dismantled into parts or completely to check if any worn parts need to be replaced. This approach has many disadvantages as it is time-consuming, incurs high costs and sometimes may not be necessary. Also, the machine can be adversely affected due to incorrect dismantling which can lead to increased probability of failure (Wang and McFadden, 1993b).

- **Predictive Maintenance** is also known as CBM, where machines are no longer maintained according to a damage- based policy, but is dependent on their condition. The purpose of CBM is to minimise machine breakdown by evaluating the state of the machine, detecting the defect, and conducting the correct procedure at the right time prior to any failure. Usually, initial machine faults provide some early warning of failure so CBM can be conducted when the machinery is running. Such a maintenance program not only reduces machine failure, but also simplifies efficient labour scheduling, enables other repairs to be included into any downtime and allows for replacements to be ordered (Wang and McFadden, 1996).

2.2.3 Condition Monitoring for a Rotating Machinery System

Rotating machines with moving parts produce vibration signals and noise. The setting up and the operating of every machine emits an individual vibration signal. Therefore, any changes in the vibration signal mean a alteration in the machines condition. This signal can be utilised to discover initial faults before they become serious. This is the main concept behind condition monitoring systems for fault diagnosis in machinery, in which the information is gained from the signal shown by a machine which reveals faults at an initial stage (Kar and Mohanty, 2006). Generally, the basic condition monitoring process is split into three main steps. First, a relevant physical quantity is measured. Second, the collected data are processed and

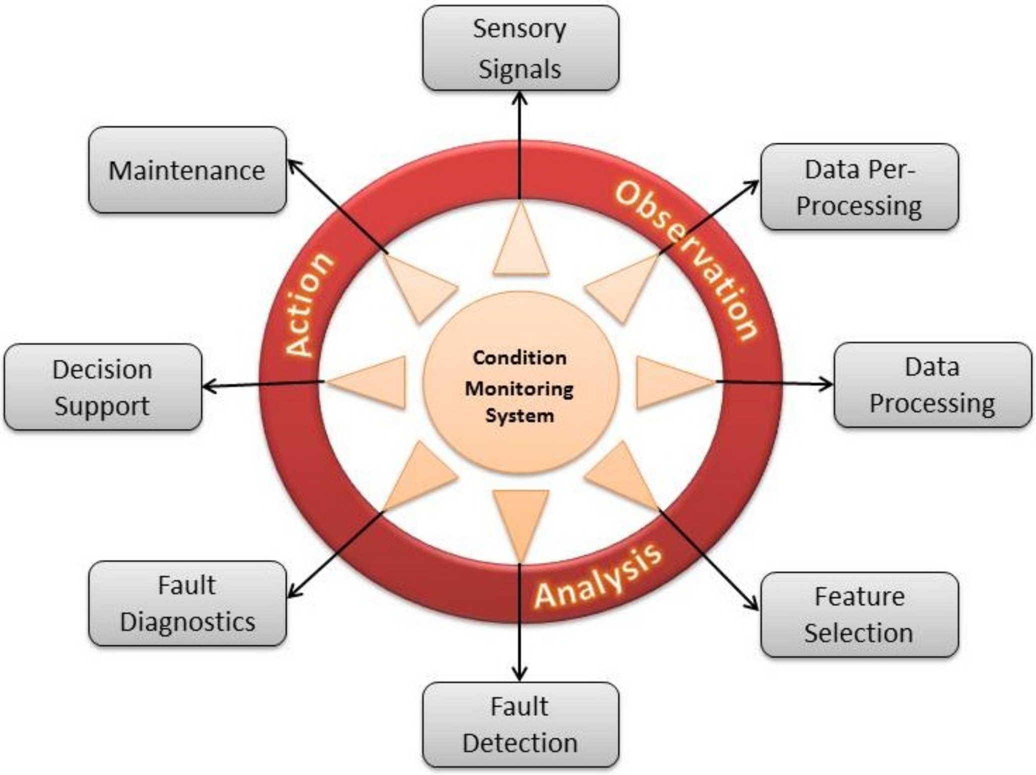


Figure 2.1: The general structure of a condition monitoring system.

machine state features are extracted, then the extracted state features are compared to the reference values in order to diagnose and predict the fault. Finally, the information obtained from previous steps is used for predictive maintenance and decision making. A schematic diagram of the process is shown in Figure 2.1. Moreover, beyond detection, condition monitoring methods can also be used in order to diagnose the type and the evolution of certain defects. Signals acquired from machines often contain contributions from several different components as well as noise. Therefore, the major challenge of condition monitoring is to pinpoint the signal content that is related to the state of the monitored component.

2.2.4 Condition Monitoring Techniques

In general, monitoring techniques can be grouped into six categories:

2.2.4.1 Human Inspection Monitoring

Visual monitoring can on occasion give a direct indication of the machine's condition without the need for further analysis. However, it is basic condition monitoring techniques using aural, tactile, and visual which may involve simple sensory devices such as microphones to help monitoring. Many techniques are available which can be used to diagnose the faults such as simple magnification lenses and low-powered microscopes. Also, there are other styles of visual monitoring including liquid penetrant inspection which is used to detect any cracks occurring on the machine surface, and the use of heat-sensitive or thermal paint. The status of a number of gearbox parts can be easily checked by human visual perception. For example, the deterioration of gear teeth surfaces provide a lot of information such as overload issues, fatigue failure and poor lubrication. They can be differentiated from the appearance of the teeth. All these styles are considered as primitive methods and experts in this field are required to deal with these which costs more time and effort (Jayaswal et al., 2008a).

2.2.4.2 Performance Monitoring

In this form of condition monitoring, operational parameters affecting a machines performance such as force, torque and speed, are monitored to identify any deterioration. Any significant deviation from the intended operational parameters is considered as an indication of a malfunction in the machine (Gaberson, 2002).

2.2.4.3 Thermal Monitoring

Temperature monitoring is an essential factor in monitoring and investigating the thermal distortion response of machine tools. Temperature monitoring includes two types of temperature which is the working temperature and the component temperature. The working temperature is a group of the operational parameters for performance monitoring. Whilst the component temperature is considered as heat resulting from the defect occurring in the machine elements, such as rolling elements, where lubricant is either insufficient or contaminated. This monitoring technique can be applied to examine the operating temperature of the process, or to determine the location which produces heat due to any fault. The temperature can be measured by the use of thermal sensors such as thermocouples and thermal cameras (Jayaswal et al., 2008a).

2.2.4.4 Oil Debris Monitoring

Wear occurs if two surfaces are moved against one another with sufficient, normal force. However, the presence of an adequate lubricant prevents occurrence of wear when operational parameters (i.e. load and temperature) within a clean working environment are properly established (or controlled). If wear occurs due to an excessive load or inadequate lubrication, material removed from contacting surfaces contaminates the lubricant and, hence, wear debris can be detected by lubricant monitoring.

Lubricant monitoring ranges from the simple use of magnetic plugs which provide evidence of ferrous debris build-up, to the spectrometric and ferrographic analysis of oil, where debris composition, rate of accumulation and particle shape can pin-point a damaged component and its mode of failure. However, this technique is not reliable for detecting faults like fatigue cracks in a component because such failures shed few metallic particles (Loutas et al., 2011). Oil debris monitoring for gearboxes is often used for off-line analysis, where oil debris samples are analysed in order to detect which component is failing. Also, chip detectors can be used which utilise a magnetic force to capture debris and form an electrical bridge between contacts that indicates a state change. Induction sensors are used to detect the damage in bearings, especially for engines. However they are not suitable for gear damage detection. Induction sensors work by measuring a disturbance to a magnetic field caused by a particle passing through the sensor (Loutas et al., 2009).

Jayaswal et al. (2008a); Yi and Quinez (2005) have performed many experimental works and published interesting results, particularly for gear testing using oil debris and vibration measurements. Their targets were to enhance the performance health monitoring gearbox systems for helicopters. They have examined gears with high shaft speeds for long periods of time. Also, authors have used correlation methods for extracted features of vibration recordings based on higher order moments with the debris mass accumulated during the tests. Furthermore, they have integrated their results in a fuzzy logic based health monitoring system with satisfactory performance.

2.2.4.5 Vibration Monitoring

Vibration monitoring is considered as the most common method for machine fault identification in rotating machines when compared with other techniques. It is based on the principle that all machine components generate vibration. When a machine is working in a steady state manner, the vibration is smooth and constant, however, when defects grow due to some of the dynamic working parameters of the machine changing, there will be changes in the vibration spectrum observed. Vibration characteristics can be used to signify many faults. Vibration monitoring is extensively applied as a diagnostic tool for mechanical systems. Several types of signal processing techniques are conducted on vibration signals in order to extract specific features and to improve the quality of the information about the problem from obtained signals. Vibration-based monitoring techniques have been widely implemented for detection and diagnosis of gearbox faults. These methods have traditionally been applied, separately in time domain, frequency domain and time/frequency domain. Most research projects in this area have shown that the vibration analysis is an effective tool for fault detection and identification in gearbox systems (Bajrić et al., 2011).

Renwick and Babson (1985) stated that the predictive maintenance of applying vibration monitoring gave promising results in the effective diagnosis of machinery malfunctions. The advantages of such procedures contain not only simple cost benefits, for example minimising machine downtime and losses in production, but also the more subtle long-term cost advantages which can result from accurate maintenance scheduling. Lebold et al. (2000) have reviewed the vibration analysis techniques in the diagnosis and prognosis faults of gearbox systems. The surveys presented some of the most conventional features implemented for machine diagnostics and presented some of the signal processing parameters that impact on their sensitivity. Polyshchuk et al. (2002) presented the development of a novel method in gear damage detection using a new gear fault detection parameter based on the energy change in the joint time-frequency analysis of the vibration analysis of the vibration signal.Wegerich et al. (2003a) developed a non-parametric modelling technique and demonstrated the use of this approach for detecting faults in rotating machinery via extracted features from vibration signals. Lei et al. (2003) presented a damage diagnosis approach using time series analysis of vibration signals to benchmark structural health monitoring problems. Sohn and Farrar (2001) have presented a procedure for damage detection and localisation within a mechanical system solely based on the time series analysis of vibration data.

2.2.4.6 Acoustic Emissions Monitoring

The use of Acoustic Emission (AE) applications in the condition monitoring of rotating machinery is relatively new and has developed rapidly over the last 20 years. AE in rotating machinery has been described as the elastic waveforms produced by the contact of two moving objects such as two gears. There are many sources of AE in rotating machinery, for example, asperities contact, material loss, cavitation, leakage, etc. AE provides useful data in the form of sound from within an operating machines such as smashing gears and bearing. As a result, it has been employed in many rotating machine applications such as gearbox systems. AE technique has received attention in this area, due to the fact that it provides some advantages over vibration monitoring. AE is a non-directional technique, which means one sensor is sufficient. AE produces signals at microscopic levels and so it opens up opportunities for identifying faults at earlier stages of damage in comparison with other condition monitoring techniques. However, the limitation of AE is that it is mainly used to detect high-frequency elastic waves, so it is not affected by low frequency which means it is not able to detect the faults that may occur at range less than 20 kHz. AE technique is the attenuation of the signal, and the place of sensor has to be near to source of the sound. Practically, the AE sensor is often located on the fixed part of the machine (i.e. the gearbox case). Therefore, the signal captured by the AE from the defective element will be subjected to severe attenuation and reflections before getting to the sensor. The frequency range of the AE starts from 20 kHz to 1 MHz. On rotating machinery, the most regularly measured AE variables for diagnosis are signal amplitude, Root Mean Square (RMS), energy, Kurtosis and Crest Factor (CF) (Tian et al., 2011).

A number of research studies have investigated AE technique, especially in condition monitoring of rotating machines. Singh et al. (1999) used AE technique in gearbox condition monitoring system, vibration technique was also applied in order to compare between two techniques where a number of accelerometers are placed on the gearbox casing. The result showed that AE provided early fault detection over vibration technique. Tandon and Mata (1999) applied AE technique using spur gear fault as case study in gearbox system. AE technique is used to investigate pitting fault. AE methods variables include energy, amplitude and counts were observed during the test. In conclusion, AE showed promising results for early stage detection of gears small defects. White (1991a) studied the relationship between oil temperature and thickness of the oil film on AE activities. AE signals collected from a back-to-back gearbox during operating time. It was observed that the RMS of AE varied with time as the gearbox reached a stabilized temperature and the variation in AE activity RMS could be as much as one third. Hamzah and Mba (2009)investigated the influence of operating conditions in recorded acoustic emission in helical gears as well.

2.2.5 Gearboxes Condition Monitoring

Gearboxes are a very important part of many industrial machines such as wind turbines, generators and helicopters. In power transmission, the gearbox function mostly operates under fluctuating load conditions during service. Due to this reason, researchers have been under constant pressure to upgrade and enhance measuring techniques and analytical tools for diagnosis of gearboxes faults in early stages to avoid catastrophic consequences. Gears are the main components used in a gearbox. Due to high demands, gears operate at varying speeds and different applied loads. As a result, gears are always subject to premature failure due to wear and material fatigue. However, the physical parameters such as sound, temperature, motor current and vibration can be used to monitor the condition of gearboxes (Cyrille, 2012; li Tang et al., 2010). Different types of defects could cause an error in transmission, which may influence and affect the gears leading to gearbox failure. Gear defects can be classified as manufacturing defects (gear material, tooth profile, etc.), mounting defects (clearance adjustment, alignment, etc.) and defects appearing during transmission (tooth breakage, wear, crack, misalignment, etc) (Kim and Melhem, 2004). Researchers have developed and established many analytical techniques for processing vibration signals to detect gear failure, obtaining information based on the assumption that any changes in the gearbox condition may be detected by changes in the gained measured vibration signal. Earlier reports on gear fault detection and diagnosis focused on the time-domain and frequency-domain vibration signal, spectrum, cepstrum, amplitude and phase modulation technique, which were introduced to detect different types of gear failures. Most of these conventional techniques may help to detect and indicate faults but could not provide much information about the location and severity of the fault which were not eligible for non-stationary signal (Elmaleeh et al., 2007; Liu et al., 2010). Most of the measured vibration signals from gear- boxes show non-stationary properties. Therefore, in recent years some methods of time-frequency domain have been considered as reliable for machinery condition monitoring of gear faults using time-frequency method.

2.3 Gearbox System

Gearbox components such as gears, bearings and shafts are designed to work for a long time based on their expected operational stress levels. However, in some cases, these components are subjected to unanticipated failures due to many scenarios. For example material error, manufacturing error, corrosion, overload, lubrication, and maintenance error are all scenarios that can cause damage (Wu and Hsu, 2009). The gears are key elements in the gearbox, and the amount of wear and fatigue to which they are exposed even under ordinary operational conditions means that they are frequently exposed to early stage failure (Yao et al., 2009).

Ma and Li (1995) stated that about 75% of deficiencies in gearboxes are caused by faults which grow in the gears, and all these faults approximately are the result of localised defects such as fatigue-induced breakage. The severe conditions under which gears operate relative to other machine components means that this machine component can deteriorate quite rapidly in comparison to other machine components. This is especially true for the teeth of the gears (Hu, 2000).

2.3.1 Gears Fatigue and Failures

Gear failures can occur for many reasons, such as defects in the material which the gears are made of, or lack of gear lubrication. Lubricant is utilised as a film between two gears to protect tooth gears from direct impact, diminishing friction, generated heat and vibration levels. Material failures are generally caused by internal structural changes, which may include dislocation and growth of microscopic cavities. Microscopic deterioration can develop into macroscopic deterioration, which may lead to the material fracturing (Tandon and Nakra, 1992).

2.3.1.1 Material Faults

Metal fatigue is caused by repeated cycling of the load below its static yield strength. It is a progressive localized damage due to unstable stresses and strains on the material. Metal fatigue cracks initiate and propagate in regions where strain is most severe. The process of fatigue consists of three stages; a) crack initiation, b) progressive crack growth across the part, and c) final sudden fracture of the remaining cross-section (Widodo and Yang, 2007).

Material failure is created by an intense stress state which the material cannot tolerate. This can be conducted by implementing the tensile testing of a gear material. If a sample is tolerated, the load up to its elastic edge is then released. The result shows that the strain is recovered and no permanent bend is observed. However, if the stress is raised past the yield strength, when the load is taken out, the elastic element of the strain is retained. In this case the plastic element of the strain makes a fundamental change to the microscopic level of the structure. Even though the plastic deformation is a sign of damage, the material may still be good to use. It is challenging to evaluate the degree of the damage. For this reason, many studies have been conducted to describe the severity of the failure (Yao et al., 2009).

2.3.1.2 Manufacturing Faults

The gear manufacturing process can produce small profile errors on gear teeth. Ideally, these defects are supposed to be similar for all gear teeth, as all teeth generate the same vibration at the tooth meshing frequency and its harmonics. However, in reality, these defects have random behavior from one tooth to another, which produces randomly varying vibrations from one tooth to another. Even though vibration defects change slightly from tooth to tooth, the full cycle of the gear will divide equally between the teeth. This means that teeth have contact for the same period of time during one rotation of the gear. Usually the gears are exposed to rigorous quality tests. These tests produce low amplitude vibrations at the beginning, but after a period of time the number of harmonics and frequency of rotation of the shaft and the gear are increased (Tandon and Nakra, 1992).

2.3.1.3 Tooth Deflection under Over Load

Tooth deflection and load are likely to give a signal waveform of a stepped nature. As result of periodically varying compliance, the load is shared between different numbers of teeth. The feature of this signal gives vibration components at the tooth their meshing frequency and harmonics. These vibrations describe the feature for different kinds of gears such as spur gears. Helical gears give measured waveforms for both of the stresses and synchronously averaged housing vibration. But the amplitude is basically

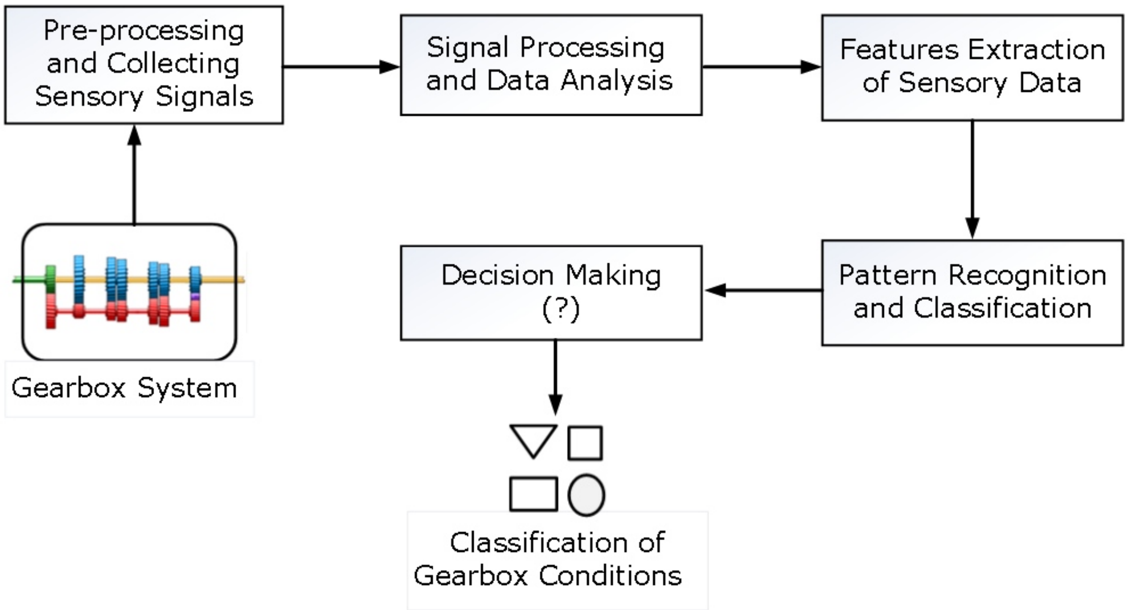


Figure 2.2: A schematic diagram representing general structure of a condition monitoring system.

affected by load. However, loadings both below and above the design load will create a higher vibration amplitude than at the design load (Hedlund and Lehtovaara, 2007; Andersson and Vedmar, 2003).

2.4 Structure of Gearbox Condition Monitoring System

Typically, most approaches used in tool condition monitoring consist of three major elements; sensors, feature extraction and decision making, as illustrated in Figure 2.2. This section will discuss these elements and the limitations associated with them.

2.4.1 Sensing Tools of Gearbox Monitoring System

A reliable condition monitoring system usually requires effective and reliable sensing tools to monitor the health condition of the machinery, and to capture structural defects at their initial stage. Commonly, when a machine is running, several types of signals are produced based on machine structure. Several types of sensors have been applied to measure intensive signals such as vibration sound, speed, torque, oil debris and temperature which may carry significant information about the events in the gearbox. The success or failure of a condition monitoring system depends on the accuracy of information captured by the sensors associated with the real status of the machine (Ho and Randall, 2000b). However, these signals based sensing are usually influenced by noise from the surrounding environment. Sensors could be categorised in two groups, fixed-position (direct measurement sensors and free position sensors (indirect measurement sensors).

2.4.1.1 Determining Sensor Location Issue

Sensor location is a significant subject for a gearbox structural monitoring system, which should take into account the number of sensors to be used, and the position and location of the sensors in order to obtain the most relevant possible information. It is uneconomical to install sensors on every part of a gearbox structure. Inappropriate position arrangement of a sensor may result in collecting undesirable signals that are overwhelmed by noise. Moreover, it will affect the accuracy of fault identification and diagnostics of the monitoring system. Therefore, in order to obtain accurate and reliable results from a gearbox monitoring system, it is essential to select an optimal position of measurement and have an appropriate number of sensors. There are many existing studies on the optimal placement of sensors in many different monitoring applications such as architectural constructions (building, bridge), which depends on how to obtain the fullest and most instructive information from limited information feedback (Bhushan and Rengaswamy, 2000). There is relatively more research on optimal sensor location in architectural construction monitoring systems, whereas investigation into optimal sensor placement methods in complex machinery such as gearboxes are limited. Guo et al. (2009) and Li and Zheng (2008) proposed sensor positioning methods to reduce the traces of the covariance matrix which was associated with the structural parameters estimation. Yao et al. (2009) have used Principal Component Analysis (PCA) to evaluate the optimum location for sensors. Monsen et al. (1993) proposed utilising information entropy method which is a measure of uncertainties in the model parameters for determining the optimal sensor configuration. Zhou et al. (2011) proposed a new method, called the Effective Independence, which orders multiple nominee sensor locations based upon their contribution using Fisher information matrix. Dler et al. (1991) proposed the optimum sensor positioning of gearbox layout using a Particle Swarm Optimization (PSO) algorithm to solve the fitness problems based on the gearbox finite element model. However, research on sensors optimal placement on the gearbox is still relatively new. AL-Habaibeh et al. (2005b) established a new method named Initial Optimisation Procedure (IOP) for optimising sensor position in order to enhance the condition monitoring system for a cutting machine. In this study, the IOP method will be modified and applied for optimum gearbox sensor position positioning to improve gear fault detection. This section will described in details in chapter 5.

2.4.2 Signal Processing and Data Analysis

Signal processing and the data analysis step is the main stage in the condition monitoring system. This step is to refine and get rid of impurity from the raw signals in order to clarify signal specifications and details. The raw signals captured by sensors commonly contain a high level of noise and some random signals carrying a characteristic of vibration components in machineries.

- **Pre-processing methods** such as filtrating are often applied to eliminate noise and improve signal-to-noise ratios. Hence, signal analysis is essential to simplify and abstract the meaningful characteristics for classification process (Liu et al., 2006). Most natural phenomenon signals are non-linear, and the majority of these signals contain diverse frequency components (Shao et al., 2013). The vibration signals produced by gear- boxes comprise of non-stationary transient signals such as the short periodic impulsive components produced by impacts between components. Usually, gearbox vibration signals include three key elements, they are periodic components such as those resulting from interactions between the gears during meshing; transient components created by short interval actions, such as frequent impacts which are the result of a tooth having broken off, and broadband background noise. In the initial stages of damage and defect inception, due to low amplitude vibration the signal is overwhelmed by other signals from different equipment present in the gearbox; it cannot be applied directly for fault detection. However, the accuracy at this stage of fault detection is highly significant. As a result of that, reliable and effective signal processing techniques are required for better analysis of measuring signals in order to develop a robust condition monitoring system and health diagnosis of the gearbox (Combet and Gelman, 2007).

Filtering signals is an important pre-processing step, and should be performed, when required, to solve the noisy input problems and aliasing. In general, signal processing methods include frequency domain, time domain and the time/frequency domain methods which have been commonly applied in many engineering applications (Zhang and Vachtsevanos, 2007b).

- **The traditional method** of monitoring signals is to display them in the time domain. In Appendix A, this domain is explained in more details. The time domain is considered as a record of what occurred to the variable in the defined time range. Statistical parameters are used to analyse the signals in time domain such as peak value, RMS, Kurtosis and CF and their use is well established in assessing the condition of gear (Liu et al., 2006).

  Stevens et al. (1996) have stated that these methods are appropriate for detecting and diagnoses mechanical faults when the fault takes the shape of impulses which impose periodic pulses in a small time period (wide frequency bandwidth) onto the base vibration signal. However, the most commonly used techniques for detecting and diagnosing gear damage is spectral analysis of captured signal in the frequency domain. The vibration spectrum of gears included: the tooth meshing frequency components, harmonics and sidebands placed on both sides of tooth meshing frequency of the gear. The attitude of the side-band can be used as a clear sign of the existence of a fault, for example through an increase in the number of sidebands and their relative amplitudes.

Randall (1982) stated that the three gear meshing frequency components at the beginning with their sidebands may offer good information about gear fault. Therefore, tracing and observing changes in the behaviour of particular sidebands can be used as a good indicator of gear failure. In reality, it is often challenging to obtain useful information from vibration signals using a simple Fourier Transform (FT). Growth defect in the initial stages usually has low frequency amplitude and can be concealed by frequency components of other mechanical parts or buried in the background noise (White, 1991b). This is especially pertinent due to the fact that individual vibration impulses produced by gear faults normally tend to be of short period resulting in the corresponding frequency pulse to be spread over a wide frequency band with low amplitude (Randall, 1982). It can also be a challenge to determine whether a certain frequency indicates a defect when a huge number of spectral components exist.

- **Advance signal processing methods** such as time-frequency domain, is applied in many monitoring applications such as gearbox fault diagnosis systems and is gradually beginning to substitute traditional methods such as time and frequency domains analysis. The time-frequency domain is a powerful technique that can be used to represent the signal in time and frequency domains at the same time as examining non-stationary signals. In Appendix A, this domain is explained in more details. The results can be easily interpreted. Peng and Chu (2004a) state that by using this domain, it is simple to describe the local features of the signal in detail, with all frequency components in the range of interest and how they change with time. All these can be presented on a single graph (White, 1991b). In the last two decades, a group of time - frequency signal processing techniques have been established as appropriate methods for analysing gearbox vibration signals. They have received considerable attention in the discipline of condition monitoring. Short-Time Fourier Transform (STFT) (Tomazic, 1996; Rosvall et al., 2001), Wigner-Ville Distribution (WVD) (Wu and Huang, 2011) and Wavelet Transforms (WT) (Yan et al., 2014; Xian and Zeng, 2009) are considered as the famous examples of time-frequency domain. Peng and Chu (2004d) have stated that the WT is a reliable technique to investigate vibration signals because the signals include a series of instant impulse and other factors which are transient and non-stationary in reality.

The WT is mathematical tool can be used to decompose the signal into different frequencies with different resolutions in time-scale (Amirat et al., 2009). Many researchers have already put their efforts to analyse vibration signals gained from multiple conditions of a gearbox system using such techniques. Barszcz and Randall (2009); Hui et al. (2009); Yiakopoulos et al. (2011) in several publications have used WVD, STFT and WT to study vibration signals of a spur gear at constant load in order to discover numerous defects developments. Wang and Hu (2006a,b) have implemented WT and STFT to detect a number of gear faults such as pitting, spalling and root crack. Accompanying of signal processing techniques with mathematical and statistical methods have been applied to improve the analysis of vibration signals. These combing methods have been reviewed in (Jia-Zhong et al., 2007; Huanqing and Peng, 2009).

Hall and Mba (2004) and Jayaswal et al. (2008b) have concluded that WT is the best-suited technique to analysing vibration signals for fault detection in gearboxes.

2.4.3 Feature Extraction

Feature extraction is a key issue to machine condition monitoring and fault diagnosis. Features must contain the necessary discriminative information for their fault classifier to have any feature extraction stage is a key element in fault diagnosis and condition monitoring system of machineries. Usually, features include distinct characteristics of information about faults.

These features can be used as inputs to fault classifier in order to have any chance of precise classification. Features are defined as variables extracted from measuring raw signals using signal processing methods to improve the quality of detecting damage in the initial stage. However, the captured signals are often in complex shape because of the randomness and the noise generated by the industrial environment, which may adversely affect the measurement of signals, increasing the signal to noise ratio significantly. Feature selection contains in comparison between the computational feasibility linked to low level features and extensive per-processing required for high level features. Feature extraction includes characteristics or advanced characteristics analysis. Characteristics analysis used simple feature extraction techniques depend on data reduction procedure, which lead to scalar representations (Lebold et al., 2005).

There are many methods for extracting features of a machines condition from the vibration signals in order to capture the diagnostic information. Some of these methods which are applied in this study, are explained in more details in Appendix A. Features were computed as many times as possible, but the choice of features is often arbitrary, which will lead to situations where several features provide the same information as well as some features providing no useful information at all. The additional burden of computing these features may decrease the preformance and affect real time applications of the condition monitoring system. So feature selection is helpful in reducing dimensionality, discarding deceptive features and extracting an optimal subspace from the raw feature space; it is critical to the success of fault recognition and classification (Timusk et al., 2008).

Rafiee et al. (2010) introduced a new automated algorithm of feature extraction for fault diagnosis in gearbox system equipment (gear and bearing) using wavelet-based signal processing. Four statistical methods were applied: standard deviation, variance, Kurtosis, and fourth central moment of continuous wavelet coefficients. Results also show the fourth central moment is the appropriate method for gear and bearing defects. Standard deviation and variance are suitable mainly for bearings. Kurtosis did not show any consequential relation to the faults. A comprehensive study including time and frequency domains, and the extraction of features for fault detection and diagnosis of gearboxes is discussed by Lei et al. (2010). The vibration-based features such as kurtosis and spectral kurtosis are extensively applied to an industrial case and demonstrate the possibility of detecting relatively small tooth surface pitting for two-stage helical reduction gearboxes. This investigation was conducted by Combet and Gelman (2009).

2.4.4 Intelligent Decision Making

An intelligent gearbox condition monitoring system is defined as an integrated system consisting of multi-sensors, signal processing methods, reliable feature extraction techniques and intelligent decision making techniques. These four requirements are necessary for an automatic monitoring system. In recent years, intelligent monitoring systems for fault detection have gained more attention because they can better expect the correct mapping pattern for the input and output of a dynamic system directly.

This feature is too difficult in the physical model which requires the derivation of very complex mathematical equations concerning measures that are difficult to determine. Many researchers have used intelligent methods such as expert system (Ran and Penman, 2008), fuzzy logic(Yuan et al., 2010), support vector machine and artificial neural network (Wang et al., 2010). For more details see Appendix A. Intelligent systems could use their learning ability to describe high non-linear characteristics of gearbox processes, superior learning, noise destruction, and parallel computation abilities (Yuan and Cai, 2005). However, the disadvantage of some of the intelligent decision making systems is that they would require significant training and they could be very dependent on their structure and configuration (Ran and Penman, 2008).

2.5 Research Gap

According to the literature review presented in this chapter, the knowledge gap can be summarised as fallows:

Many researchers have attempted to develop reliable condition monitoring of gearbox system to diagnose gear faults. These methods are an area of active research because gearbox condition strongly influences the entire machinery performance. In addition, a reliable gear monitoring system can increase the machine performance and decrease machine downtime caused by defect in gears. The information obtained from the gearbox using sensors can be used for detecting several types of faults, including gear defects and bearings defects. But there is a lack of understanding in the effect of tools sensing and its locations on gearbox condition monitoring systems. Also, there is limited research in studying the relationship between detecting and diagnosing faults in gearbox condition monitoring system and sensors selection and its locations. In order to identify problems in condition monitoring development and the draw-backs of current practice, it is important to describe the basic structure of a monitoring system. In order to monitor an on-line machining process, the system must provide the following:

1. Identifying the appropriate sensors types which can be used effectively to extract the emitted information from the process in a form of sensory signals.

2. Determining the appropriate signal processing methods to analyses the sensory signal and simplify the incorporated information into a form suitable for classification model.

3. The extraction of valuable information from the suitable sensitive sensors and the suitable features and signal processing methods.

4. The improvement of a classification system strategy based on the available sensory data and processing methods to identify the condition of gearbox.

Usually operation of machinery can produce different types of information. This information can then be used to define the status of machinery.

Consequently, it has to be possible to select one or group of sensing tool to recover information about the process which identifies the status of the machinery. The selection of an appropriate sensor and its location could be a challenging task in order to obtain reliable information at initial stage of the fault. When the process to be monitored on-line is complex, such as gear fault, it is difficult to immediately recommend a suitable sensor for on-line monitoring the condition of the machinery. Therefore, the selection of suitable sensors and its location is the most significant issue. The selection of proper signal processing technique is also necessary, because, the information extracted by sensors are usually interfered by undesirable signals including noise or other relevant information. Hence, number of signal processing and feature methods elicit are required to elicit the essential information. The classification stage is highly significant step in categorising the extracted information by the sensing tools and taking the decision regarding the status of the machine.

2.6 Discussions

Gearbox condition monitoring systems are important for detecting faults which may occur while gearbox systems are in operation. Consequently, this leads to an improvement in the quality of the product, reduces the downtime for maintenance, increases the productivity and reduces the total cost. The success of the gearbox condition monitoring system depends on the location and types of sensors, as well as on the quality of signal processing, the reliability of feature selection, and the extraction and robustness of classification methods for accurate decision making. This is in addition to dependency on the reliability of the hardware and data acquisition systems. Many approaches have been implemented in regard to gearbox fault diagnosis monitoring systems including speed, torque, acoustic emission, vibration and oil debris analysis. For signal processing and data analysis, many techniques have been applied to detect the state of the gearbox from time series, frequency components such as FFT, STFT, and wavelet. Feature extraction for many simple and advance statistical and mathematical approaches have been conducted. The simple methods are mean, maximum, minimum, skewness and kurtosis. The advanced methods included PCA and Kurtogram. These methods were combined with computational intelligence techniques such as ANN, fuzzy logic and SVM. In this regard the research is conducted to provide a more reliable, robust and precise gearbox condition monitoring system which are required in recent industrial applications.

Chapter 3

Methodology

3.1 Introduction

This chapter presents the research methodology which is adopted in this study. It gives a summary of research gap in industry related to the design of gearbox condition monitoring systems. The condition monitoring system has been utilised to detect and diagnose the fault in gearbox systems such as damage in gear teeth. It also presents the implemented condition monitoring methodology for gearbox. The chapter illustrates the main steps of the proposed approach.

3.2 Gearbox System Information Analysis

In order to identify the problems in gearbox condition monitoring design and drawbacks of current practice, it is important to understand and study the general structure of gearbox monitoring system. The main sources of information condition monitoring system for the gearbox is illustrated in Figure 3.1. Fault can be produced for many reasons such as inappropriate operating conditions, lack of or inadequate lubrication, high load, and installation problems. Defect in gearbox can be measured mainly by monitoring three main elements; which are load, noise and lubricant. These elements are essential for the most condition monitoring and fault diagnosis of gearbox systems.

Lubricant information can be measured by temperature, weight, and debris size and shape which are collected from samples of the lubricant. Noise information can be measured by vibration, acoustic emission and sound. Load information can be measured by speed, torque and power of motor. All these measurements are conducted in order to detect several types of faults that can occur in any part of gearbox such as gears, bearings and shafts. The obtained information is analysed to pick up relevant and discard redundant information using advance techniques and methods. Then the extracted information are integrated and used as base knowledge for fault diagnosis and prognosis model for gearbox system. However, this information may negatively influenced by many factors including type of sensor, sensor location and analysis signal methods. Therefore, there is a need to take all these factors into account to develop appropriate monitoring system of fault diagnosis. The following sections will describe the methodology of how to select these factors.

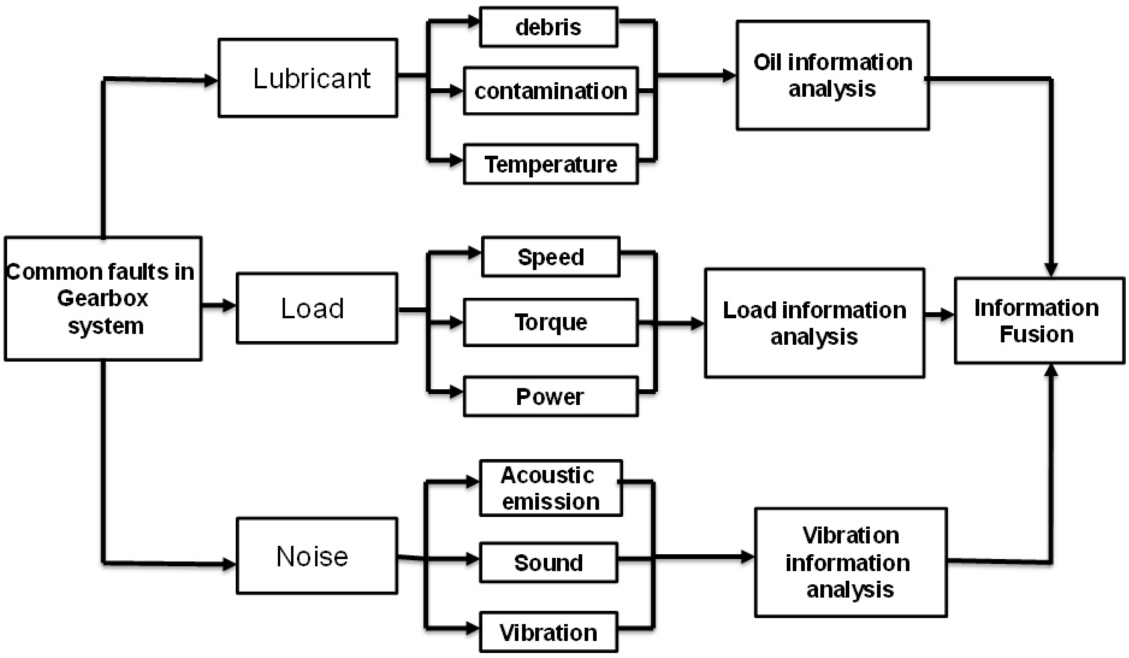


Figure 3.1: Integrating framework for gearbox information analysis.

3.3 Problem Associated with Gearbox Monitoring System

Current studies in condition monitoring system covered some facets for designing reliable monitoring system while others aspects remain and need further investigation. For example, decision-making and classification stage have been well investigated especially in the case of determining the existence of the obvious faults (Williams et al., 1994; Widodo and Yang, 2007; Widodo et al., 2009). In reviewing previous research, it was noticed that the interest of most studies has been concerned with decision-making step using many types of methods such as statistical methods and computational intelligent techniques. However, it has been found that this step is not considered as the main difficulty in condition monitoring design for the following reasons:

The performance of classification and decision-making method is often relied on the quality of the information been given. Usually raw data is analysed and processed to extracted useful information then this information is fed to the decision-making stage; if the extracted data contains useful and the required information about the gearbox operation and its conditions, the decision-making stage is normally expected to produce acceptable results. However, the decision-making method is expected to produce misleading results when the used data does not include relevant information about the process and its conditions.

Regardless the source of data used in the decision stage and what it may present, the decision-making techniques can still be used to evaluate the processed data and make a decision on the essential prediction or classification. The response required from this stage is application dependent. For the same processes and faults, different techniques can be used based on the requirements or the outputs of every technique. Therefore, it has been found from literature that the success of a condition monitoring system relies on three significant aspects:

1. The selection of optimal sensors locations.
2. The selection of appropriate sensors.
3. The selection of appropriate signal processing techniques.

Sensing technology is considered as the most significant part for designing gearbox condition monitoring system. Many different types of sensors which are based on type of measuring data such as oil parameters, sound and vibration are applied in many studies to investigate the faults in gearbox systems. Some common methodologies have been found practical in selecting the sensors used in a condition monitoring system. In order to expand the failure coverage and reduce the number of sensors used, however, these methodologies provide broad guidance on use of sensors and determining its locations. The techniques has failed to provide practical information or a structured methodology on how to select sensors and its location which can provide high quality information about the process with reduced budget. The idea of selecting sensors which are used in previous research can provide a primary point to start with. However, it might not be right to assume that these sensors would produced the same results if they were applied in this study. This is because gearbox systems are generally different in their internal structure and operation conditions.

The next issue that needs to be investigated to develop reliable condition monitoring systems for gearbox, is the selection of suitable feature and signal processing techniques. The selection of these techniques are based on the type and performance of sensors been used if the selected sensors or their locations are inappropriate, then the applied features and signal processing techniques are not expected to give useful information. Different features and signal processing techniques have been proposed and implemented in gearbox monitoring systems including statistical methods, time domain, frequency domain and time-frequency domain. The current practice in selecting the signal processing techniques is normally done by a manual procedure such as visual inspection to search for abnormal pattern within the signals. This approach, although it is successful, can be considered costly and time consuming.

The final step is to develop an effective gearbox monitoring system, it is required to evaluate the sensitivity of the sensors, and the associated features and signal processing techniques. Therefore, if the system performance is acceptable, then the sensors and the signal processing techniques are assumed appropriate and satisfactory. When the system does not work effectively as expected, then another investigation for other sensors or signal processing techniques is restarted. This technique of constructing a complete system could also include a detailed examination of fault processes to view the signals and search for the sensory features which allow the pattern recognition system to provide better results. In addition, when computational intelligent techniques are used, the training and testing procedures repeat and require long periods of time and computational effort. If the sensors or signal processing methods are not appropriate, the recurring training methods could take longer and not give good results.

It can be concluded from previous discussion and background presented in Chapter 2, that the related work examining the development problems of gearbox condition monitoring systems are limited. Despite the fact that there is wide range of research investigating condition monitoring methods of gearbox systems, very few studies have examining sensors reliability and their locations in order to reduce the cost and maintaining high efficiency of the design. Most research reviewed so far has focused on detecting and diagnosing faults. A method found to be successful in one application may not give an adequate results in another. The methods found in the literature cannot provide an automated design methodology for monitoring systems even when providing sufficient results. Hence, this research develops a design methodology for gearbox condition monitoring systems, and offers structured and automated design methodology. This methodology can provide practical selection criteria of sensors, their locations and features/signal processing methods with reduced experimental work, time and cost.

3.4 Problem Domain and Objectives

The purpose of this study is to investigate the condition monitoring system for gearbox especially gear defects. Many studies have been conducted to develop trustworthy Gearbox Condition Monitoring system (GCM). However, a number of parameters may impede the performance of developing GCM such as unsuitable selection of sensors and their locations. The domain of this research is to implement new enhanced approach for selecting the sensors and features /signal processing methods essential for observing gearbox operation and situations. The decision-making and classification step is used to evaluate the methodology for selecting sensors and signal processing methods. An approach, named Automated Sensor and Signal Processing Selection (ASPS), which is applied on machining process, is developed by Al-Habaibeh et al. (2002). ASPS approach is adopted and improved to be suitable for gearbox system. This approach, which will be introduced in Section 3.6.1, is based on self-learning and multi-sensor techniques. Also, ASPS approach has been implemented for milling and turning of machining process (Abbas et al., 2011) and (Al-Azmi et al., 2009). Although the ASPS approach can give good results for condition monitoring system, this approach dose not consider some significant aspects ASPS approach such as sensor location which will be addressed in this research. The ASPS approach is designed for machining process, but in the present study the approach is developed to fit with gearbox system. Accordingly, it is defined as a new approach named Automated Sensor and Signal Processing Selection for Gearbox (ASPSG) system. The ASPSG, is considered as a novel approach which is used for analysing and simplified sensory signals to prove and evaluate the proposed methodology for choosing effective sensors, features and signal processing techniques and to investigate the relationship between sensors in terms of (sensitivity and locations) and the performance of designing gearbox condition monitoring systems.

The overall goal of this research is to develop a reliable condition monitoring system for detecting faults in gearbox with high quality. It also aims at reducing number experiments and sensors, which will lead to reduce the cost by using sensor-fusion model.

3.5 The Concept of Proposed Approach

This research present a review of the state of the art in methodologies of sensors and signal processing which are used as tools for condition monitoring system. The gap in literature is the lack of standredised form of designing monitoring system which can be used to detect faults in all gearbox systems. This could be due to difference in nature of sensors measurement which are used for different purposes and no single form can serve all of them. This study will use the same sensors, features and signal processing techniques which are applied in previous research. It Also will propose the same classification techniques that's used in earlier studies. The proposed ASPSG approach employed group of sensors, features and signal processing techniques and classification techniques to develop intelligent and automated monitoring system of gearbox. The main aspect which differentiates this study from previous research is its approach to reduce time of and cost of the monitoring system. It also provides a systematic design procedure for condition monitoring systems. Moreover, it offers relevant information collected from the gearbox monitoring system and its conditions.

The ASPSG approach is conducted to reveal the best collection of sensitive sensors, features and signal processing methods which can help to design a monitoring system with minimising number of experiments. The first step in the methodology is to extract Sensory Characteristic Features (SCFs) which are gained from raw signals by using several signal processing and feature techniques. The SCF is used as sensitivity measurement for such sensor. If any SCF, which is extracted from any sensor, provides high sensitivity this means that SCF is appropriate feature for detecting the faults. Conversely, if any SCF shows low sensitivity, this indicates that SCF inappropriate feature for detecting the faults.

In this section a description of how the suggested condition monitoring design methodology is conceived based on previous evaluation and implementation of this approach in end milling process (Abbas et al., 2011). In addition, it is based on enhancing the design tools and methods of previous research described in the literature. The author's main contribution is to implement the ASPSG approach and to combine previous points with the idea of developing a generic structured sensor-fusion model using the following three techniques:

1. Assessing the new ASPSG method (Automated and Sensor and Signal Processing Selection for Gearbox).
2. An automated idea for simplifying the complexity of raw signals into simple Sensory Characteristic Features (SCFs) for gear monitoring.
3. Automated methods for measuring of sensitive SCFs and enhance the associated sensors and signal processing methods.
4. Examining novel approach using neural networks methods for gearbox system.
5. The method of reducing the cost of the gearbox monitoring system based on eliminating the unused sensors when possible.

The main techniques developed will be described in details in following sections with more technical description and examples in the subsequent chapters.

3.6 The ASPSG Approach

The proposed approach Automated Sensor and Signal Processing Selection for Gearbox (ASPSG) process is shown in Figure 3.2. It is a systematic approach used to identify reliable sensory signals and signal processing techniques in order to detect abnormal conditions or the physical phenomenon for any mechanical application such as the gearbox system. The ASPSG approach initiates by using a wide range of sensors that are installed on the gearbox casing at different locations. The gearbox is operated with varying speed and torque in order to generate sensory signals that should contain useful information about the status of gearbox parts. The next step of the proposed approach is to extract SCFs gained from the sensors. If a SCF shows high sensitivity to the fault, this means that this sensory characteristic feature is useful in detecting or evaluating that fault. A particular number of sensitive sensors and signal processing methods are then selected as an initial monitoring system. Cost reduction can then be performed by reducing the number of SCFs which are extracted from the selected sensory signals. Insignificant numbers of SCFs which are extracted from a sensors should be eliminated from the monitoring system i order to reduce thier costs. More details about the main concept of the ASPSG approach are followed in the next sections of this Chapter. The following

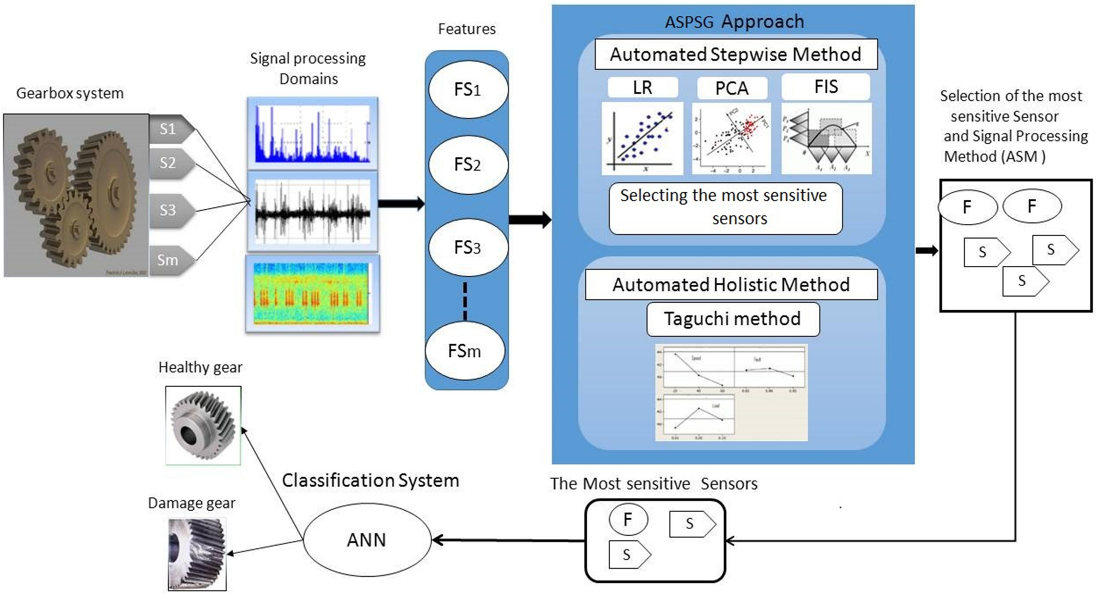


Figure 3.2: The essential structure of the ASPSG approach.

Sections are the main steps of proposed approach.

3.6.1 Simplifying the Raw Signals and Extraction of Features

The raw sensory signals are captured from complex structure of gearbox system and require to be processed in order to extract the appropriate information. This process starts by eliminating the unwanted information from sensory signals then the results are grouped into a set of simplified sensory signals named Sensory Characteristic Features (SCFs). SCFs can be gained from a combination of conventional and advanced signal processing techniques to simplify raw data. Then, a number of feature methods are used to extract useful information. Usually, operating machinery starts from a healthy condition and continue until unexpected fault occur at any time thereafter the fault gradually increase till breakdown. It is difficult to detect the abnormal condition of the process from the generated complex signal. So, simplification methods are required to take out the SCF. Numerous numbers of SCFs can be computed by picking number of samples of sensory signals at constant intervals with different conditions and analysing these signals using wide range of features and signal processing methods. The SCFs could be a good method to examine the essential information regarding the presented process conditions, see Figure 3.3.

3.6.2 Automated Sensitivity Detection

Efficiency of sensitive SCF highly relies on the content of information about the condition of machinery operation which may lead to excellent classification. The SCF value is expected to be affected by the significant change of operation conditions. The sensitivity of a SCF can be assessed by numerous methods such as:

- Using a normal observation and visual inspection of the signals.
- Using of a classification methods as automated processes such as ANN and FRBS .
- Using statistical techniques to detect the change in the SCFs levels.

Figure 3.3 shows the changes in SCFs which can be distinguished visually. The raw sensory signals are simplified into simple SCFs. SCF_1 is raised

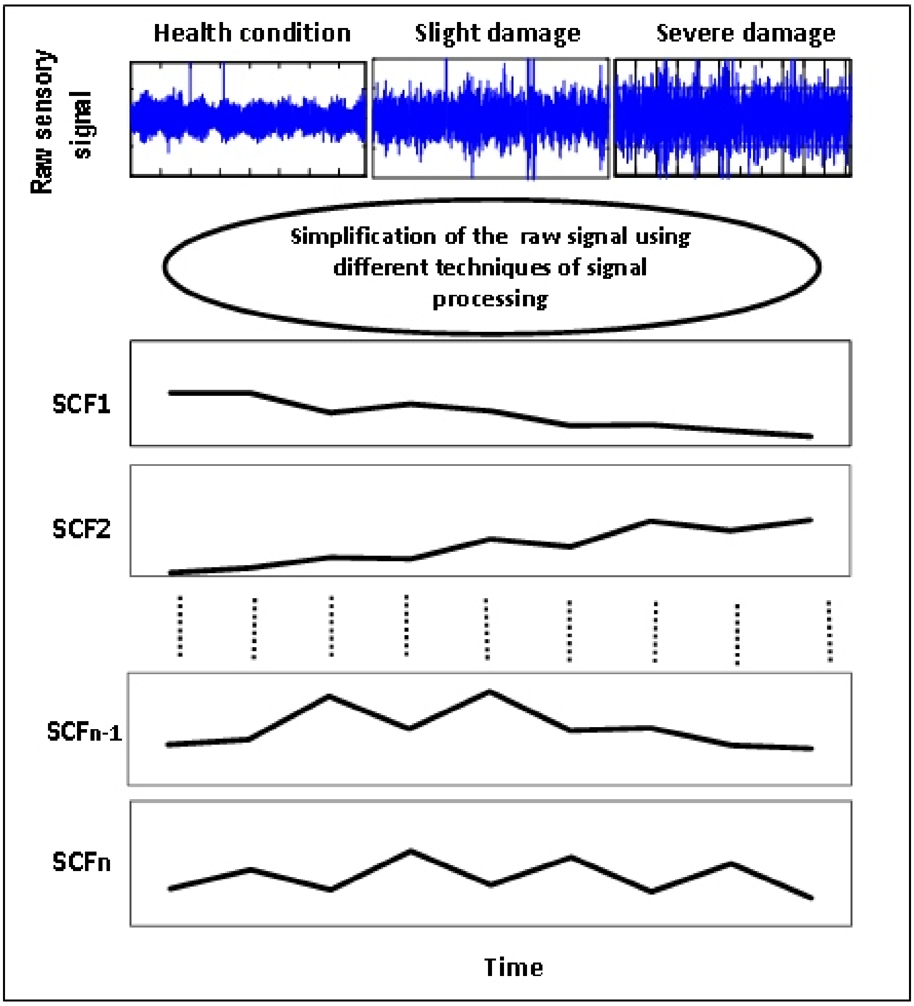


Figure 3.3: Simplification of complex sensory signal into simple SCFs.

progressively as result of changing that occur between two conditions or more of the process. Moreover, SCF2 is declined gradually between two conditions of the process when the process changes from fresh to damage. SCF_{n-1} and SCF_n could be randomly fluctuated between the two status after period of time. Two sensory characteristics features SCF_1, SCF_2 show that there is significant changes based on two status of the process. Even though the difference between SCF_1 and SCF_2 is one which has positive change and second has negative change; difference between the two conditions can be easliy noticed. Therefore, both SCF_1 and SCF_2 are identified as sensitive SCFs. While sensory characteristics features SCF_{n-1} and SCF_n are identified as insensitive SCFs, because they are not showing difference between two conditions (healthy and damaged). Measuring sensitivity of the SCFs should to be automated to design enhanced methodology of choosing reliable sensors and signal processing techniques. A number of methods can be applied as shown in Figure 3.6 which can be utilised in order to measure sensitivity of sensor characteristics features, for example principle component analysis, the slope of a linear regression and Taguchi's methods.

3.6.3 Association Matrix

After computing the sensitivity characteristic feature for each sensor on gearbox conditions, another matrix is generated and labelled as Association Matrix (ASM). The ASM contains the gained sensitivity values for the corresponding sensory features. It provides clear picture of the sensitivity values which are related to each feature f_{ij}:

The ASM matrix is defined as follows :

$$Y_{ASM} = \begin{bmatrix} f_{1,1} & f_{1,2} & f_{1,3} & .. & .. & .. & f_{1,n} \\ f_{2,1} & f_{2,2} & f_{2,3} & .. & .. & .. & f_{2,n} \\ f_{3,1} & f_{3,2} & f_{3,3} & .. & .. & .. & f_{3,n} \\ .. & .. & .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. & .. & .. \\ f_{m,1} & f_{m,2} & f_{m,3} & .. & .. & .. & f_{m,n} \end{bmatrix} \tag{3.1}$$

where $1 \leq i \leq n$ which represent sensors and $1 \leq j \leq m$ represent features The parameter f_{ij} is named coefficient of the sensitivity for feature of gearbox condition which is achieved by using the sensory signal; where the ith represent sensor and the jth indicate feature and signal processing method. The ASM provides clear picture for the most appropriate sensor and signal processing method to be utilised since each column in the matrix is represented one feature and signal processing method while each row is represented one sensor. Essentially, high sensitivity parameter of SCFs are the most sensitive to fault detection and they are the most appropriate features to be used. Therefore, the related sensory signals and features/signal processing methods are the most appropriate ones and then selected as an initial monitoring system.

3.6.4 Sensor Fusion and Cost Reduction

To develop a reliable gearbox monitoring system with high sensitivity to the faults, a set of high-sensitivity features SCFs should be applied in combination of sensor and signal processing techniques. Usually, all SCFs features are extracted from the sensory signals. Then, they are ranked based on their sensitivity values, the highest sensitive number of SCFs can be used together to form the initial monitoring system. The cost of the monitoring system can be simply computed based on the quantity and type of sensors have been utilised. The cost of the monitoring system is The value of the highest sensitive number of SCFs can be selected based on the cost of the system, the required quality of interpretation, the speed of signal processing and the implemented decision making method. The value chosen in this research is 20 based on a previous implementation of the ASPS approach for end milling machining processes (AL-Habaibeh et al., 2005a). The last value is also found satisfactory in providing sufficient monitoring capability with reasonable signal processing speed.

The $(m \times n)$ matrix of sensory characteristic features as mentioned in Figure 3.4 where m indicates number of sensors and n represents number of signal processing methods. These features require to be computed during the operation in order to categorise the sensitivity of the SCFs. Then, the SCFs are sorted from high to low sensitivity and the highest numbers of SCFs are selected to be produce reliable condition monitoring system, the cost of the monitoring system can be computed depend on the sensors of the selected features SCFs. The cost reduction step can be applied to

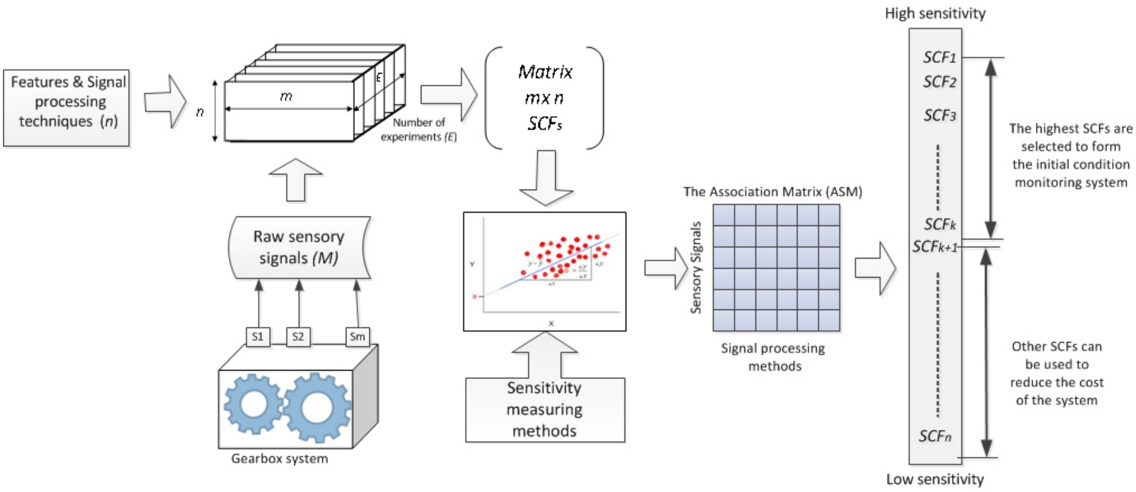


Figure 3.4: The rank and the selection of features SCFs.

minimise the budget of the monitoring system. This step may or may not affect monitoring performance of the system. It is conducted by removing sensors which are inactive and they have less contribution to the abnormal condition. Also, it need to replace them by SCFs which come next on the rank, see Figure 3.4, from sensors already in the system without having to significantly reduce the overall sensitivity of the system (i.e. the new SCFs should still have relatively high sensitivity).

A sensor contribution in a system is described as the utilisation of a sensor. It is defined as the number of SCFs features which are applied in a system for specific sensor proportion to the entire number of SCFs utilised in the overall system. Also, the utilisation is described in this thesis as the total number of signals produced by the sensor.

Assume, for the process shown in Figure 3.4, that the first sensitive number SCFs are found from sensors $(S_1, S_2, S_3, \cdots, S_i, S_{n-1}, S_n)$. Therefore, the cost of the hardware will be the cost of the sensors in addition to their signal conditioning devices. Assume CS_j is the cost of the jth sensor and its signal conditioning devices and all the associated hardware.

Assume that the sensor S_{n-1} contributes in only h SCFs where h is much less than the contribution of the other sensors. Then that SCF from the $Sn-1$ can be removed from the system and replaced by another h SCF from the other sensors as long as these new SCFs have relatively high sensitivity on the rank. Consequently, the cost of the new system will be:

$$Cost = CS_1 + CS_3 + CS_5 + \cdots + CS_{n-1} + CS_n \tag{3.2}$$

where the new system is reduced by CS_{n-1}. The number of sensors is reduced, even if the number of SCFs in the system is still not changed, and therefore the cost of the system is also reduced. This removal process can be very efficient as long as:

- The new SCFs have high sensitivity so that the overall system performance does not decline.
- The eliminated sensor is relatively expensive.

3.7 The Framework of ASPSG Approach

The main concept behind the Suggested approach is defined in this section. Practically, further detailed procedures for the ASPSG will be explained clearly with more detail and experimental examples in the following chapters of this thesis. The aim of the ASPSG is to develop a gearbox moni-

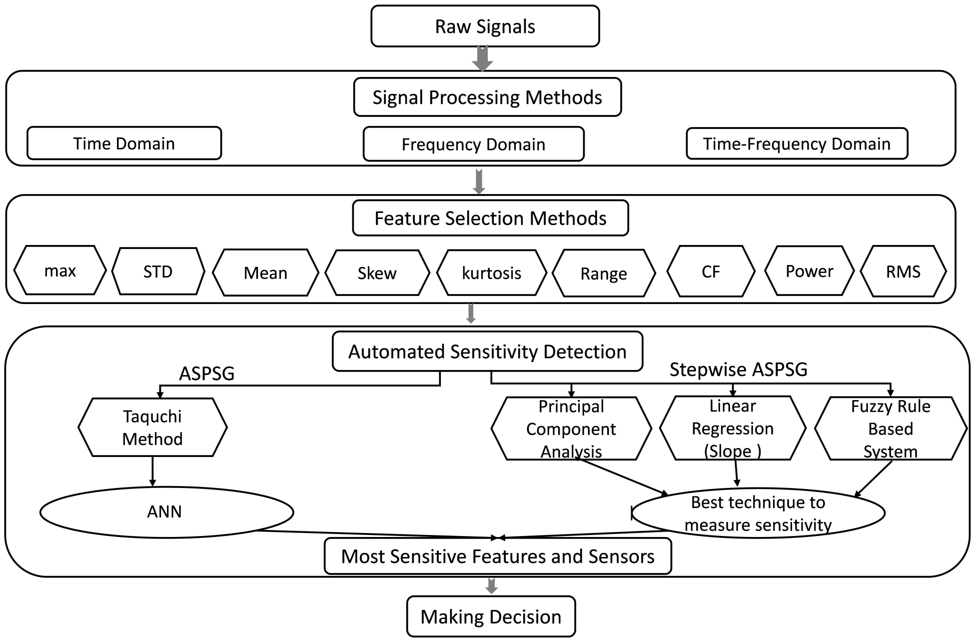


Figure 3.5: The framework of proposed approach.

toring system for detecting fault in helical gear using an automated simple procedure to identify the SCFs. These features SCFs should offer high sensitivity to abnormal conditions or faults and should give less sensitivity to other operating factors. The main target of any condition monitoring of gearbox system is to detect the fault in initial stage taking into account the cost of the monitoring system. Therefore, the ASPSG is based on the ASPS approach which is used to prove that there is a strong relationship between a measured sensory signals and the state of monitored physical phenomenon. The monitoring system budget is significant issue and should be considered as well; the sensors with high cost should be excluded from the monitoring system whilst a low-cost sensor can be utilised to do the same job instead of an using expensive tools. Figure 3.5 shows the basic framework of the proposed approach.

Analytically, captured sensory signals are analysed using signal traditional and advanced processing methods applied to observe the anomalous condition of the physical phenomenon which needs to be discovered or evaluated. The ASPSG approach begins by defining the operation to be monitored and its states (e.g. normal or abnormal condition). Then, a number of sensors are installed on the optimal places to collect relevant information which is associated with the events on monitoring system. In order to produce sensory signals that contain useful information about the process, gearbox system is operated under heath and fault conditions with varying speed and load. The following stage of the proposed approach is for extracting SCFs obtained from the sensory signals using a wide range of signal processing methods and then discovering the sensitivity of such features on the investigated process state. If a specific feature from a specific sensor shows high sensitivity to the fault, this means that the sensory characteristic feature is useful in detecting or evaluating that fault. A particular number of sensitive sensors and signal processing methods are then selected as an initial monitoring system. Cost reduction can then be performed based on the number of SCFs extracted from the selected sensors. Consequently, and to reduce the cost, the sensor might be eliminated from the monitoring system if extracted numbers of SCFs from a sensor are insignificant. More details about the main concept of the ASPSG approach are explained in the following chapters.

3.8 Implemented Methods to Develop ASPSG Approach

This research uses different types of sensors such as accelerometer, AE, speed and torque. It also applies several techniques of signal processing including time, frequency and time/frequency domains. Moreover, Many traditional and advance statistical features implemented to reduce the dimensionality and simplifying large amount of raw signals in order to obtain features characteristics of sensory data. Several measuring sensitivity techniques have been developed in this research and implemented to measure the quality of information are captured from the sensory signals.

Two novel approaches named, holistic procedure and stepwise procedure, are proposed to measure sensitivity of features characteristics of sensory SCF. Holistic procedure is considered as a measuring tool using Taguchi's method based on orthogonal array to calculate the quality of information offered by each sensor. It provides a general picture of sensitivity for each sensor based on all the changes in the values of speed and load to operate the gearbox. Stepwise procedure used three different methods to calculate sensitivity for every sensor gradually, so that the sensitivity of each sensor is calculated depending on any change in driving parameters of the gearbox which are speed and load. Three classification techniques are applied; namely, PCA, LR and FRBS. All these techniques are considered as statistical methods which are used to evaluate the sensitivity of the SCF. All these methods also be used and evaluated throughout this thesis. Four different type of neural networks will be used to measure the capability of each method and define the most accurate method. A brief definition for each method is provided in the following sections.

3.8.1 Automated Stepwise Method

3.8.1.1 Linear Regression Analysis

It can be observed that the change in SCF value is due to the change in a gearbox system state. For example, if the average of the broken teeth signal is increasing gradually in a gearbox process, this could be due to broken teeth developing. The likelihood of a SCF shows a specific and clear sign and change in values as random behaviour is rather low and it is ignored in this research particularly when using several SCFs.

Data points of SCFs change with time as shown in Figure 3.6 (a): the values of SCF can behave randomly so they make low or even no change in the average value of the SCF as a function of time. When SCF changes randomly, it is described as being a low sensitivity of SCF which means no information about the process and the slop angle of a linear regression line is expected to be relatively low compared with a high sensitivity of SCF which changed in specific pattern as show in the Figure 3.6 (b). The absolute slope angle is a relative measure and it depends on the process. The advantage of using linear regression; firstly, the slop angle can present a good indication of the sensitivity of the SCFs by indicting the average change in the SCF value to calculate the linear regression and the position

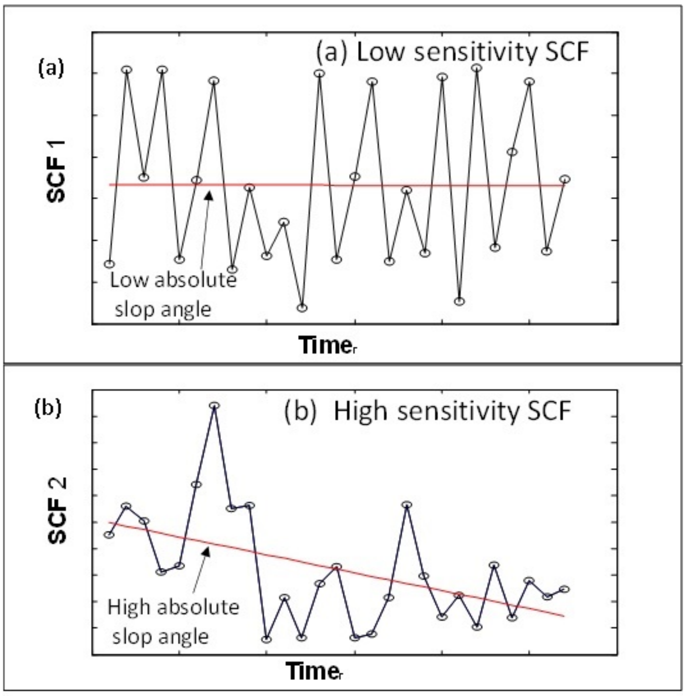


Figure 3.6: The Framework of Suggested approach.

of the data to the states to be monitored. Secondly, easy to compare the result if several SCFs obtained from different sensors and signal processing methods by normalising the SCF value during the same period of time.

3.8.1.2 Principal Component Analysis

The steps of implementing the PCA start by subtracting the mean of the data from the original dataset and then finding the covariance matrix of the dataset. The following step is calculating the eigenvalue which is equal to the distance between the zero mean and each variable of the row data. The biggest value indicates the more effect on the data (Zou et al., 2006). Therefore, it is useful to select a sensor which shows an Immediate response to the event during the gearbox operating. Each eigenvalue of the used sensor is combined to create the PC of Feature. All the PC of SCFs are arranged to form the eigenvalue sensory matrix which will be fully described in Chapter 7. Further information about the PCA in general can be found in the reference section. The advantages of the PCA are summarised as follows:

- It is a way to identify patterns in data, and to expressing the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where the luxury of graphical representation is not available, PCA is a powerful tool for analysing data.
- The other main advantage of PCA is that once you have found these patterns in the data, and you compress the data, i.e. by reducing the number of dimensions, without much loss of information.

3.8.1.3 Fuzzy Rule-Based system

As described in the aforementioned sections, that there are different methods to measure the sensitivity of the features. In this thesis, the FRBS is used to characterise the sensitivity of the features when all the sensitivity measuring methods are combined together. This will be implemented by a membership function (0–1) which associates with each element of universe and represents the grade of membership specify for the condition each case. The features obtained from each method have been interred in the fuzzy rules, these rules to evaluate each type of the method and then the results of the rules are combined to determine the most sensitive features.

3.8.2 Automated Holistic Method

3.8.2.1 Taguchi Method

Taguchi orthogonal array (OAs) methods has been applied to design an experimental work for reducing the number of experiment which needs to be optimised for quality process. Instead of using a full factorial technique where one variable is varying at each run, Taguchi's method uses a small number of experiments to predict the best quality of each variable and and calculate the most significant variables in an experiment. The use of Taguchi's method is described in chapter 6. The Taguchi method implements specially constructed tables know as orthogonal arrays (OAs). The use of these tables makes the design of experiments easy and consistent practically when applied to experiments with high number of variables (or factors in Taguchi terms). A full factorial design will identify all possible combination for a given set factors. Since most industrial experiment usually involve a significant number of factors a full factorial design results in a large number of experiments. Taguchis approach complements two important areas. First, it define a set of OAs each of which can be used for many experiments. Second, it provide a standard method for analysis of the results. This research propose to use Taguchi methods for calculating sensitivity of the sensory characteristic features (SCFs) which obtained from gearbox sensory signals under different condition such as healthy and fault. Dependency values of Taguchi's method are used as a sensitive measure. The use of Taguchi method will be described in details with experiments and results in Chapter 7.

3.9 Discussions

This chapter has summarised the methodology used and the investigations of this research work. The aim is to develop a systematic structured methodology for the design and implementation of the ASPSG approach of condition monitoring systems gearbox system. The problems of condition monitoring design have been described and compared with the current practice in the field. Not only the way the ASPSG approach is conceived has been described but also techniques modified as a result of previous research and more recent development. The chapter has explained the general steps of the ASPSG approach and described its applicability for gear faults with multi-sensor fusion.

Chapter 4

Experimental Apparatus

4.1 Introduction

This research provide the early diagnosis and prognosis condition monitoring system for two type of helical gear faults; distributed pits and gradually tooth breakage. An experimental apparatus is developed to obtain relevant and useful information about helical gear faults and also test different faults. This chapter presents detailed information about test rig equipment which was designated to monitor faults in industrial gearbox systems. In this respect, general descriptions of test rig facilities including the mechanical tools and condition monitoring devices are explained. Mechanical tools comprise gearbox system, AC motor, and DC generator whereas monitoring system devices include sensors and data acquisition system.

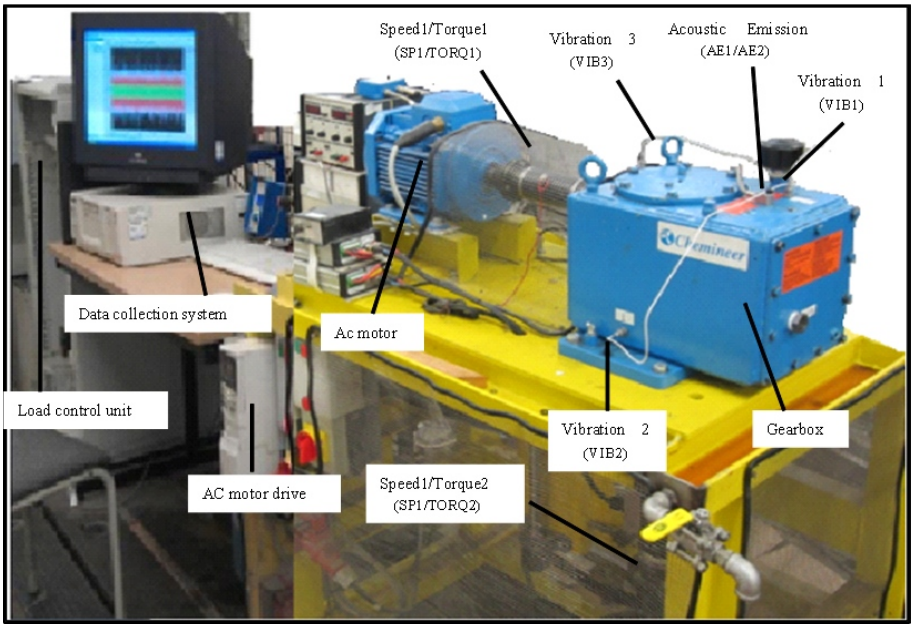


Figure 4.1: Experimental test rig.

4.2 Experimental Setup

Figure 4.1 presents the experimental test rig developed by this research and associated data acquisition unit including sensors and data acquisition system. This rig is designed to study and to investigate healthy and unhealthy conditions for the gearbox systems under different operations. This system contains mechanical system, three accelerometers, two torque/speed transducers, acoustic emission sensors, data acquisition devices, monitoring computer and appropriate software. The system under monitoring is the gearbox, which is a part of the driving system used in the agitator of chemical system provided by Chemineer Ltd. More details are provided in the following sections.

4.2.1 Mechanical Equipment

The mechanical side comprise an input drive and an output drive developed to test an industrial gearbox for a chemical agitator. The input drive consists of a $3\,kW$ variable speed AC motor to drive the gearbox via an input shaft, and a torque limiter set to stop applying the load at $18\,Nm$ for preventing the overload of the gearbox. The drive motor is fitted with the gearbox by delivering the rotational speed between $100\,RPM$ and $1440\,RPM$.

The output drive includes a DC motor (generator) for applying a load to the gearbox to change gear engagement, and a control station in conjunction with the DC motor to control the output of the load. The DC motor can supply a load of $18\,Nm$ to the gearbox by tuning the voltage/current of the control station, and transmit the load to the gearbox via an output shaft and a 2-level transmission belt. The gearbox mounted in the mechanical test rig is part of driving system for HT agitator which is a chemical mixer supplied by Chemineer company. It includes a helical gear drive, a bevel gear drive, bearings, and shafts for transferring loads. Gearbox fault such as wear or failure of gear teeth can be discovered by monitoring vibration of the gear. While the gear is running, the gear transmits vibration that it generates to the bearing; the vibration data are then acquired by the sensor and transmitted to the computer via the data acquisition hardware for data processing and fault diagnosis.

4.2.2 Data Acquisition System

To collect data from sensors, National Instruments USB device the negative distance USB-6259) is used. This device is a multifunction analogue, digital, and timing I/O boards for PC AT as shown in Figure 4.2. The card has 12-bits ADCs with 64 analogue input single ended or 32 differentials with a guaranteed sampling rate up to 1200 k sample. The analogue input used was configured as differential inputs because of the low voltage levels involved, the noisy environment, and long wires used in connecting the signals to the data acquisition card. The analogue channel is used to acquire the machining data using high sampling rate. The card is used in a bipolar mode of $+5\,V$ or $-5\,V$ with a board gain of 0.5. Hence, for 12-bits data samples the resolution is up to $9.76\,mV$.

The data sampling rate is $100\,kHz$. In this research, the monitoring computer collects 65530 sampling data point from data acquisition device and generates one data group with nine parameters using these data for further analysis.

4.2.3 Sensors

Many sensors are integrated into the test rig to extract useful information about the gearbox health conditions (e.g. gear teeth breakage, gear teeth wear, shaft condition, oil temperature, etc.) and transfer physical quantities such as vibration, acoustic emission, torque, speed and temperature to analog voltage, which are then digitised by the data acquisition de-

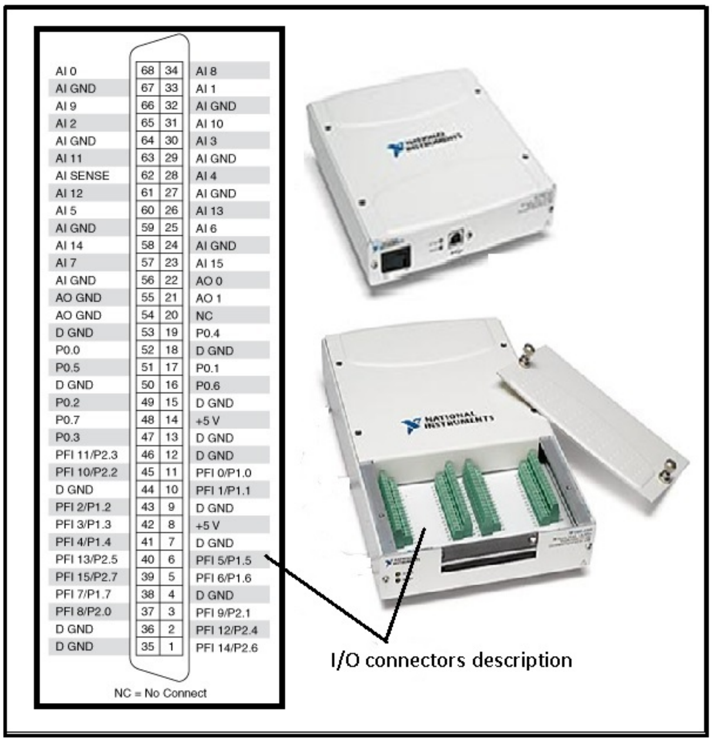


Figure 4.2: High-speed National Instruments M series multifunction data acquisition device.

vice. The outputs are transmitted to a monitoring computer. M420 rotary torque transducer from datum electronics is used to measure the torque and speed signals. It is a non-contact torque sensor with a standard sampling rate of 100 samples per second. The data measured are allowed to transmit in either in digital format via a USB interface or in analog format through a data acquisition device. M420 rotary torque transducer used in this research is shown Figure 4.3(-c).

Vibration of the gearbox is measured by accelerometers (vibration sensors). Three Kistler accelerometers with the identical dynamic performance are located on the top of gearbox housing at positions near the driving helical gear, driving bevel gear and driven bevel gear. Vibration sensors are connected to a coupler (5134B) which serves as a power supply and a signal amplifier, and also provides the excitation to all accelerometers and amplifies the signals from them. An output signal of 0-5 V is then transmitted to the data acquisition device, which is connected to main computer. Kistler accelerometer 8704B used in this research is shown Figure 4.3(-a).

The AE sensor is used to measure the stress waves. This sensor is suitable for measuring sound emissions more than 50 kHz. The Kistler AE sensor 8152B is mounted on the surface of the gearbox near the bearing of the driving gears. It is connected to an AE-coupler with integrated RMS converter, which is specially used for processing high-frequency acoustic emission signals from the AE sensor. A variable amplifier embedded in the AE-coupler amplifies the AE signals by a factor gain of 10. Kistler AE 8152B sensor used in this research is shown in Figure 4.3(-b).

Figure 4.4 shows the configuration of the condition monitoring system where location of sensors are also shown. More details about the utilised sensors are provided in the following sections.

4.2.3.1 Accelerometer Sensor

The significant relationship between tool conditions and vibrations during machining is well recognised, and the comparably low noise implication of the vibration sensors is discussed in other tool condition monitoring investigations. Accelerometers are used to measure acceleration and vibration. Among the several vibration detection techniques, piezoelectric

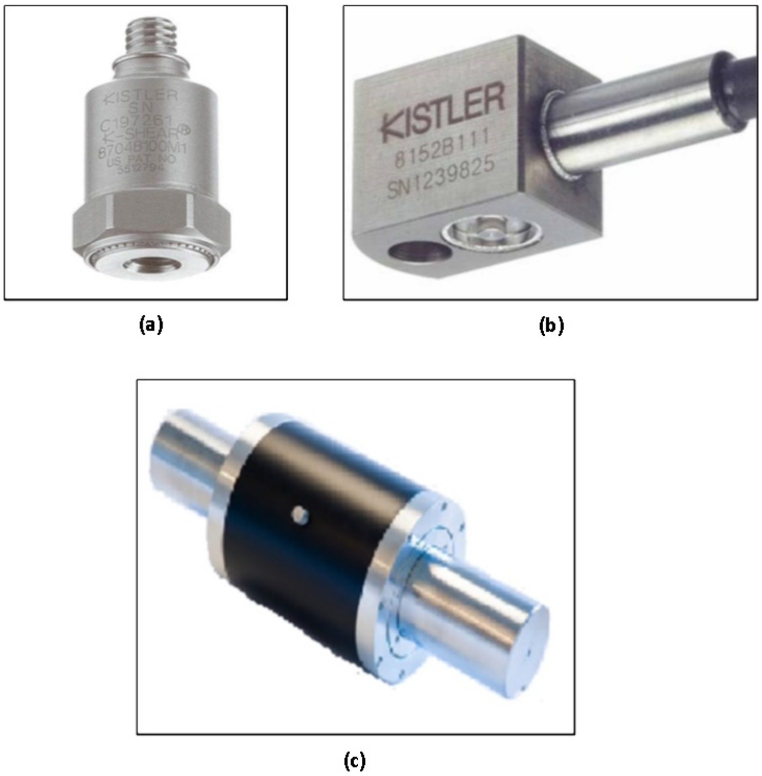


Figure 4.3: Sensors; a) M420 rotary torque transducer, b) Kistler accelerometer Sensor, and c) Kistler acoustic emission sensor

accelerometers are often adopted for gears investigation and for measuring vibrations. These instruments rely on the piezoelectric effect of quartz or ceramic crystals to generate an electronic output related to acceleration. The piezoelectric effect produces an opposed accumulation of charged particles on the crystal. This charge is proportional to the applied force or stress. The main advantage of using vibration based monitoring systems for monitoring gearbox and other industrial machinery is that they are simple, accurate and inexpensive. Moreover, they are easy to use and no modification to the machine is required. However, vibration methods do have drawbacks such as dependency of the vibration signals on conditions,

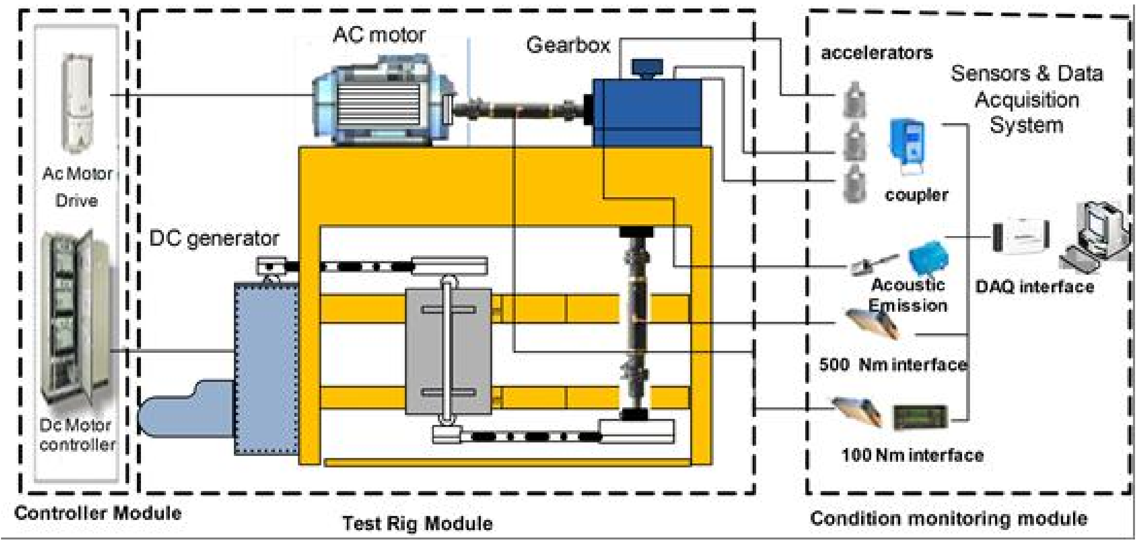


Figure 4.4: Configuration of the gearbox condition monitoring and fault diagnosis system.

and machine structure.

4.2.3.2 Acoustic Emission Sensor

Acoustic emission refers to the generation of transient elastic waves during the rapid release of energy from localised sources within a material. The source of these emissions in metals is closely associated with the dislocation movement accompanying plastic deformation and the start and extension of cracks in a structure under stress. Other sources of acoustic emission include: melting, phase transformation, thermal stresses, cool down cracking, and stress build up.

In recent years, AE instruments have been adopted for use in structure integrity valuation, non-destructive testing, and quality testing for advanced material industries. AE is also proposed as a possible signal source to detect the gear condition in a number of studies (Tan et al., 2007). AE can be defined as: low amplitude, high frequency elastic stress wave generation due to a rapid release of strain energy within a solid material associated with the plastic deformation, fracture and phase transformation of the material. AE sensor is attached to the gearbox housing to monitor AE signals transmitted during gear running. Recently, AE based monitoring systems are finding increased applications in condition monitoring (Loutas et al., 2011). Acoustic emission and audible sound waves produced during gears meshing have been found useful in several researches for identifying gearbox condition.

4.2.3.3 Torque/Speed Transducer and Monitoring Unit

The non-contact torque/speed transducers are utilised to measure the torque and speed, which are generated from the driving/driven shaft. M420 rotary torque transducer from datum electronics is used to measure the torque via a monitoring unit. This unit, also known as torque trip box, is used to connect torque/speed transducers and DC motor controller. The unit is developed as a fail-safe device to prevent overload of the loading equipment (DC motor). It controls the switch of the DC motor controller to guarantee the gearbox runs in a normal load condition. The maximum load for the DC motor needs to be set in the gearbox first. The adjustable load is within a range of 0 to 18 Nm. When either the rotating speed of the driving shaft reduces below a given value or the load exceeds a given value, the DC motor stops immediately and its output workload changes

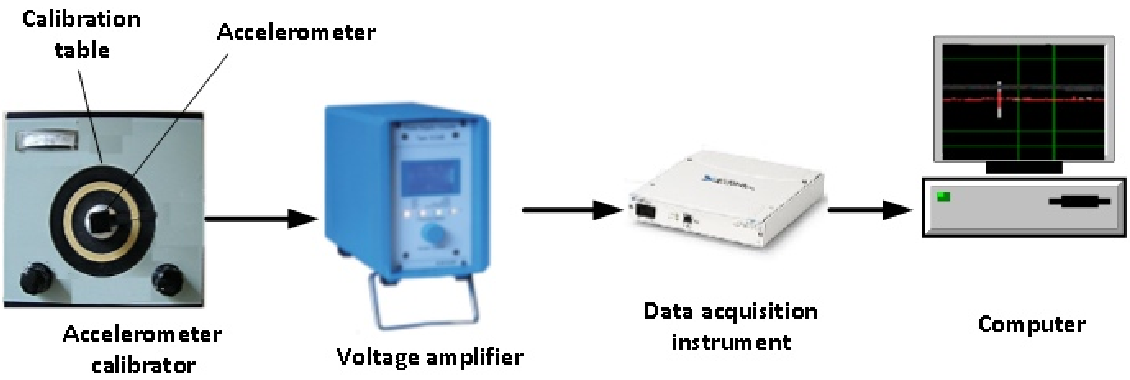


Figure 4.5: Calibration setup for the accelerometer (8152B).

to zero automatically. Thus, the gearbox can run tests normally without manual intervention.

4.2.4 Calibration and Testing Devices

The acquired working condition data from the gearbox are transmitted to the data-acquisition computer. Collected data are calibrated and converted into real physical values quantities, such as Newton-Meter (Nm) and Rotation Per Minute (RPM). The process of calibration of the sensors is detailed in the following sections.

Table 4.1: A/D conversion coefficients of three accelerometers.

Sensors	A/D conversion coefficients
Accelerometer 1:	amplitude per volt = 96.993 g
Accelerometer 2:	amplitude per volt = 96.339 g
Accelerometer 3:	amplitude per volt = 96.712 g

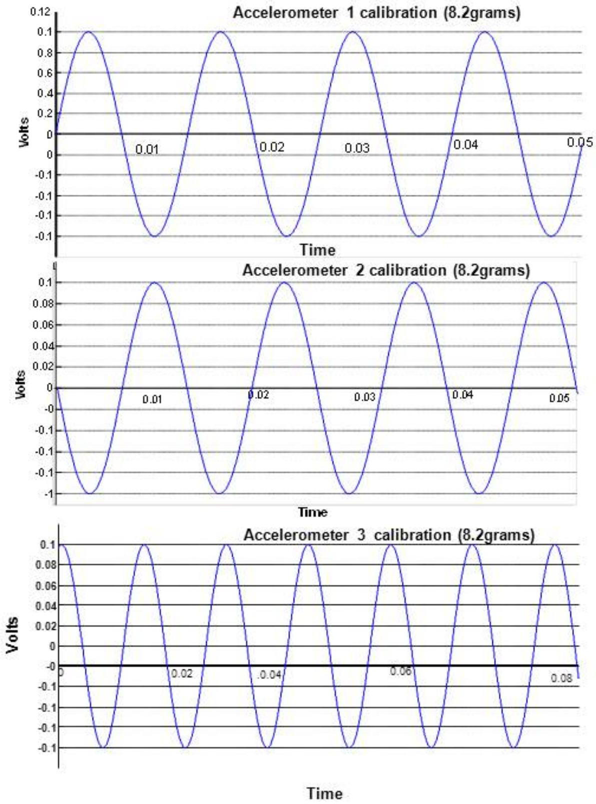


Figure 4.6: Calibrations of accelerometers with the use of the calibrator (8152B).

4.2.4.1 Calibration of Accelerometers

Accelerometer sensor calibration process is conducted using the accelerometer calibrator B&K 4291. The accelerometer calibrator consists of a built-in 79.6 Hz sinusoidal generator. The accelerometer is fixed on the calibration table of the calibrator and subjected to a vibration system shown in Figure 4.5.

The calibration process starts by adjusting the Acceleration Level of the accelerometer calibrator to the accelerometer used. The sensitivity of the voltage amplifier is then adjusted to the sensitivity of the accelerometer.

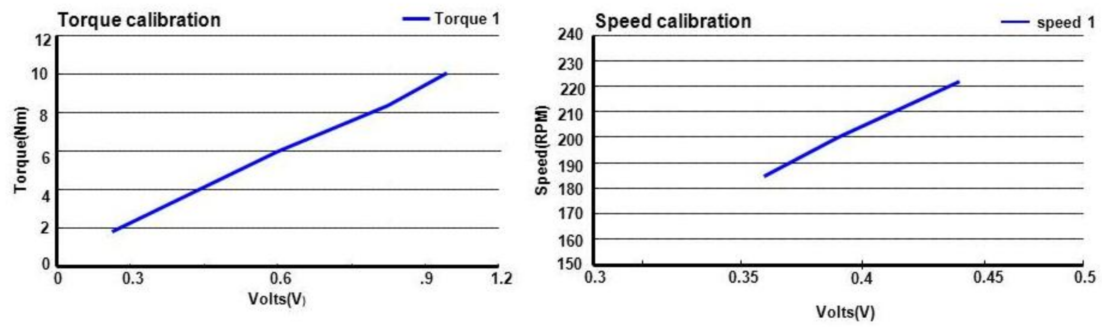
Figure 4.6 shows the calibration results of the three accelerometers. The sensitivity of the accelerometers are measured as 10.31 mv/g (g=9.80665 m/s^2), 10.38 mv/g, and 10.34 mv/g while the gain of the amplifier is set by default. According to these sensitivities, the Analog-to-Digital (A/D) conversion coefficients of three accelerometers are obtained, which are listed in Table 4.1.

4.2.4.2 Calibration of the Torque/Speed Transducers

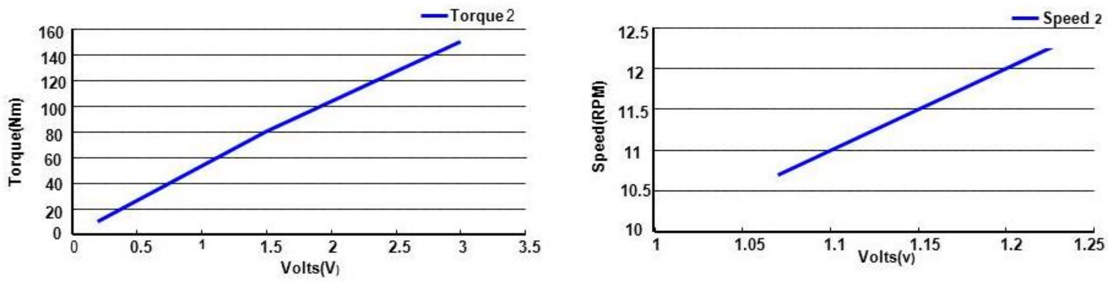
The calibration of the torque/speed transducers are implemented by calculating the linear factors, which reflects the linear relationship between the voltage data of the transducers and real working condition values, which are acquired by the digital tachometer. Figures 4.7 shows a linear relationship of the torque/speed transducers under different working conditions.

The linear factors, also known as the A/D conversion coefficients of torque/speed transducers, are obtained as follows:

1. torque per volt (driving shaft) is $10Nm$,
2. speed per volt (driving shaft) is 500 RPM,
3. torque per volt (driven shaft) is 50.76 Nm, and
4. speed per volt (driven shaft) is $10RPM$.



(a)



(b)

Figure 4.7: Calibrations of Torque and Speed Transducers; a) b)

4.3 Tooth Gear Faults

Local gear tooth fault such as pitting and broken tooth are result of transient events when the defective tooth contacts another gear tooth. The size and period of these transients are based on the severity of the tooth defect and contact ratio of the gear pair. If the tooth fault severity is small and the contact ratio is relatively high, the resulting transient may not be seen clearly on the vibration signal. Time and frequency domains analysis can be effectively applied to identify such events. This section presents simulation of two types of industrial helical gearbox pitting and broken tooth faults.

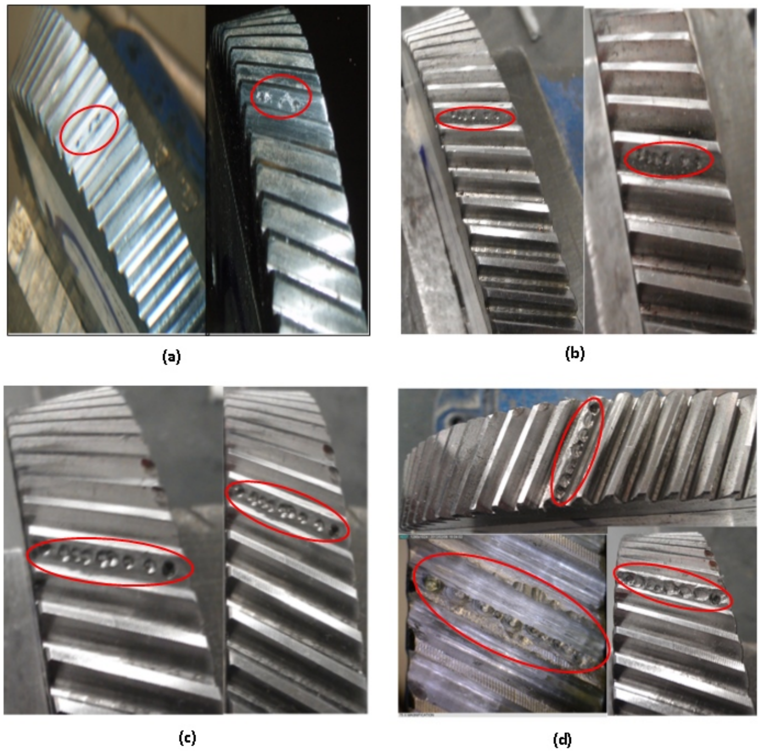


Figure 4.8: Simulated pitting tooth: a) 25%, b) 50%, c) 75% and d) 90%.

4.3.1 Distributed Pitting Fault

Pits are seeded on some of the gear teeth in differing degrees of fault severity as small spots bottomed cavities and intended to replicate the fault developing on a few teeth due to shock or load fluctuation. Gear load can be overrode result of shock or unbalancing cyclic load. This event may occurs on one tooth or group of teeth on the same gear. In such cases, a pitting fault may probably occur in time on the tooth surfaces on which a higher load is experienced. All the simulated surface pits were introduced to some of the wheel gear teeth using an drilling machine and were intended to replicate a pitting failure initiating firstly on a single tooth, and then increasing the number of pitting on the same tooth surfaces. First of all,

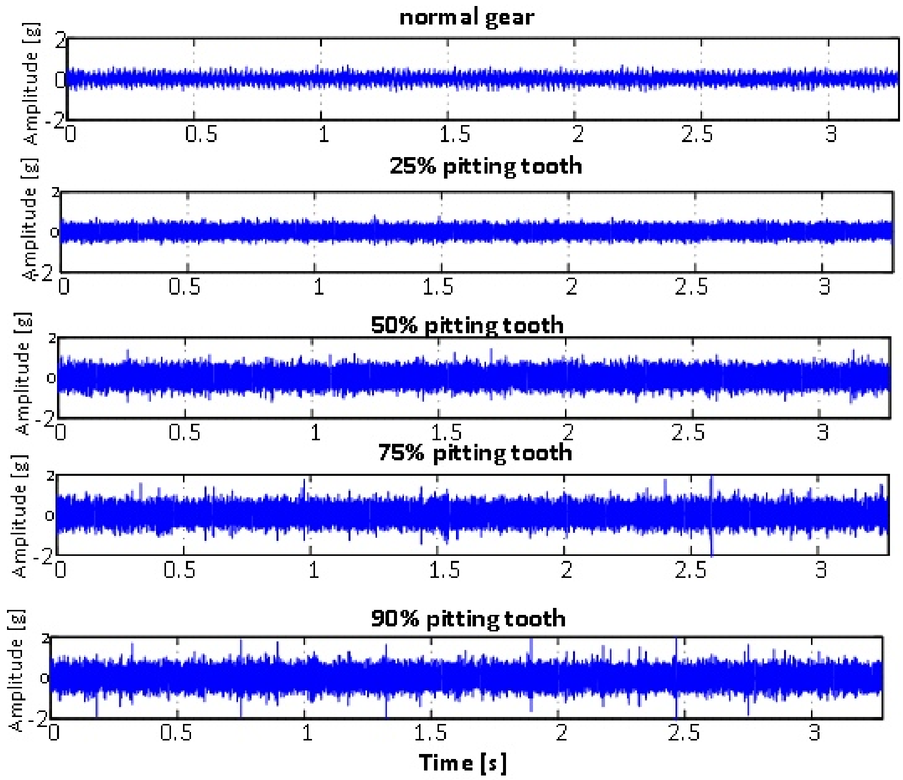


Figure 4.9: Time domain analysis of four gradual pitting gear tooth conditions.

a circular pit (diameter and depth are approximately 0.7 mm and 0.1 mm respectively) was seeded onto a single tooth surface as shown in Figure 4.8. After that, in order to represent the advancement of fault, the number of defected teeth was increased. Figure 4.8-(a), Figure 4.8-(b), Figure 4.8-(c) and Figure 4.8-(d) show 25%, 50%, 75% and 90% pitting tooth respectively. Moreover, the severity of fault was increased by doubling the number of pits on the same gear tooth. At the final stage of the fault development, the number of pits was redoubled on the same gear tooth during which the surface of the centre tooth was completely covered by severe pitting.

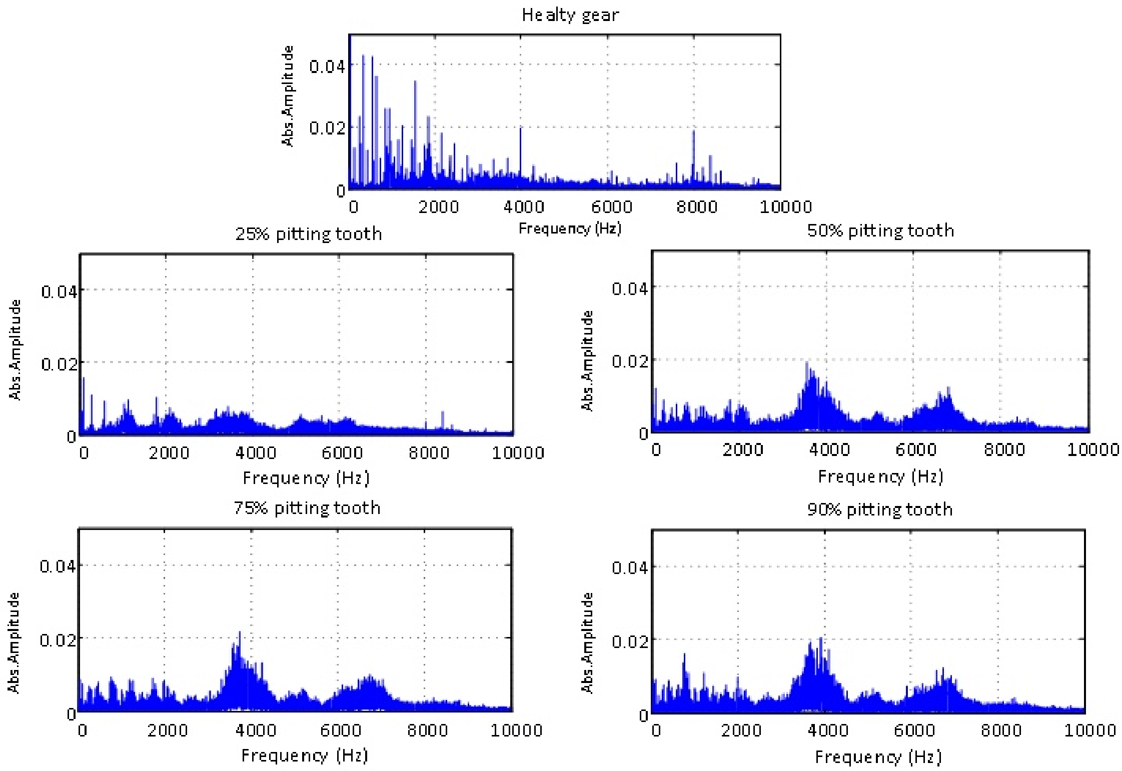


Figure 4.10: Frequency domain analysis of four gradual pitting gear tooth conditions.

4.3.2 Time and Frequency Domain Analysis of Pitting Gear Tooth

Figures 4.9 show the time domain representation of the simulated pitting tooth of helical gear vibration. It can be seen from the time domain representation that the vibration signal is modulated, but it is difficult to determine clear characteristic of each conditions from the time domain analysis. In contrast, the frequency domain representation provides much better understanding of each condition properties such as harmonic amplitudes and harmonic spacing as shown in Figures 4.10.

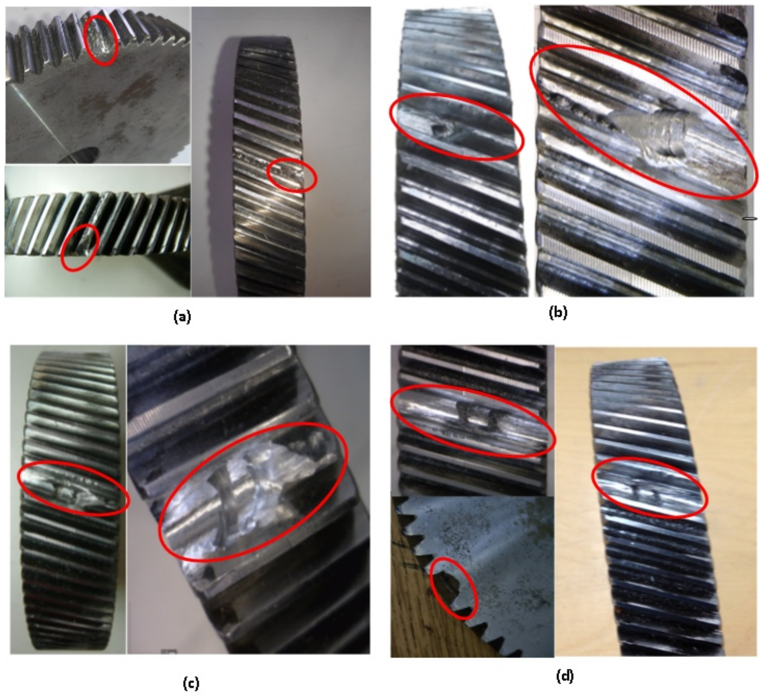


Figure 4.11: Simulated broken tooth: a) 25%, b) 50%, c) 75% and d) complete tooth removal.

4.3.3 Distributed Broken Tooth Fault

Tooth breakage is one of the common faults of gearbox in industry applications. In this study, four degrees of the tooth breakages were simulated which is 25%, 50%, 75%, and 100% of the tooth damage as shown in Figure 4.11-(a), Figure 4.11-(b), Figure 4.11-(c) and Figure 4.11-(d) respectively. It is produced by removing the percentage of the tooth face on the wheel gear in the width direction. Sensory signals collected from a same gearbox in which the four broken gears were tested individually. The larger fault of 100% tooth breakage is used to help with the understanding of the data analysis techniques.

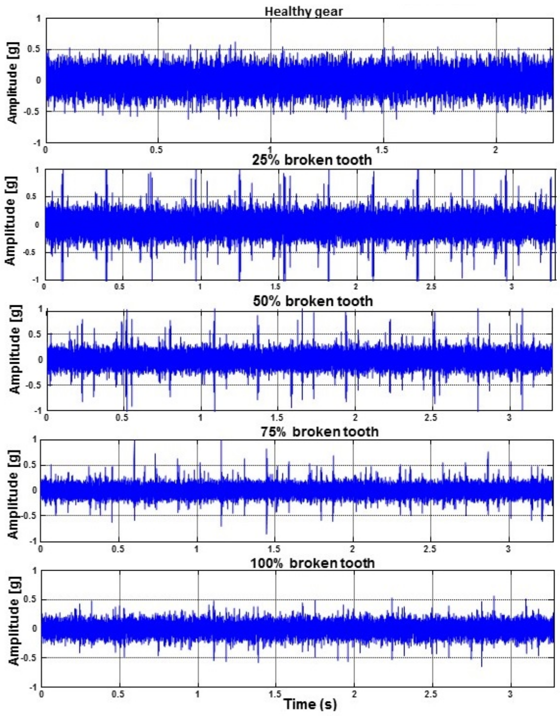


Figure 4.12: Time domain analysis of four gradual broken gear tooth conditions.

4.3.4 Time and Frequency Domain Analysis of Broken Gear Tooth

Figure 4.12 illustrates the time domain representations of the simulated broken gear tooth. The time domain signal does not show any discernible amplitude variation throughout the time. On the other hand, the frequency spectrum reveals major differences between healthy gear condition and other conditions of broken tooth as shown in Figure 4.13, which can be used as clear evidence to distinguish between healthy and unhealthy gearbox. Also, it can be seen that the frequency spectrum exhibits two major peaks located on the broken gear tooth figures. A close inspection upon the frequency spectrum reveals that these peaks are progressively decreased to

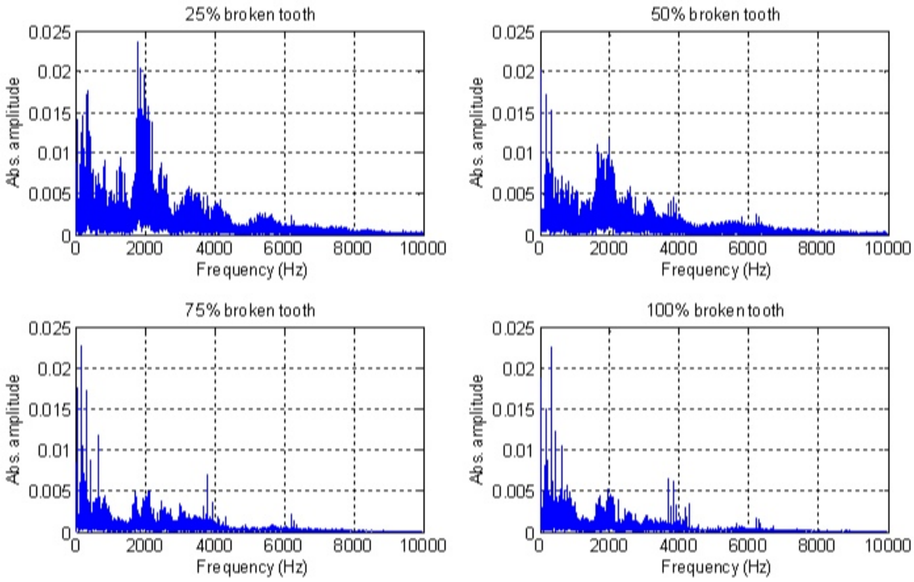


Figure 4.13: Frequency domain analysis of four gradual broken gear tooth conditions.

show the fault propagation from figures 25%, 50%, 75% and 100% respectively.

4.4 Discussions

This chapter outlines the general experimental set-up for carrying out the present work. It describes the test rig used to implement the experimental condition monitoring systems, including gearbox system, AC motor, and DC motor generator. It also highlights the sensor types, their extensions and the data acquisition card. Consequently the environment, in which the practical research work was conducted, was similar to an industrial environment and practical gearbox applications.

Chapter 5

Sensor Location Optimisation

5.1 Introduction

The results of fault diagnosis system will be affected when many sensors are located in different positions. Using the same sensors in different locations will produce different outcome and subsequently the results of overall signal processing will be affected. Therefore, it is important to find optimum locations where sensors could be used and to improve overall performance of the diagnosis system. This chapter discusses the experimental aspects of the selection of optimum location of sensors. Initially, a general description is provided, followed by a practical example relating to how to choose the best location and how to adjust the sensor conditioning system.

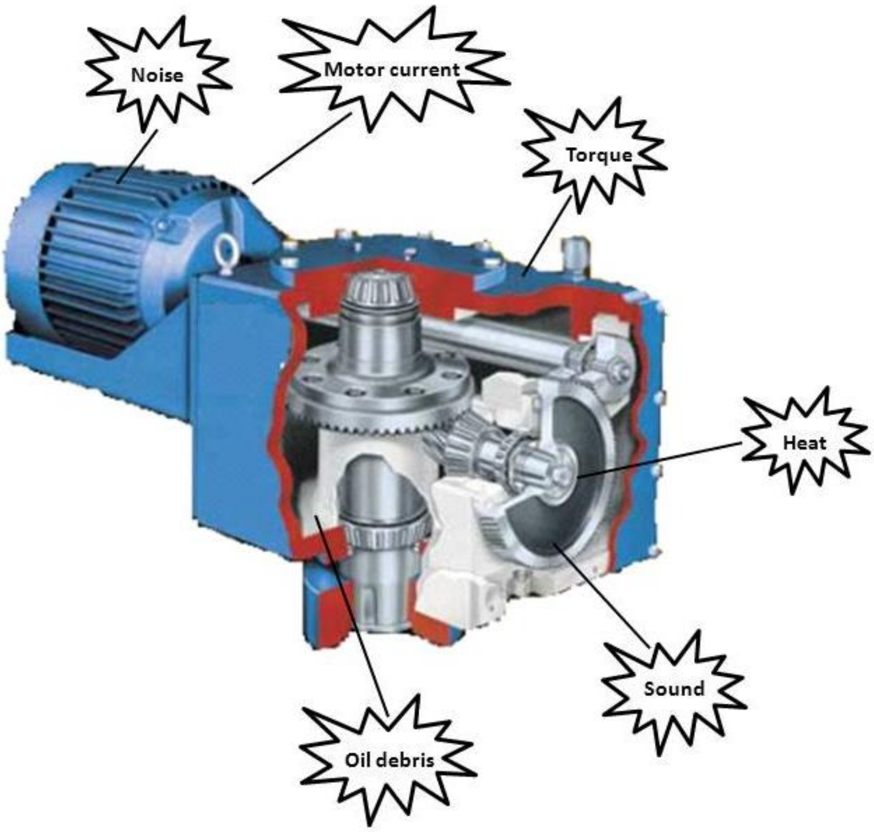


Figure 5.1: Measured signals emitted from gearbox system.

5.2 Sensing Tools Reliability

Consider the gearbox system shown in Figure 5.1. Sensors connected to the gearbox capture signals such as vibration and sound, which are directly associated with the operation condition of the gearbox. Accelerometers and AE sensors are also applied in many different contexts (Staszewski and Worden, 2001). However, signal-based sensing is influenced by noise from surrounding environments. The negative impact of signal measurement can be substantial at the incipient stage of a fault, when the intensity of the associated vibration is often overwhelmed with the background noise. For example, the vibration signal of the monitored inner components of the gearbox are influenced by the noise of the motor and shaft, which could lead to unreliable data (Worden and Burrows, 2001). In order to enhance the quality of sensing information, the high signal-to-noise ratio needs to be maintained. This can be attained by either selectively adjusting the sensor characteristics (i.e. bandwidth), sensitivity, or by optimizing the placement of the monitoring sensors. Taking such measures will ensure a comprehensive coverage of the signal features with minimal structural repercussions (Udwadia, 1994).

Sensors could be categorised in two groups; fixed-position sensors (direct measurement sensors) and free position sensors (indirect measurement sensors). Fixed-position sensors are located in predefined positions on the machine, according to manufacturer instructions or their functionality. These sensors are usually mounted directly to mechanical components or installed close to certain places in order to measure physical quantity (for example, speed and torque sensors). Conversely, free-position sensors do not have specific locations on machines and can be installed at any location on the machine as long as there is no isolation between sensors and the machine body. Furthermore, there is no specific methodology to determine the location and position in certain locations on the gearbox or its tools.

5.2.1 Direct Measurement Sensors

Fixed-position sensors which are located in predefined positions are usually mounted directly to the mechanical component or installed close to a certain place to measure the natural phenomenon such as measuring speed and torque. Torque and speed measurements are significant mechanical parameters related to the functional performance of rotating machinery. The accurate measurement of these values is important for defining a machines efficiency and for creating operating systems for machines that are both secure and conducive to long life working and reliable services. Speed and torque measurement are insensitive to surrounding noise on the gearbox, because they are directly connected to the signal sources (Mardia, 1974). They are usually attached to input/output of gearbox shaft which means that they are placed outside the housing of the gearbox. Therefore, speed and torque measurement are less sensitive to gearbox state.

5.2.2 Indirect Measurement Sensors

Free-position sensors do not have specific locations on machine and they could be installed at any location. These sensors are usually mounted remotely from desirable components such as vibration and sound sensors which disturb those functions and general performance. These kinds of sensors are usually influenced by noise from surrounding environment. There are many factors that cause inaccuracy in indirect sensors measurements. The sensor location error is one of the most significant sources of inaccuracy in values obtained from sensors. Normally, sensors cannot be placed right at the locations or close to the components they are supposed to observer (Fu and Li, 2009). This causes a difference between the actual signal at the location of interest and the sensory signal. Adding many sensors can resolve this problem, but this comes at a heavy cost, which of course is undesirable. Accelerometer and AE sensors are considered as indirect sensors because there is no specific location to place them.

5.3 Determining Sensor Location

Obtaining optimal sensor location is a significant research area for the structural monitoring systems of gearboxes. The research challenges should take into account the number of sensors to be used and the position of the sensors in order to obtain as much relevant information as possible. It is uneconomical to install sensors on every part of a structure. The inappropriate positional arrangement of a sensor may result in collecting undesirable signals that are overwhelmed by noise. Furthermore, it is likely to affect the accuracy of fault identification and diagnostic system. Therefore, in order to guarantee the accuracy and reliability of the monitoring and identification results of the system, it is essential to select the optimal position of measurement and number of sensors to design robust gearbox monitoring system.

There are many existing studies on optimal placement of sensors in many different monitoring applications such as architectural constructions (building, bridge) which depend on how to obtain as much instructive information possible from limited information feedback (Sarrate et al., 2007). Researches on sensor optimal location of architectural constructions monitoring system are relatively more, whereas investigations on sensor optimal placement method on complex machinery such as gearboxes are limited.

Indirect sensors are usually located on the outer surface of gearbox casing. Mechanical components with different structures (e.g. shafts, gears, and pinions) are mechanically connected to the gearbox casing in certain places by bearings. The way in which these components are connected depends on the structural design of each gearbox. The sensors will pick up vibration signals, surrounding noise and in addition to the defect impact induced vibrations. At the initial stage, the fault is generally weak in magnitude and of short duration, due to the small size of the defect. Usually, indirect sensor are located remotely from the defect; as result of that the signal attenuation along the distribution route will be reinforced by environmental noise contamination, leading to poor signal-to-noise ratio. This makes fault detection at initial stage and during gearbox operations a challenging measurement duty. In order to solve the problem, the indirect sensors should be placed at the optimal location or close to defect (Hajnayeb et al., 2011a).

5.4 Proposed Sensor Location Methodology

This study proposes a new approach for locating free-position sensors, such as vibration and AE sensors, for gearbox systems to perform high quality of information regarding the characteristic of the gearbox tool. Al-Habaibeh et al. (2005) established a new method named Initial Optimisation Procedure (IOP) for optimising sensor position in order to enhance the condition monitoring system for the machining process. In this study, the IOP method will be enhance and applied for gearbox optimum sensors positioning to improve gear fault detection.

In the first step, sensory data were captured using full factorial method with three factors which are; three levels for speed and torque, and two levels for gearbox condition. Nine from eighteen experiments of loose bearing condition used to determine best location of vibration and acoustic emission sensors. To analyse the collected data, an initial step is proposed that will involve obtaining representative characteristics by using proper signal processing methods. The second step will be to extract the optimum frequency value using Spectral Kurtosis (SK) method to obtain useful feature representing the fault. The last step involved clustering to determine the optimum location of sensors and understand sensors behaviours in terms of characteristic and response to fault. Location of sensors for indirect measurement are illustrated in Figure 5.2

5.4.1 Scheme of Optimum Sensor Location

The IOP procedure is used to establish optimum sensor location for condition monitoring systems. The procedure as shown in Figure 5.3 consists of three main steps: the first step is an extreme value of variables test, which is used to comprehend the behaviour of the required signals in order to identify the parameters that approximately provide the upper and lower signal levels. The second step, sensor optimisation, is used to change the sensor position to an ideal place where sensor is most sensitive to the gear-

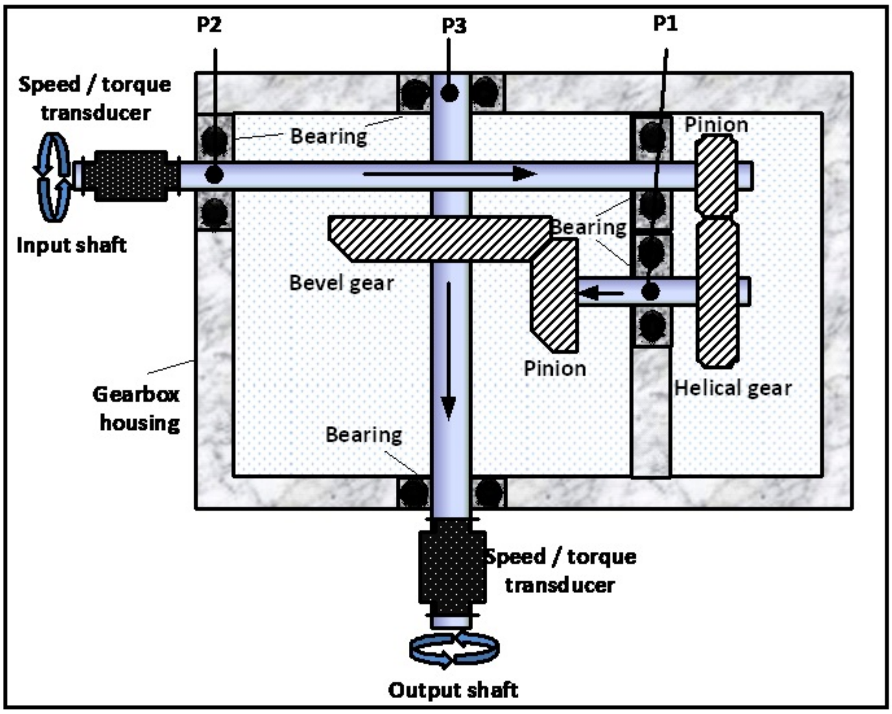


Figure 5.2: Longitudinal section of gearbox illustrating location of direct measurement sensors.

box condition under consideration. This step enables the best positions for the sensors to be determined. The final step is called regulating signal condition, and is used to adjust the gains and ranges of the signal conditioning system to guarantee high amplification of the signals without reaching the saturation point which would guarantee a high quality of signal.

5.4.1.1 The Extreme Value of Parameters Test

Experimentally, 18 tests are conducted with varying speeds and loads from low to high. It was found that in order to be able to select a suitable initial position for the sensors and initial readings, it is important to use tried and tested machine parameters in order to produce the maximum and mini-

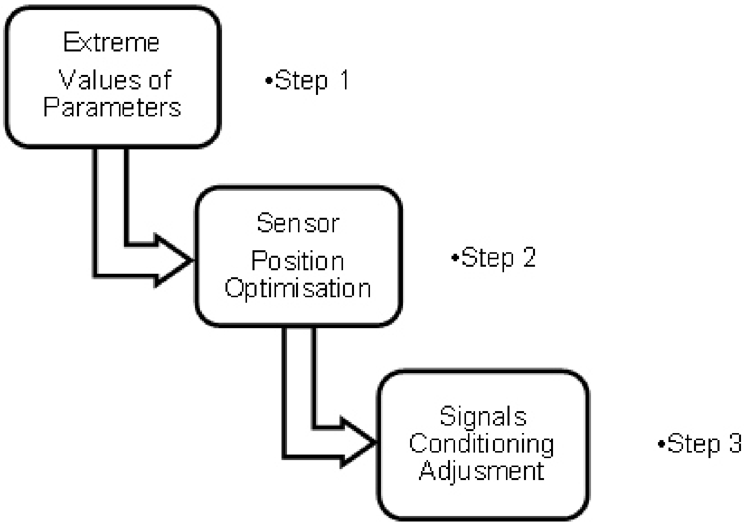


Figure 5.3: Sensor location optimisation procedure.

mum absolute levels of machine signal. An example of such tests is that the highest vibration is normally generated by the maximum speed, while minimum speed generates low vibration. Therefore, by using this test, in the minimum value it is possible to ensure that the sensor can sense the abnormal machine condition and the maximum values are used, to make sure no saturation level is reached. In order to develop a better understanding of machine signals and find the parameters that give extreme values (i.e. maximum and minimum voltage levels), the researcher develops a practical procedure that should help in adjusting the monitoring system. The procedure of Extreme Value Parameters Test (EVPT) requires a number of experiments with variety of input factors to find the parameters which gives the absolute maximum and minimum values of voltage in order to adjust signal conditioning and identifying sensors location. The EVPT procedure has been found useful for the initial adjustment of the system and the sensory position. In order to describe the EVPT of machine condition, it is necessary to search for parameters that cause minimum and maximum signal values by conducting the following experiments for gearbox condition monitoring system in order to optimize sensors location.

5.4.1.2 Sensor Position Optimisation

By identifying the parameters that generate the maximum and minimum voltage values, it is possible to reach a better position for the sensors using the minimum level signal. Following the placement of the sensor in the new position, a new test is implemented using the minimum level machine parameters. The place that offers the highest signal levels and best frequency sensitivity is then selected as the optimum position for the sensors under the position optimisation process. Following this, the sensor conditioning adjustment step is performed to guarantee suitable magnification of signals without saturation.

5.4.1.3 Sensor Conditioning Adjustment

Sensor conditioning is performed separately for each group of sensors which have the same extreme value parameter. The procedure starts by operating the machine with the parameters that give absolute minimum level signals. The gain/rage of the sensors is adjusted to have an absolute output voltage of about 30% of the upper/lower limits. Then the loose bearing test which gives the high level signal is performed to make sure that the absolute voltage is between 60% to 70% of its corresponding limit. If the absolute voltage is higher than 70% there could be a risk of reaching satu-

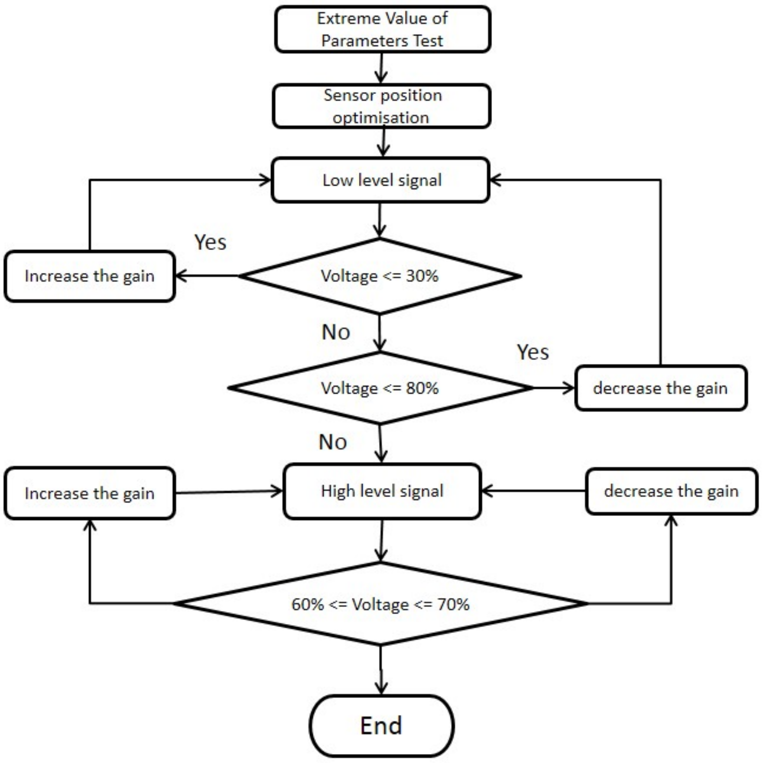


Figure 5.4: Sensor location optimisation procedure.

ration during some normal conditions, therefore the gain /range has to be adjusted to a suitable magnification value as show in Figure 5.4.

5.4.2 Full-Factorial Design of Experiments Method

The DOE method is used to examine and analyse the quality of products based on some essential design of parameters and levels during the manufacturing process. This analysis explores the influence of factors on overall system performance and the interdependency between factors and levels. The DOE method has been extensively applied in various industries and academic contexts depending on the requirements of the state. The full-factorial design needs a great number experiments or calculations. However, it provides high precision results on the relationships between factors without losing information. The first step for analysing DOE is to determine the number of factors and the levels that need to be investigated. To explore the main and interaction effects of factors and obtain the maximum power density output, this study uses the full factorial method to deal with the test matrix of two factors, three-levels and one factor, two levels. Table 5.1 lists the design factors and levels considered. The model includes three factors, including speed, load and gearbox condition (healthy and loose bearing condition). As the results suggest, runs are necessary to identify 18 sets.

Table 5.1: Full factorial for (2^3, 1^2) factors.

No of Experiments	Levels			Values	
	speed	Load	Gearbox Condition	Speed (PPM)	Load (Nm)
1	1	1	1	100	
2	1	2	1	500	3
3	1	3	1	900	
4	2	1	1	100	
5	2	2	1	500	9
6	2	3	1	900	
7	3	1	1	100	
8	3	2	1	500	15
9	3	3	1	900	
10	1	1	2	100	
11	1	2	2	500	3
12	1	3	2	900	
13	2	1	2	100	
14	2	2	2	500	9
15	2	3	2	900	
16	3	1	2	100	
17	3	2	2	500	15
18	3	3	2	900	

5.4.3 Signal Processing and Features Selection

Sensory data captured from machinery is usually affected by high levels of noise and other random characteristics. As such, signal analysis is required to simplify and extract the meaningful information for maintenance and decision-making process. Filtering and amplifying signals are often used to minimise noise and to improve signal-to-noise ratios. Time domain and frequency domain methods, such as FFT are used to analyse the behaviour and the pattern of measured signals. In this study the FFT spectrum is applied to select optimum features of the un-healthy status of the gearbox with high precision. Condition monitoring systems considerably rely on data analysis and features selection. Feature selection can considerably improve the accuracy of results for classification model. Kurtosis is used to extract reliable information from the spectrum of healthy and faulty data, which are used as features to be fed into classification model for fault detection. In this research, the specific values of the spectral kurtosis are obtained as the extracted features for the classification model in order to determine the best locations for sensors.

5.5 Experimental Work

A test rig is designed to study and to investigate healthy and unhealthy conditions of gearbox systems under different operating conditions. In this investigation just indirect sensors are Targeted for study which are accelerometer and acoustic emission sensors. Here, three different locations

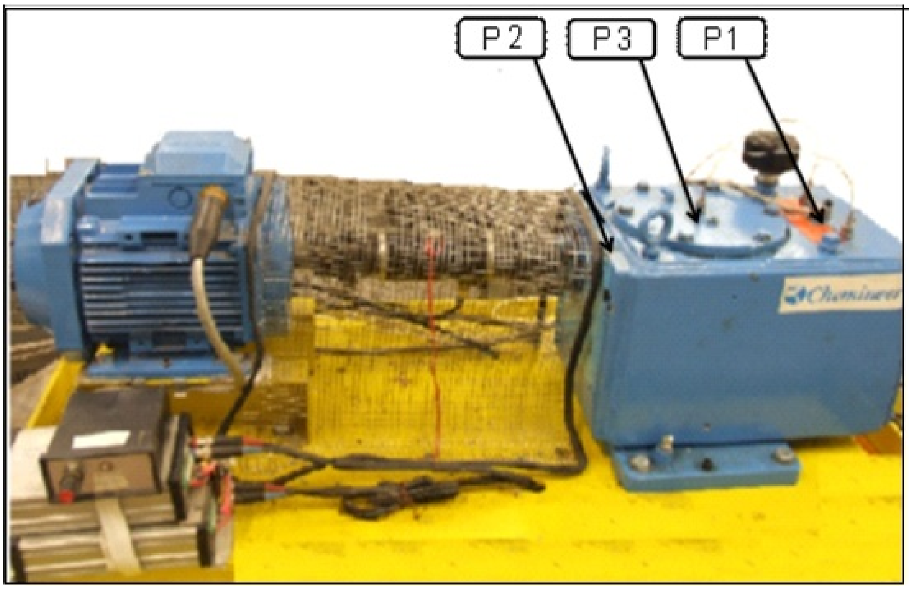


Figure 5.5: Three position of acoustic emission and vibration sensors were tested.

$P1$, $P2$, and $P3$ will be investigated shown in Figure 5.5.

5.6 Results

Optimum sensor position procedure is applied on gearbox system with loose bearing defect to identify sensitive sensor location to the fault. Three possible sensor locations are investigated using AE and vibration sensors. Three sets of experiments are conducted. Each set of experiments are based on changing speed and load as mentioned in Table 5.1 using full factorial method. Loose bearing condition has been investigated to identify the best place for sensor with high sensitivity to the fault. Figures 5.6 and 5.7 show samples of signals in time domain and power spectrum in three position.

Spectral kurtosis (Sk) features are extracted from the power spectrum to

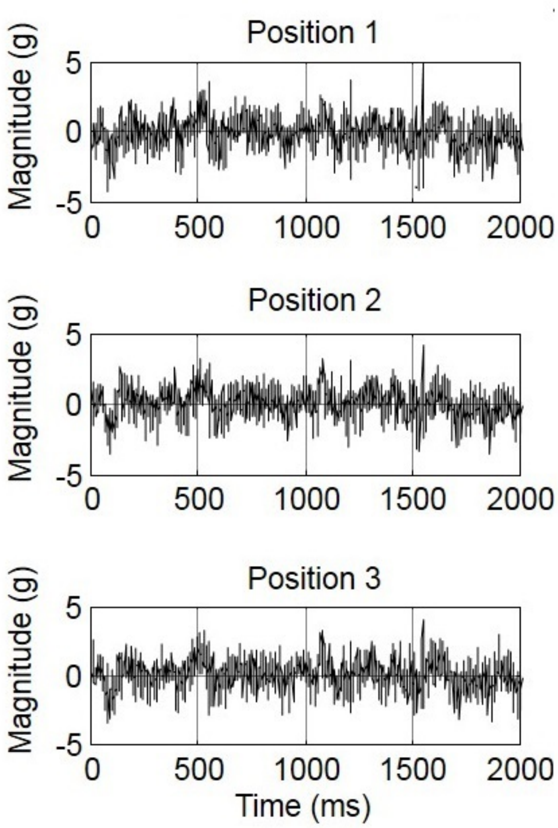


Figure 5.6: Sample of raw data in time domain for vibration signal for three position.

represent each experimental condition. Figure 5.8 shows the spectral kurtosis for vibration signals based on three acceleration sensors in three different locations ($P1$,$P2$ and $P3$). The x-axis represents variation of speed and torque based on the full factorial method outlined in Table 5.1. Projected curves represent spectral kurtosis of vibration features under loose bearing gearbox conditions denoted by three carves. Based on the spectral kurtosis of the vibration signals in $P1$, $P2$, and $P3$ positions have the same pattern and are significantly influenced by changing the sensor, especially

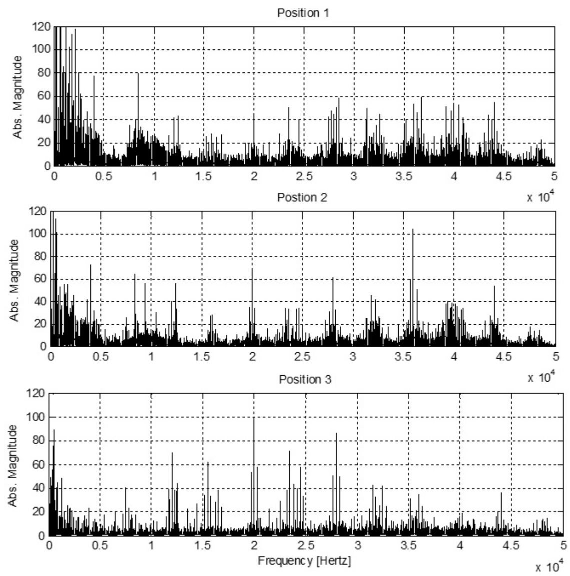


Figure 5.7: Samples of power spectrum analysis for vibration data in three position.

$P1$ and $P2$ positions. Therefore, it can be concluded that SK features of vibration signals are significant to determine optimum sensor location.

Data sets are captured and analysed using FFT and SK methods in order to select useful information representing every position separately. Three curves in Figure 5.9 represent locations in the gearbox for sensor positions $P1$, $P2$ and $P3$ respectively. From this figure, it can be observed that P2 and P3 locations are inappropriate to receive signals with high sensitivity compared with $P1$. It could be argued that the $P1$ position is the most sensitive location as it provides the highest amplitude reading for all combinations of speed and load.

Figure 5.10 shows the SK for AE signals. The circle shapes in this figure represent feature data of the $P1$ position, the star shapes represent feature

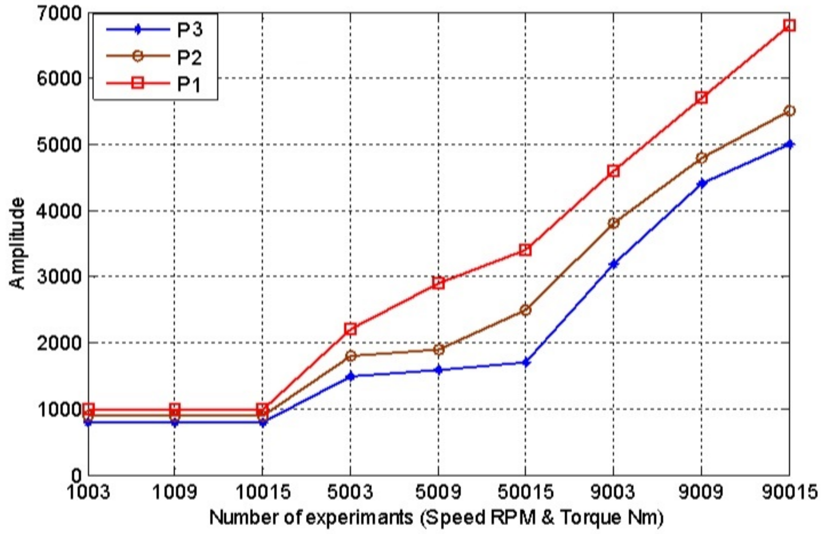


Figure 5.8: Spectral kurtosis features of vibration sensor using loose bearing data for three positions.

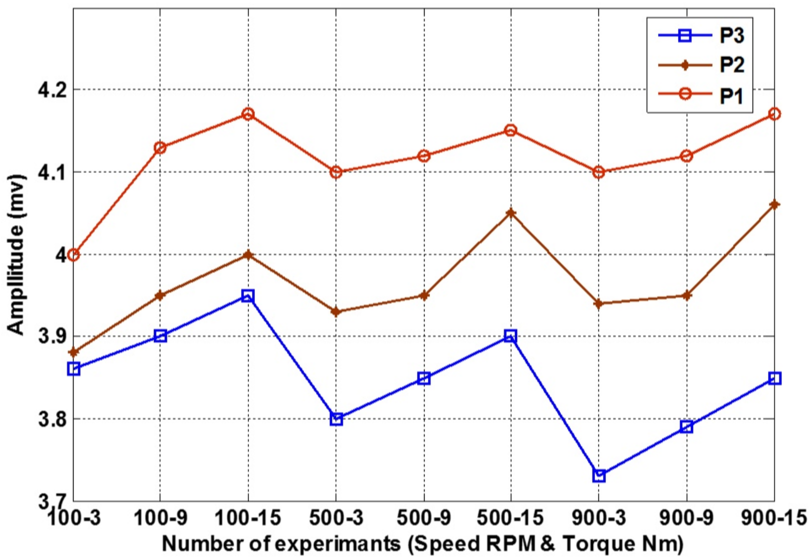


Figure 5.9: Spectral kurtosis features of acoustic emission sensor using loose bearing data for three positions.

data of the $P2$ position, and the square shapes represent feature data of the $P3$ position. The data represented in this figure can be easily separated

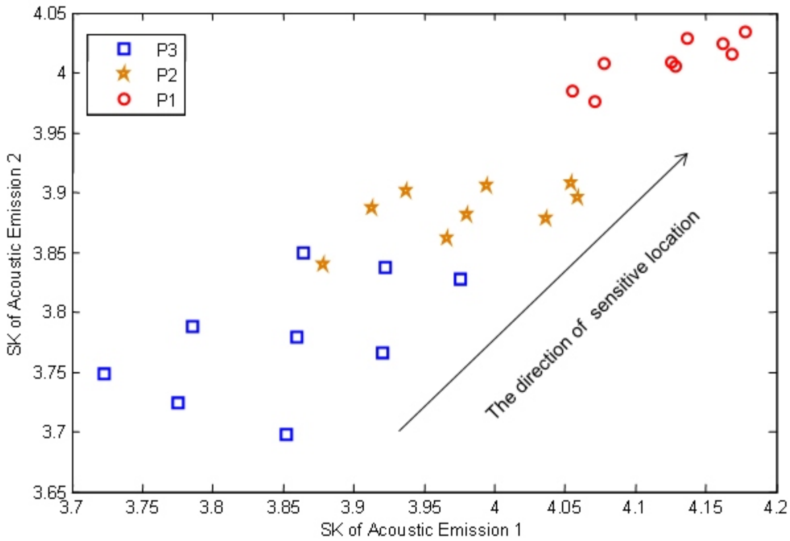


Figure 5.10: Clustering for optimum position of acoustic emission sensor.

(linearly). Therefore, it can be seen clearly that the features of SK of AE signals are sufficient features to determine the sensitive sensor location for an unhealthy gearbox condition. This tool is used to display the data sets into three groups relating to sensor locations. It provides a better understanding of these data sets in terms of sensitive locations for sensors. Also, according to EVPT procedure, it can be argued that the $P1$ position is the best location for the sensor. This is because the SK Features of acoustic emission give the highest levels compared to other locations ($P2$ and $P3$).

5.7 Discussions

A new practical procedure based on IOP scheme is proposed for positioning of sensors and signal conditioning adjustment in gearbox systems using vibration and acoustic AE. The procedure has been found to be experimentally useful for identifying the optimum position for the sensor conditioning of the gearbox system. It has also been found that the suggested procedure can indicate the most sensitive position for the sensors among the initially selected ones to ensure high quality signals and reliable condition monitoring systems.

Chapter 6

ASPSG Approach Based on Taguchi Procedure

6.1 Introduction

This chapter explains and evaluates the Automated Sensor and Signal Processing Selection approach for Gearbox system referred as ASPSG using Taguchi method. It will illustrates how the suggested approach can be utilised to develop a condition monitoring system for detecting and diagnosing faults in gearbox system. The suggested approach can be implemented to develop a condition monitoring system for group of machining parameters in a systematic way taking into account the cost of the implemented monitoring system. This chapter also introduces the details of the proposed approach using gradual broken tooth of helical gear fault. Experimental tests and evaluation of the approach will be applied in this chapter.

6.2 Proposed Concept

Although several techniques are proposed in the literature for feature extraction, not all these features techniques always produce efficient features for all problems. In reality, efficiency of features extraction methods is highly depending on problem itself. That mean, features extracted utilizing one method may conduct extremely well for some problems, but may not perform well for others. The problems (faults) in rotating machinery especially in gearbox systems are complex and sophisticated, (Roy, 2001). Therefore, the designers are in charge for selecting suitable feature extraction methods for each problem given manually and individually. Also, they are required to choose a set of features based on numerous feature extraction methods are available, which is optimal features for each problem in particular taking into them account the performance of classification model. It is still remaining a challenge to implement a condition monitoring and fault diagnostic system in real-world due to the complexity of rotating machinery structures and operating conditions. The designers must consider all steps mentioned to design condition monitoring and fault diagnosis systems for gearbox.

6.3 ASPSG Approach Based Taguchi's Method

The ASPSG algorithm purpose is to design a condition monitoring system for rotating machinery using an automated simple procedure to identify from simplification of the sensory signals matrix SCFs which are most sensitive or they have high dependence to abnormal condition variable such as faults in the gearbox system. Also, they have less sensitive to other machine parameters. The SCFs provide essential information for classification or detection of machining faults. SCF can be considered as feature extraction matrix of sensory data from raw sensory signals using a specific signal processing method, for example the spectral kurtosis value of an acceleration signal, or the standard deviations of acoustic emission signal. The introduced approach applies the black box idea where the condition monitoring system is constructed based on the input and output parameters of the process rather than its mechanics. This procedure (black box) can be applied for several of condition monitoring systems considering the application structure. In this way, it is only required to relate some information in the machining signals (i.e., SCFs) to the identified faults or conditions. Figure 6.1 shows the main idea behind the black box model and its applications in gearbox system. The black box scheme should has capability to transfer the design of condition monitoring problem from being a specific problem for a specific application to a more general problem that can be described in generic terms and the solution might be provided for different groups of processes that have specific criteria in common.

Taguchi's method of OAs are applied to design a short test, either on/off-

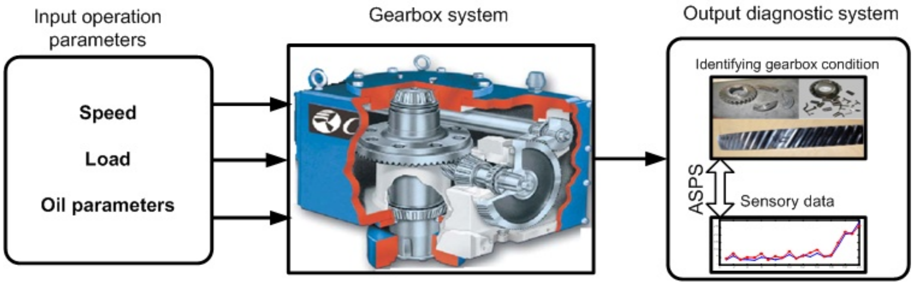


Figure 6.1: The block box concept and the method it can be applied to diagnose the fault in gearbox system.

line, to reduce the number of experimental work required; bear in mind the sensitive of sensory signals to the faults for many of the machine parameters. The dependency values of Taguchi's OAs are used as measurement for sensitivity of the SCFs to detect machining faults and to discover the most sensitive SCFs to the faults under investigation. The condition monitoring system is designed based on a number of SCFs in order to select the most sensitive group of SCFs, which represent high dependency on the observed faults. For example, in this research has shown that due to the damage on helical gear tooth; there is a steady increase in the RMS values of vibration signal. Therefore, it can use the changing in the SCF of average RMS level of vibration signal as the basis for designing a condition monitoring system. So for example the increase in the average RMS of vibration signal shows the development of damage in helical gear tooth.

Figure 6.2 represents a structure diagram the ASPSG approach based on Taguchi's orthogonal arrays theory. The ASPSG technique is conducted by installing a number of sensors on gearbox system. The captured signals from sensors, are then analysed using many common and advance signal processing methods; after that statistical and mathematical feature

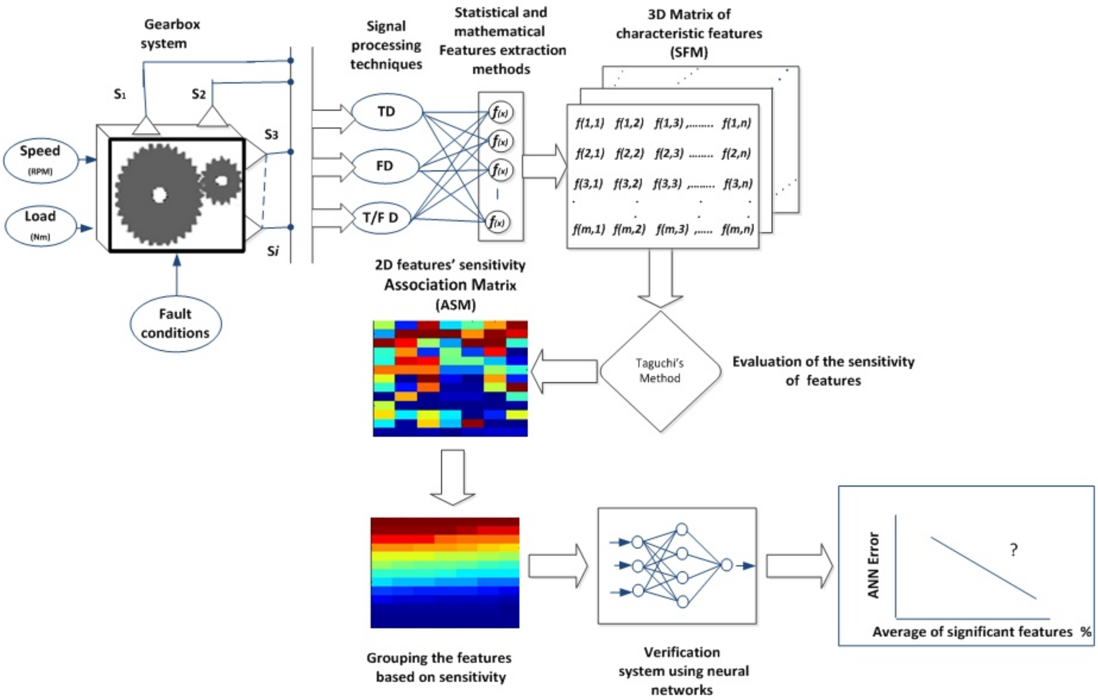


Figure 6.2: A simplified block diagram of the ASPSG approach using Taguchi method.

selection and extraction techniques are applied to reduce irrelevant and redundant information. Self-acting procedure, using Taguchi's method, is then implemented to select the most sensitive SCFs to build reliable condition monitoring system. The less significant sensors, signal processing and feature selection methods are discarded from the designed condition monitoring system. However, only sensors are associated with signal processing and feature selection methods which are discovered its effective. Therefore, they are kept in the monitoring system. Then, cost reduction phase is achieved to exclude the sensors that are less utilised due to not its sensitivity to the event and in order to reduce the cost of the monitoring system whereas maintaining the system's performance within its reasonable range.

6.4 Taguchi Method

Taguchi's based on OAs is usually applied to eliminate a number of experiments that do not have any impact on the process in order to optimise the quality of the process (Gunes et al., 2011). The main concept behind Taguchi's method is to utilise least number of experiments rather than the whole full factorial technique to calculate the contribution of each element of experiment individually (i.e., independent variable) and compute the dependency of factors outcomes for each experiments. In the Taguchi's method the dependency means that the proportion of contribution values gained by analysing the variance. The dependency of variable reflects the portion of the total variation observed in an experiment attributed to that factor. Taguchi's method applied in the ASPSG approach based on the SCFs obtained from the sensory data captured from gearbox system to calculate their dependencies (sensitivities) on the investigated machine faults. SCFs represent high dependency on the machinery faults, rather than the machinery parameters, are potential candidates for use in a monitoring system.

The percentage contribution (P) of a factor (F) can be expressed as follows (Roy, 2001):

$$P_F = \frac{SS_F - V_e \upsilon_F}{SS_T} \times 100 \tag{6.1}$$

where

$$SS_T = \sum_{k=1}^{K_F} \frac{F_i^2}{nF_i} - \frac{T^2}{M} b \tag{6.2}$$

and

$$SS_T = \sum_{i=1}^{N} y_i^2 - \frac{T^2}{M} \tag{6.3}$$

V_e is the variance due to the error and is given by:

$$V_e = \frac{SS_T - \sum_F SS_F}{m - 1 - \sum_F V_F} \tag{6.4}$$

where y denotes the matrix of SCF, T represent the total of summation for all SCF values, F denotes the factor of gearbox parameters such as, conditions of gearbox fault, gearbox shaft speed, gearbox torque, K_F the number of levels for each factor F in this study $K_F = 3$, M represent the total number of observations where $M = 27$ in this study, υ_F the number of degrees of freedom associated with factor F; V_F $=K_F - 1$, F_i the sum of observations under the i^{th} level of factor F, and nF_i the number of observations y under level i of factor F. In order for the approach to be useful, two main assumptions need to be tested, i.e.:

1. Partial number of runs using Taguchi's method is sufficient to design the monitoring system for full factorial runs.

2. SCFs with high dependency values to a fault have high sensitivity to that fault.

6.5 The Experimental Work

The gearbox test rig shown in Figure 4.1 utilized to collect sensory signals such as vibration, AE, speed and torque for developing a reliable condition monitoring system in in order to diagnosis gear damage failure. Gearbox system includes a three phase AC drive motor which used to drive the gearbox which in turn is used to lead the DC motor generator all connected by shafts and couplings. The load was applied through the DC motor generator. Two speed and torque transducers are attached between the input/output shafts of the gearbox and the AC motor/DC generator shafts. The gearbox system contains bearing, shaft and two types of gears, bevel gear and helical gear but the research will focus on the helical gear. The vibration signals are recorded by three accelerometers (Kistler 8704B500), namely $SVIB1$, $SVIB1$, $VIBS3$ are mounted at three different locations on the housing of the gearbox system which are connected to 4-channel-couplers (Kistler 5134). AE sensor (Kistler 8152A) is installed on the case shell of the gearbox which is connected to the AE-Piezotron coupler type (Kistler 5125), in order to measure sound signal that omitted from gearbox components.

6.5.1 The experimental methodology and conditions

The gear damage is made on the helical gear tooth surface at different breakage levels, namely: semi-damage with 25% breakage, moderate damage with 50% breakage and the severe damage with complete breakage of

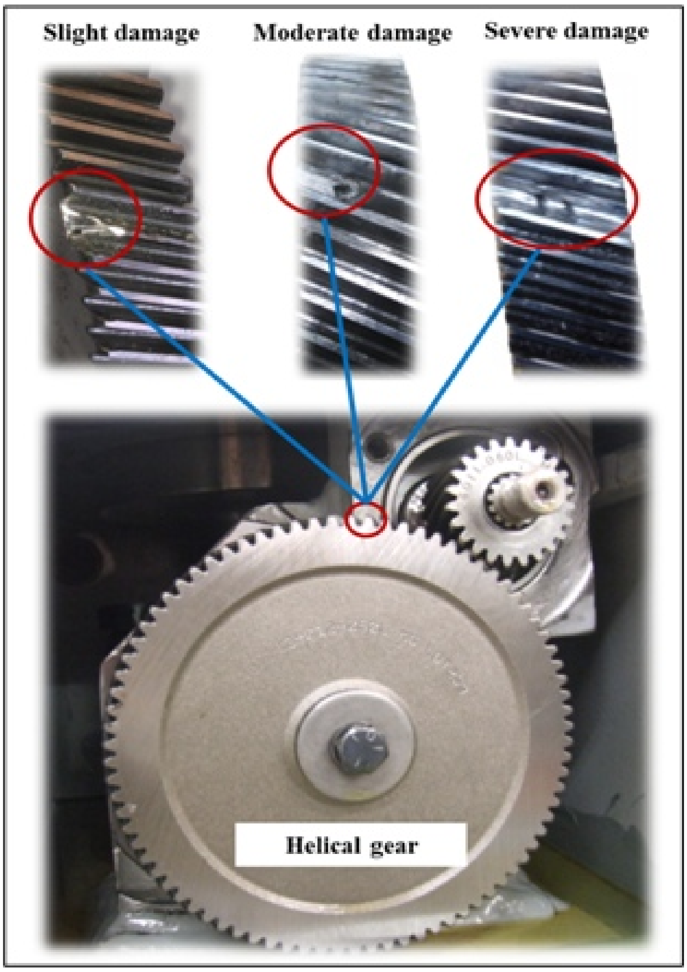


Figure 6.3: Helical gear with artificially created damage at different severity.

the gear tooth (100% breakage), as illustrated in Figure 6.3. These faults are applied to evaluate the performance of the proposed method in order to recognise different fault categories. Figure 6.4 shows the summary of the complete study.

Signals are collected from all the sensors with a sampling frequency up to 500 KHz. The work done with three speed conditions of the driving motor (i.e. 200, 500, and 750 RPM) and adjusting load conditions with three levels applied by the load motor as displayed by torque sensor. The applied load

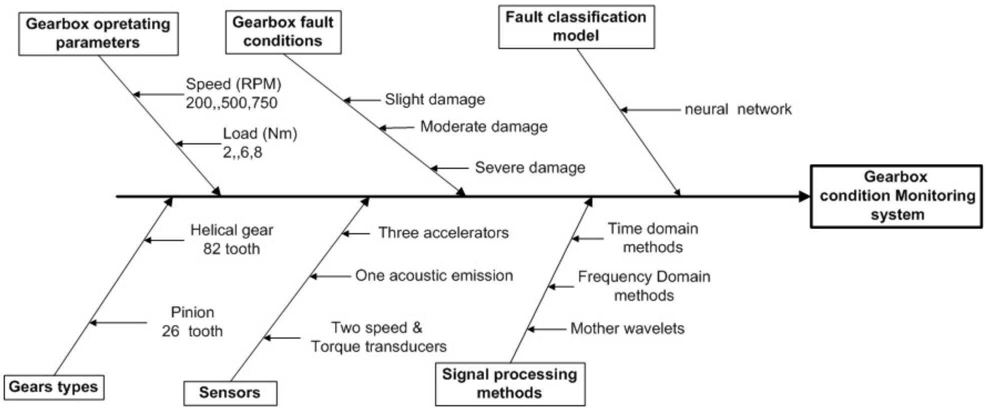


Figure 6.4: Summary of the complete experimental work.

on the output shaft of the gearboxes is 2, 6 and 8 Nm. A full factorial test of the parameters requires 27 runs for every each gearbox condition. However, the proposed application of Taguchi's method can reduce the number of runs to 9 runs using the $L9$ table (Roy, 2010). For the three conditions of helical gear of broken teeth progression, the experimental program involved 9 runs based on OAs $L9$ and a further $L27$ full factorial runs as shown in Figure 6.1 and Figure 6.2. The experimental 9 test is used for the design process as well as training the neural networks. The full factorial test is used to test the capability of four neural networks to recognise the gear conditions.

6.6 Sensory Signal and Signal Processing/Features Extraction Methods

In literature, researchers have done great efforts to identify diagnostic parameters with interesting behaviour and high sensitivity to the faults during gear fault monitoring. However, it is still difficult to find which are the sensitive parameters to the abnormal event in gearbox system; this is because the sensitive features (SCFs) could be case dependent and sub-

Table 6.1: Experimental layout using L27 Taguchi's table.

No of Experiments	Levels			Values		
	Load	Speed	Gear tooth damage	Speed (RPM)	Load (Nm)	Gear tooth damage
1	B1	A1	C1	200	2	25%
2	B1	A2	C1	500		
3	B1	A3	C1	750		
4	B2	A1	C1	200	6	
5	B2	A2	C1	500		
6	B2	A3	C1	750		
7	B3	A1	C1	200	8	
8	B3	A2	C1	500		
9	B3	A3	C1	750		
10	B1	A1	C2	200	2	50%
11	B1	A2	C2	500		
12	B1	A3	C2	750		
13	B2	A1	C2	200	6	
14	B2	A2	C2	500		
15	B2	A3	C2	750		
16	B3	A1	C2	200	8	
17	B3	A2	C2	500		
18	B3	A3	C2	750		
19	B1	A1	C3	200	2	100%
20	B1	A2	C3	500		
21	B1	A3	C3	750		
22	B2	A1	C3	200	6	
23	B2	A2	C3	500		
24	B2	A3	C3	750		
25	B3	A1	C3	200	8	
26	B3	A2	C3	500		
27	B3	A3	C3	750		

Table 6.2: Experimental layout using L9 Taguchi's table.

No of Experiments	Levels			Values		
	Speed	Load	Gear tooth damage	Speed (RPM)	Load (Nm)	Gear tooth damage
1	A1	B1	C1	200	2	25%
2	A2	B1	C2	500		50%
3	A3	B1	C3	750		100%
4	A1	B2	C2	200	6	50%
5	A2	B2	C3	500		100%
6	A3	B2	C1	750		25%
7	A1	B3	C3	200	8	100%
8	A2	B3	C1	500		25%
9	A3	B3	C2	750		50%

ject to the mechanical system and operational conditions. In this work, various features are extracted from each sensor (three accelerometers, one AE sensor, and two transducers measuring speed and torque). To extract the SCFs; the sensory signals are analysed using several signal processing methods and transformed into time and frequency domains. In order to obtain a better representation with perfect resolution of the signals, feature extraction techniques are employed to extract 24 SCFs from every sensory signal as shown in Table 6.3. The SCFs supposed to be real numbers in order to use Taguchi's method to compute the dependency values (i.e. sensitivity). The signal processing and feature extraction methods are select based on previous research in gear monitoring. However, any other methods of signal processing and features extraction can be applied provided that they produce real numbers. The key objective of these processes is to simplify the forms of the complex signal for analysis. The feature extraction methods used in the time domain are the average, STD, absolute maximum, RMS, power, kurtosis, and skew value. In Frequency domain (FFT); envelope spectrum is applied first then the same features methods are used as in time domain.

6.6.1 Envelope Spectrum

Envelope spectrum is defined as a curve which envelopes the frequency - amplitude plane, obtained from Fourier magnitude spectrum. This curve could carry useful information and facilitate about faults. Envelope spectrum analysis can be used for diagnostics and investigation of machinery where faults have an amplitude modulating effect on the characteristic frequencies of the machinery such faults in gearboxes. In order to automate the selection process of the sensitive frequencies to the fault under investigation; the Envelope spectrum is used as sensory feature for the system. The values of the envelop spectrum are normalised with respect to frequency amplitude. These features calculated using statistical methods as shown in Table 6.3.

6.6.2 Wavelet Analysis

The wavelet is used to study diagnostic parameters precisely and examine their pattern during the tests. Wavelet concept is to divide the main signal into number of versions by shifted and scaled the mother wavelets. In this research, the standard deviations of 11 level decomposition of wavelets are used as SCFs for the proposed monitoring system. For each level, the number of wavelet signals used to construct the signal equals 2^i where i is the level number. The dilation equation is used to define the basic scaling function $\varphi(x)$ from which the $D4$ discrete wavelet original signal is calculated as following:

$$\varphi(x) = \sum_{j=0}^{3} c(j)\varphi(2x - j) \tag{6.5}$$

where $c(j)$ represents the wavelet coefficient and j the index. The primary wavelet signal is computed from the scaling function which is expressed as following:

$$\psi(x) = \sum_{j=0}^{3} (-1)^i C(i+1)\varphi(2x-j) \tag{6.6}$$

The four coefficients for D4 wavelets are as follows:

$$\begin{aligned} c(0) &= \frac{1}{4}(1+\sqrt{3}) \\ c(1) &= \frac{1}{4}(3+\sqrt{3}) \\ c(2) &= \frac{1}{4}(3-\sqrt{3}) \\ c(3) &= -\frac{1}{4}(\sqrt{3}+1) \end{aligned} \tag{6.7}$$

For discrete D4 wavelets transformation the original function can be reconstructed form the equation:

The standard deviations are calculated from the wavelet levels are used as SCFs features for the proposed monitoring system. In general, the 4 wavelet SCFs used is denoted as $ED1 - ED4$.

6.6.3 Methodology Process to Verify Applied Approach

Figure 6.5 shows the block diagram of the proposed method for diagnosing gear tooth surface damage using ASPSG. Firstly, sensory signals are captured 25 features described in Table 6.3 were calculated for each of the nine sensors. Secondly, features from all the sensors are combined, making the total number of features be 216 (i.e. 24 × 9), and the whole data set be 648 (i.e. 216 samples/level ×3 levels). Thirdly, feature selection is conducted using the feature selection method proposed in Section 6.4 Finally,

Table 6.3: Time domain features definitions.

Definition	Equation
Average	$TD_1 = \frac{1}{N}\sum_{i=1}^{N} x_i$
STD	$TD_2 = \sqrt{\frac{\sum_{i=1}^{N}(X_i - TD_1)^2}{N-1}}$
Abs Average	$TD_3 = \left(\frac{1}{N}\sum_{i=1}^{N}\sqrt{\lvert X_i\rvert}\right)^2$
RMS	$TD_4 = \sqrt{\frac{\sum_{i=1}^{N}(X_i)^2}{N}}$
Abs Maximum	$TD_5 = max\,\lvert X_i\rvert$
Skewness	$TD_6 = \frac{\sum_{i=1}^{N}(X_i - TD_1)^3}{(N-1)TD_2^3}$
Kurtosis	$TD_7 = \frac{\sum_{i=1}^{N}(x_i - TD_1)^4}{(N-1)TD_2^4}$
Crest Factor	$TD_8 = \frac{TD_5}{TD_4}$
Clearance factor	$TD_9 = \frac{TD_5}{TD_3}$
Shape factor	$TD_{10} = \frac{TD_4}{\frac{1}{N}\sum_{i=1}^{N}\lvert X_i\rvert}$
Impulse factor	$TD_{11} = \frac{TD_5}{\frac{1}{N}\sum_{i=1}^{N}\lvert X_i\rvert}$

Table 6.4: Frequency domain features definitions.

Definition	Equation
Mean frequency	$FD_1 = \frac{1}{K}\sum_{i=1}^{K} S\,(i)$
VAR of frequency	$FD_2 = \frac{\sum_{i=1}^{K}(S(i) - FD_1)^2}{K-1}$
Skewness of frequency	$FD_3 = \frac{\sum_{i=1}^{K}(S(i) - FD_1)^3}{K(\sqrt{FD_2})^3}$
Kurtosis of frequency	$FD_4 = \frac{\sum_{i=1}^{K}(S(i) - FD_1)^4}{K\{FD_2^2}$
Frequency centre	$FD_5 = \frac{\sum_{i=1}^{K} f_i S(i)}{\sum_{i=1}^{K} S(i)}$
STD of frequency	$FD_6 = \sqrt{\frac{\sum_{i=1}^{K}(f_i - FD_5)^2 S(i)}{K}}$
RMS of frequency	$FD_7 = \sqrt{\frac{\sum_{i=1}^{K} f_i^2 S(i)}{\sum_{i=1}^{K} S(i)}}$
Energy Ratio	$FD_8 = \sqrt{\frac{\sum_{i=1}^{K} f_i^4 S(i)}{\sum_{i=1}^{K} f_i^2 S(i)}}$
Energy operator	$FD_9 = \frac{\sum_{i=1}^{K} f_i^2 S(i)}{\sqrt{\sum_{i=1}^{K} S(i)\sum_{i=1}^{K} f_i^4 S(i)}}$

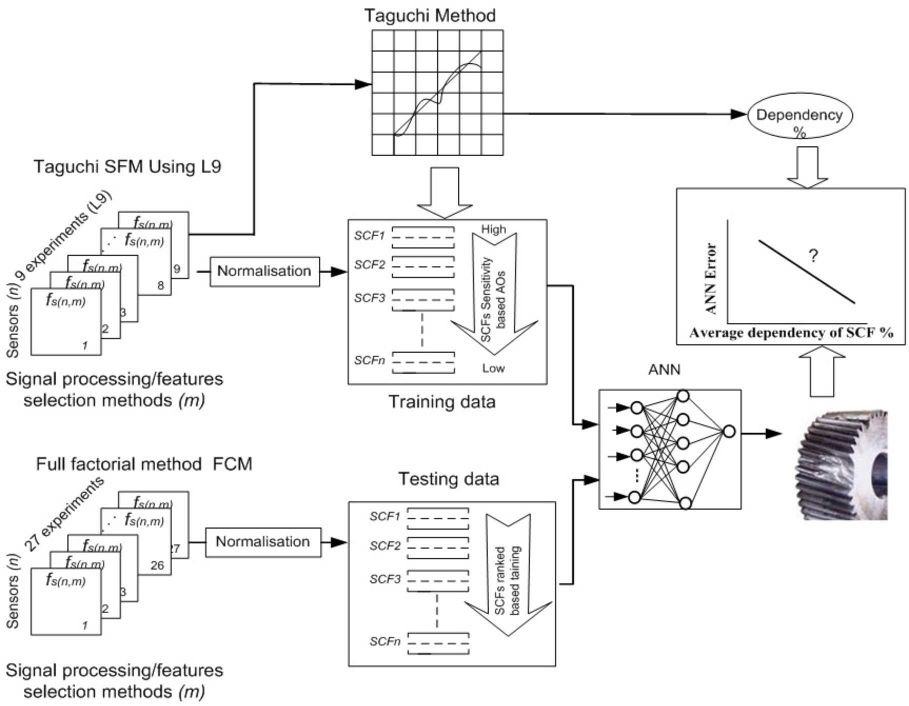


Figure 6.5: The relationship between sensitivity value of SCFs and the classification error of ANN.

the selected feature subset is imported into ASPSG algorithm as described in Section 6.3 to diagnose the damage levels, and find which the sensitive sensors to faults.

6.7 The Experimental Results

The signals obtained corresponding to healthy and unhealthy gear conditions are used to determine the faults. Sampled signal in time domain cannot be used directly as inputs to classifier. Because, the number of samples has to be fixed for a given sampling rate; however, it is a function of speed. So features have to be extracted before classification. Figures 6.6

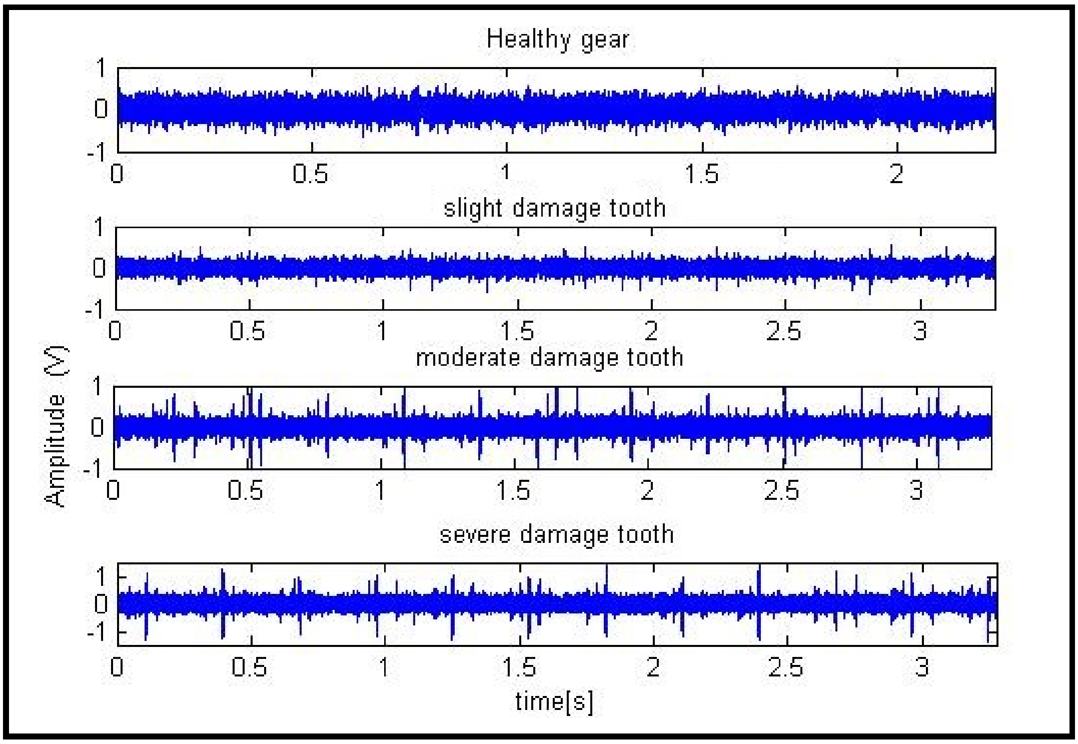


Figure 6.6: Examples of the raw signals of vibration data for the four conditions of the gear.

and 6.7 present examples of the raw and FFT signals of the three conditions on helical gear for one of the vibration sensors. Notice the complexity of the raw signals and the need for a suitable signal processing methods to improve and clarify its dependency on gear conditions.

6.7.1 Data Analysis of the Experimental Work

The calculated Sensory Feature Matrix (SFM) for this test has dimensions of $(9 \times 24 \times 9)$ thus presenting 9 sensory signals, signal processing methods and 9 runs of experiments is the L9 OA. For every feature located in the SFM matrix, the dependency on helical gear damage conditions is

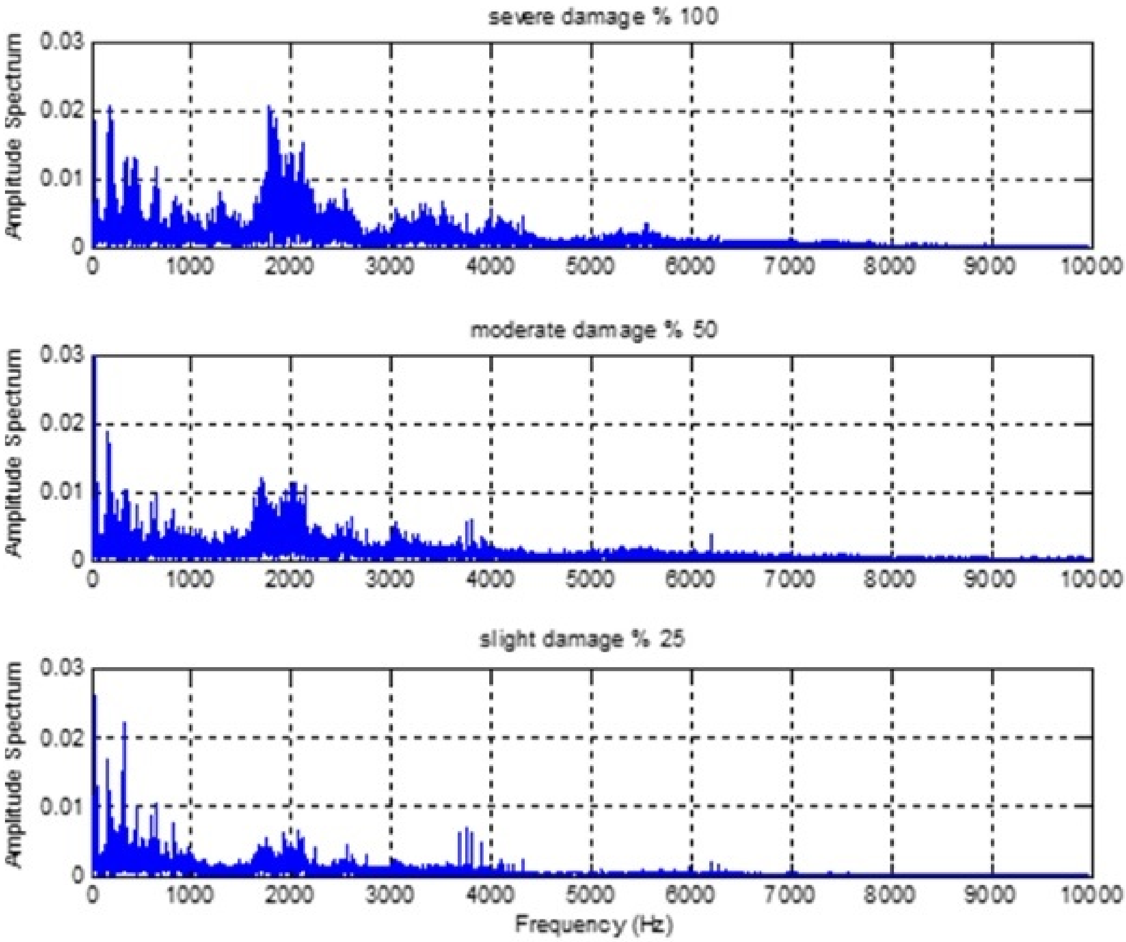


Figure 6.7: Examples of FFT of vibration signals for the three conditions of damage gear.

calculated and placed in the Association Matrix (ASM). Consequently, the ASM matrix for helical gear damage conditions has a size of 9×24, making a total of 216 SCFs. The dependency coefficients of the ASM are used as an indicator of the sensitivity of the features to gear conditions. The 216 SCFs are divided into 7 different groups/systems where each system contains 30 features. The features are arranged in a descending order so that system number 1 contains the features of maximum dependencies while system number 7 groups contains the features of minimum dependency. The suggested number of 30 features in every system is based empirically on the author's previous experience with condition monitoring and neural networks. Normally, such a range of inputs provides good identification and relatively fast training time. However, other values might also be used depending on the application and the neural networks topology. The monitoring systems with each consisting of 30 SCFs, includes SCFs from different sensors using different signal processing methods.

6.7.2 Selection of the Most Sensitive Feature Based on Taguchi Method

The sensitivity of SCFs based Taguchi method is significant step in ASPSG approach to determine relevant and irrelevant sensors and signal processing methods. The sensitive SCFs should be able to indicate the faults prognostic with a significant change in their values, regardless of the change in other operating conditions. Figure 6.8 presents the ASM of the conducted analysis, which represent all SCFs obtained from the implemented sensors and signal processing methods, indicates clearly the sensitivity of each individual SCF. The light colour indicates high sensitivity and dark colour represent low sensitivity as indicated by the colour-map. Each column is associated with a sensory signal and each row is associated with a signal processing method. The colour-map of the ASM can provide a clear indication of the most appropriate sensors and signal processing methods to monitor the fault under consideration. A SCF can be presented as SCF(S,

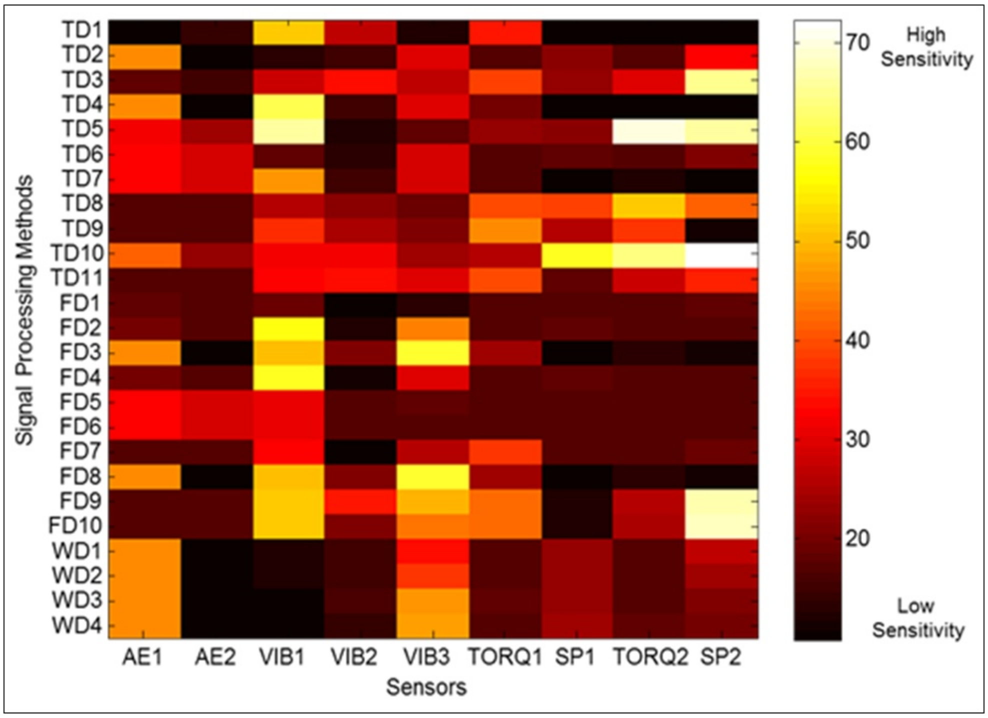


Figure 6.8: The association matrix of the ASPSG approach which indicates the sensitive sensors and signal processing methods in detecting gear faults using Taguchis dependency value as a sensitivity measure.

SP) where "S" is the sensor and "SP" is the signal processing method. It can be observed that among the SCFs as shown in Figure 6.8, some are more sensitive than others. For example, from the general visual observation the SCF with high sensitivity to the gear damage is SCF($SP2, TD10$); while SCF($VIB2, TD4$) is not considered sensitive to the fault. Therefore, it can be concluded that ASPSG based Taguchi method could help in finding the sensitivity of the sensory features signal. In order to develop reliable condition monitoring system with low cost and time.

Each row and column of the ASM of Figure 6.8, could also indicate the average sensitivity of each implemented sensor and signal processing method.

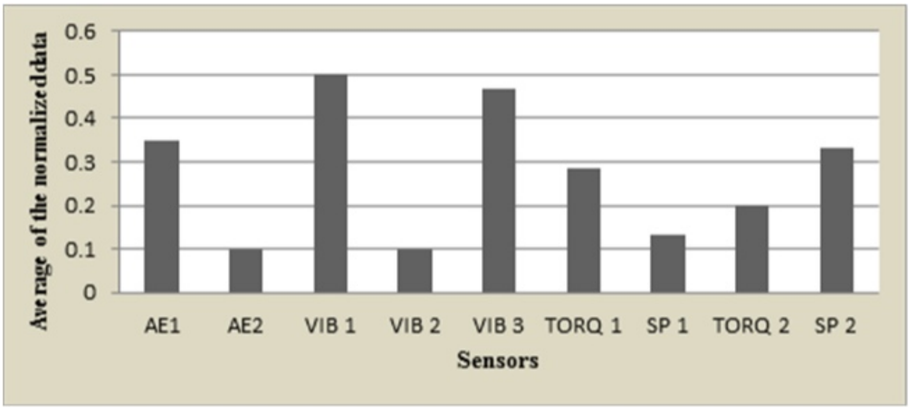


Figure 6.9: Average of the most sensitive sensors based on Taguchi method.

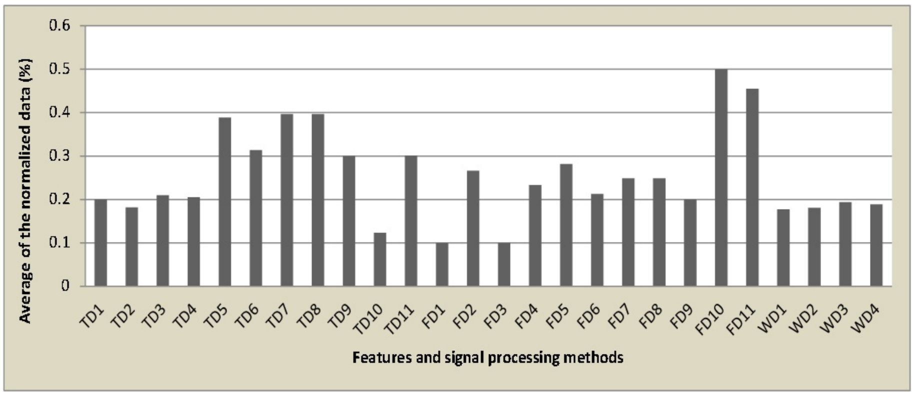


Figure 6.10: Average of the most sensitive features and signal processing methods.

Figures 6.9 and 6.10 represent the average sensitivity (dependency) values for the implemented sensors and signal processing methods respectively. The results show that, on average, vibration sensor 1 ($VIB1$), vibration sensor 3 ($VIB3$), acoustic emission sensor 1 ($AE1$) and speed sensor 2 ($SP2$) are the dominant sensors while $FD10$, $FD11$, $TD7$ and $TD8$ are the most dominant signal processing methods.

6.7.3 Neural Networks Classification

As aforementioned, four types of neural networks models are utilised to prove if the SCFs with high dependency can actually offer a greater sensitivity that should consequently result in better identification of abnormal patterns as shown in Figure 6.11. The neural networks are two supervised and two unsupervised neural networks implemented. The neural network architectures included (BP), Radial Basis (RB), Elman neural network (ELM) and Learning Vector Quantisation (LVQ), as shown in Table 7.5

6.7.3.1 Results for Binary Input Data

Since the 7 proposed systems have 30 SCFs each, the neural networks implemented here are designed to have 30 inputs, A normalising process is performed using Equation 6.8 below so that every sensory characteristic feature will have a value between 0.1 and 0.9 thus making it possible to fuse

Table 6.5: The implemented neural networks.

Neural networks	Type	Key parameters
Back Propagation Neural Network (BP)	Supervised	Learning rate =0.001; momentum =0.9 ;target error =0,01; transfer function (hidden layer and linear (output layer)
Radial Basis (RB)	Supervised	Target error =0,01maxmum number of Neurons =500 spread of radial basis Function = 10 .
Elman Back Propagation (ELM)	Supervised	Learning rate 0.1; hidden layer size =50 ; training iteration =500 bias time constant =0.99
Learning Vector Quantitation (LVQ)	Unsupervised	Learning rate =0.05 hidden layer size =500;training iteration =500; bias time constant=0.99

and com- pare all the calculated sensory features relative to each other:

$$\ddot{f}_{ij} = 0.1 + \frac{0.8}{max - min}(f_{ij} - min) \qquad (6.8)$$

where max is the maximum value of the feature f_{ij}, min the minimum value of the feature f_{ij}, and $\ddot{f}_{ij}$ is the normalised values of the feature f_{ij}.

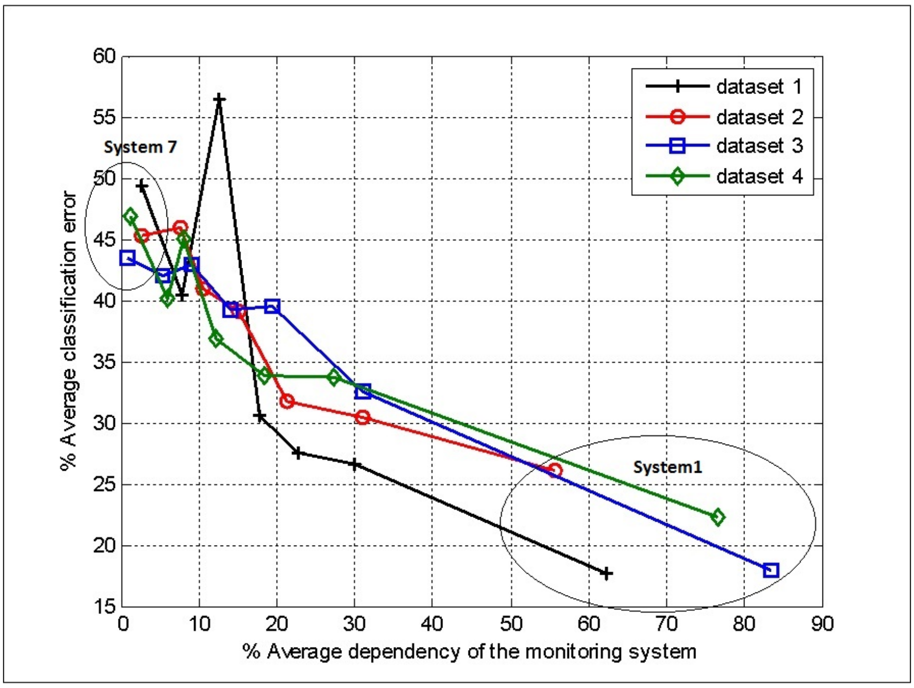


Figure 6.11: The relation between the average dependency and the average classification error of the neural networks of back propagation.

The neural network parameters are chosen from experience in order to give a reasonable response; however, it is important to point out that neural networks are not optimised for this application since the objective here is to compare systems in order to select the most appropriate sensors and signal processing methods. The $L9$ runs are used to train the neural networks while the full factorial tests are used to test them (i.e. using new 9 runs).

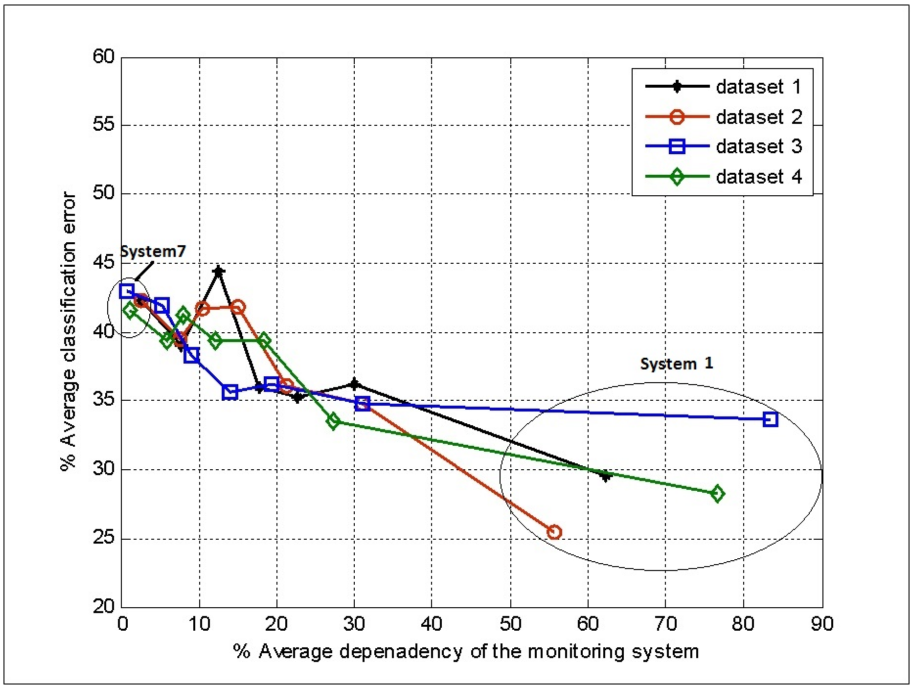


Figure 6.12: The relation between the average dependency and the average classification error of the neural networks of elman back propagation.

Although the 27 runs contain different machining parameters, this should not pose a problem for the neural networks since the SCFs which show high dependency on the helical gear conditions should show low dependency (sensitivity) to the other machining parameters. Three independent training and testing processes are performed for each tested system. The average classification errors of the BP, RB, ELM and LVQ neural networks for the three data sets. As shown in the previous figures, there is a clear trend that systems with high average dependency values produces less classification error (i.e. better identification). Moreover, for systems with dependency greater than 45%, the results are steadier and have lower average variation relative to each other. Therefore, it can be concluded that the higher is the average dependency of the system, the better and more stable is the classification of the pattern recognition system. The ASPSG approach is found to be very useful in predicting the behaviour of condition monitoring systems with- out the need to use any iterative methods. The average classification errors of the four neural networks have proved that high dependency means better information for the neural networks, as illustrated in Figure 6.5.

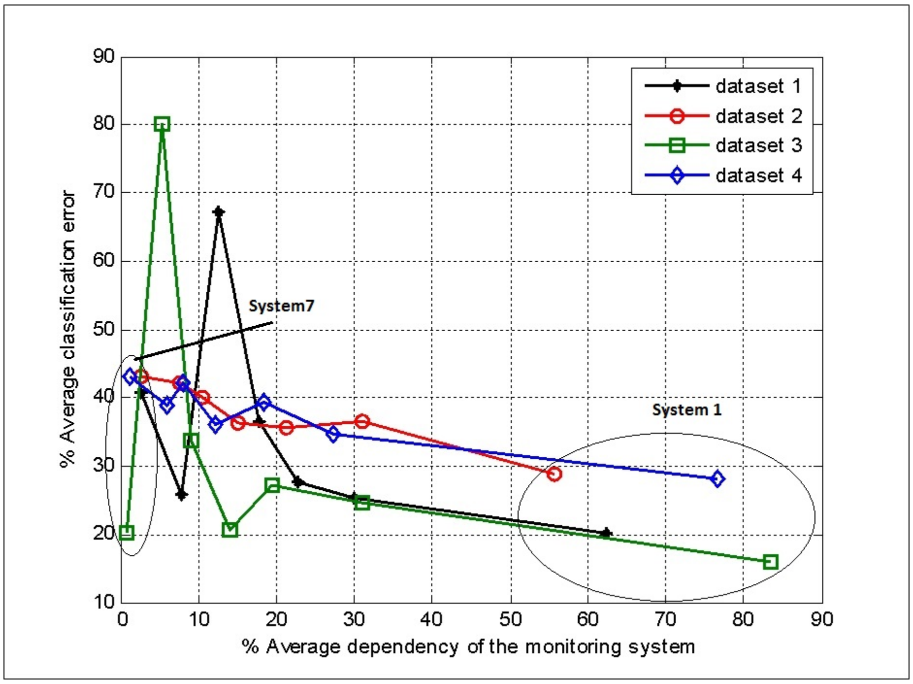


Figure 6.13: The relation between the average dependency and the average classification error of the neural networks of radial basis.

6.7.4 Gear Damage Classification Based on Most Sensitive Models

Figure 6.16 shows a comparison between helical gear damage for three stages (and the most sensitive sensors and features for 7 compared mod-

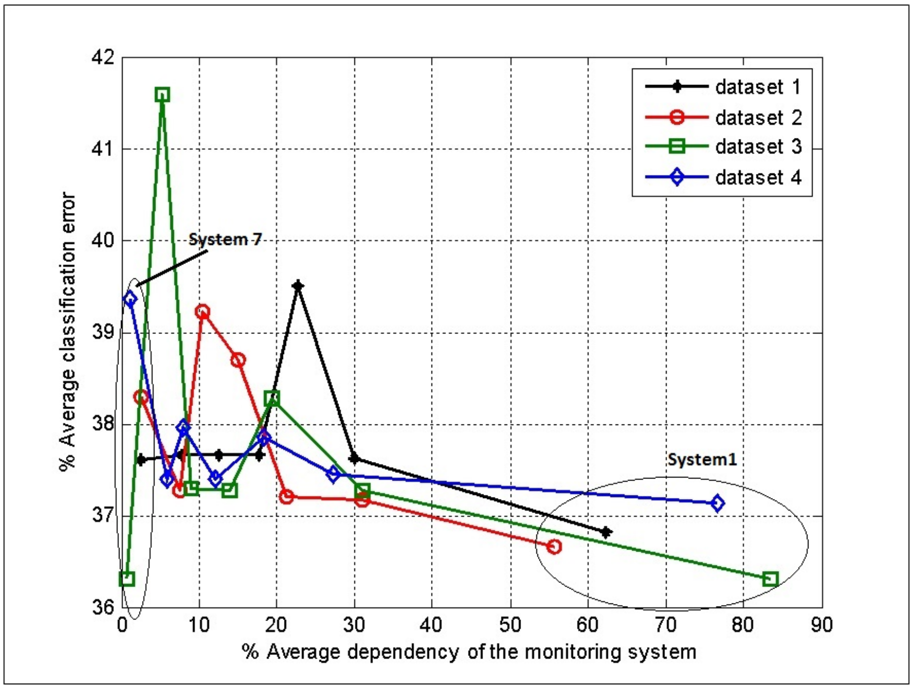


Figure 6.14: The relation between the average dependency and the average classification error of the neural networks of learning vector quantitation.

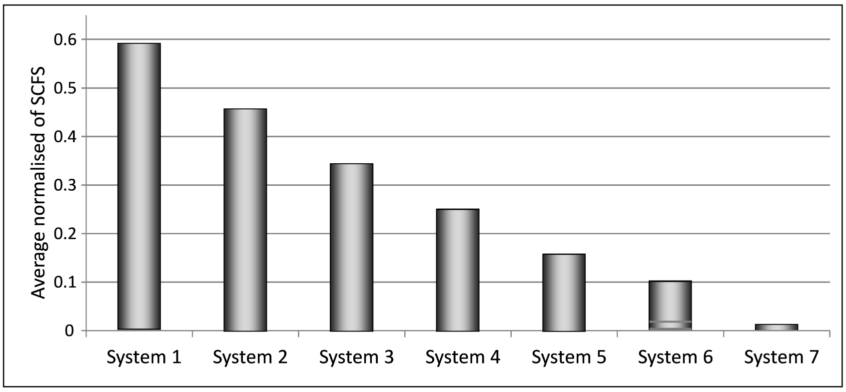


Figure 6.15: Average sensitivity for each system

els). The system 1 represent the most sensitive groups of sensory features to conditions in gearbox system and systems 7 represent the groups of sensory features with less sensitivity. From the Figure 6.16, it can be seen that

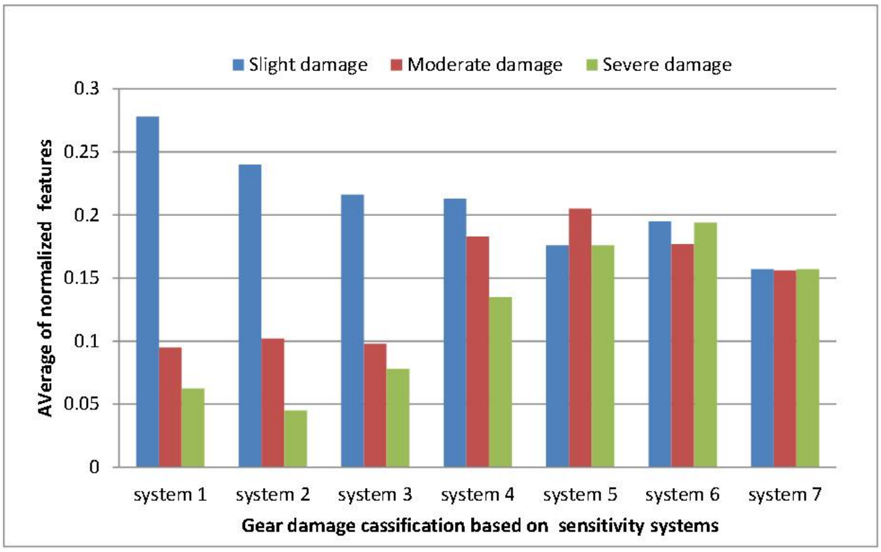


Figure 6.16: The relationship between systems sensitivity and gear damage classification.

systems numbers 1 to 4 are good classifying models but the other systems (5-7) are not able to categorise three faults levels of damage gear. On the other hand system 1 has the best classification compared with the other systems (2-4) as shown in the Figure Figure 6.15; it be can notice that the performance of damage classification of the helical gear is decreased gradually based on models sensitivity, it is essential to compromise between specifications sensors in terms of (type and cost) and performance of gearbox fault diagnosis system if a cheaper system with good performance is needed. The experimental results show that the proposed method is very effective for gearbox fault diagnosis. Although the input features have the all most the same pattern, it still can be identified by this method with high accuracy. Therefore, it can conclude that the proposed model has more strong robustness of data analysis and better generalization ability than conventional selection for sensors and Features extraction models for gearbox fault diagnosis.

6.8 Discussions

Experimental work and analysis shows the capability of the ASPSG approach. The ASPSG approach provide a scientific basis of the methodology for selecting the optimal features and signal processing methods which in turn select reliable sensors to the condition in gearbox system. In this chapter, three type of faults in helical gear are performed a slight damage in tooth, moderate damage in tooth and sever damage in tooth. For each test; ASPSG approach has shown that the most sensitive sensors and insensitive sensors to the gear defect; also it illustrates which more useful than others in monitoring at specific type of faults. For example, vibration sensor $VIB1$ is significant to damage gear, but vibration sensor $VIB2$ is insignificant; because the vibration sensors $VIB1$ is mounted in the top of gearbox housing and close to bearing while vibration sensors $VIB2$ is installed at the side of gearbox housing and bit far from the structure components inside the gearbox. Hence, the observation can be explained by the fact that the SCFs that are sensitive to tooth helical gear damage. Each gearbox component has own specific nature and the generated faults produce different types of signals and frequencies. Therefore, every sensor extracts different information about the fault. The sensor which extracts more information is more likely to provide the sensitive SCFs for the monitoring system. The results confirm that only a partial number of the experimental tests are required in order to predict the machining condition for the full combinations of machining parameters and machining faults.

- investigating the most appropriate sensors and signal processing method to detect gear faults;
- the reduction in cost of machine and process monitoring systems without affecting the system's performance using a suitable fusion model;
- reducing the development time;

Chapter 7

ASPSG Approach Based on Stepwise Procedure

7.1 Introduction

This chapter explains the concept and implementation of the automated sensor and signal processing selection for gearbox system based on stepwise. The chapter shows how the ASPSG approach can be used to develop a novel approach of sensory integration model of a condition monitoring system to detect gradual gear damage in gearbox system in an effective way. The chapter introduces the details of the ASPSG approach based on stepwise method using a gradual broken tooth fault with multi-sensor signals during a gearbox process. This chapter uses a number of sensors to examine the suitability of the ASPSG condition monitoring. It covers the main stages of the ASPSG approach, the association matrix of the damage gear test, the sensitivity detection, the selection of the most sensitive SCFs for a condition monitoring system and the cost of the implemented monitoring system. More experimental work for the evaluation of the ASPSG approach for other sensors will be described in the following chapters. The implementation of the ASPSG approach will answer the following questions:

1. Which is the most sensitive sensors and features to gradual helical gear damage?
2. How many sensory signals is sufficient to detect the condition of gearbox system?
3. What is the relationship between the changes in gearbox driving parameters (speed and load) and the sensitivity of sensory signals?
4. What is the relationship between proposed approach and measuring sensitivity of CSFs matrix using three techniques FRBS, LR and PCA?
5. How can we choose between those sensors so that we can design an efficient monitoring system?

7.2 ASPSG Approach Based on Automated Stepwise Method

In this section a novel approach is named ASPSG approach based on stepwise method which is proposed to develop an effective condition monitoring for gearbox systems with high-performance, less cost by discarding inefficient sensors, and time-consuming by reducing the number of irrelevant experiments. The theoretical idea of this approach is highlighted in Chapter 3. In this chapter, the practical concept of the ASPSG approach based on stepwise procedure is explained in details as follows: Nine experiments are conducted based on changing the input parameters of gearbox system (speed and load) under three conditions of gear damage. In each experiment, the monitoring system has n number of raw signals which can be processed by numerous signal processing techniques. The processed signals then are used to extract m number of features in order to produce SCFs which are grouped in matrix named Sensory Feature Matrix (SFM). This matrix can be calculated for every set of sensory signals, at each experiment and with different condition of gear damage. For any sensory characteristic feature, it is possible to study its behaviour in relation to tool wear. For example, SCF extracted from the Kurtosis value of the $VIB1$ sensory signal can be presented as SCF ($VIB1$, Kurtosis). SFM matrix is used to measure sensor sensitivity to the gear damage using three different techniques which are linear regression, fuzzy inference system and principle component. These techniques are used in parallel to select appropriate technique for calculating sensors sensitivity.

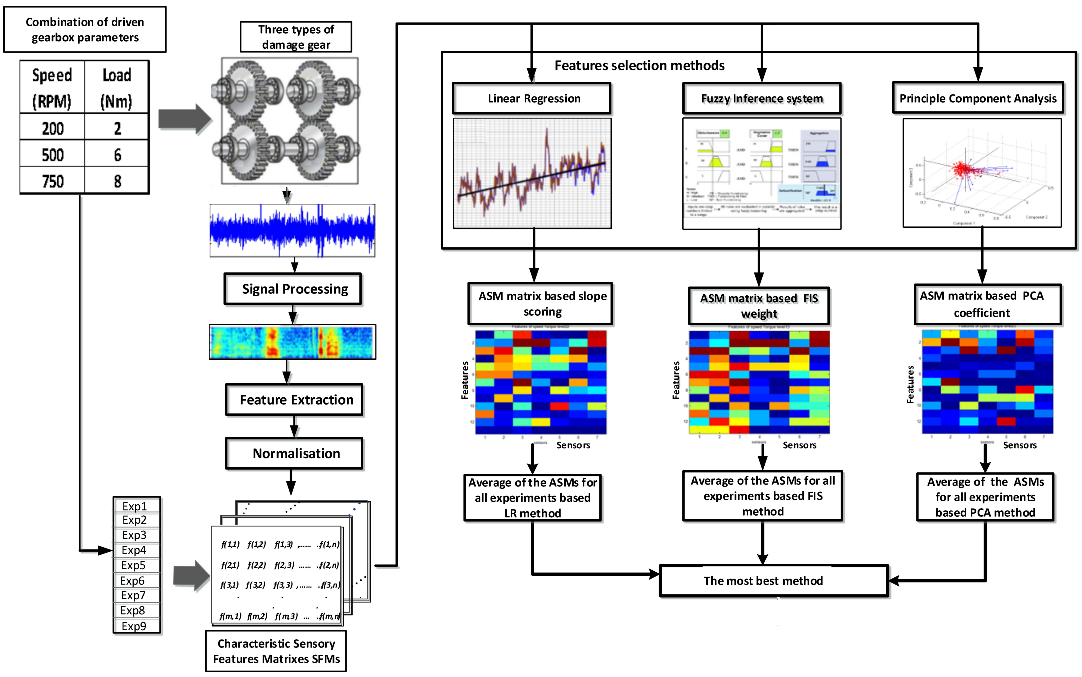


Figure 7.1: A simplified block diagram of the proposed approach using stepwise method.

Figure 7.1 illustrates the framework for the practical stages of the ASPSG based on the stepwise approach. The raw signals which are captured from sensors are facilitated and processed to provide sensory characteristic features are then arranged in the SFM matrix. The SFM can be utilised to compute the sensitivity of every feature on gear conditions. The sensitivity weights are then grouped in the Association Matrix (ASM) for further analysis. After computing the sensitivity of each SCF for each level of gear damage, another matrix is generated. The ASM contains the gained sensitivity values for the corresponding sensory features. It offers a clear presentation of the sensitivity values for sensory characteristic feature. The ASM provides the key assessment for the most appropriate sensor and feature where each row is associated with a feature while each column is associated with a sensor. Therefore, the sensory characteristic features with relatively high sensitivity coefficient are the most sensitive to the gear conditions. ASMs of nine experiments are averaged for every measuring sensitivity techniques (LR, FRBS, and PCA).

7.3 The Experimental Work

In this chapter, nine experiments are conducted to examine the behaviour of the signals for different types of helical gear condition, and to find the most sensitive sensory characteristic features to the gear damage. Seven sensors are used in the this study as mentioned in the previous chapter. Twenty five statistical features are applied which are illustrated in the table as the following: $(TD1 - TD11)$, represent the features of time domain, $(FD1 - FD10)$ represent the features of frequency domain, and $(WD1 - WD4)$ represent the features of wavelet. The twentieth five features are used to process seven sensory signals to construct an association matrix of (25×7) which allows the investigation of 175 SCFs for the design of the monitoring system. Figure 7.2 shows an example of the raw signals of damage gear for all sensors used in this investigation.

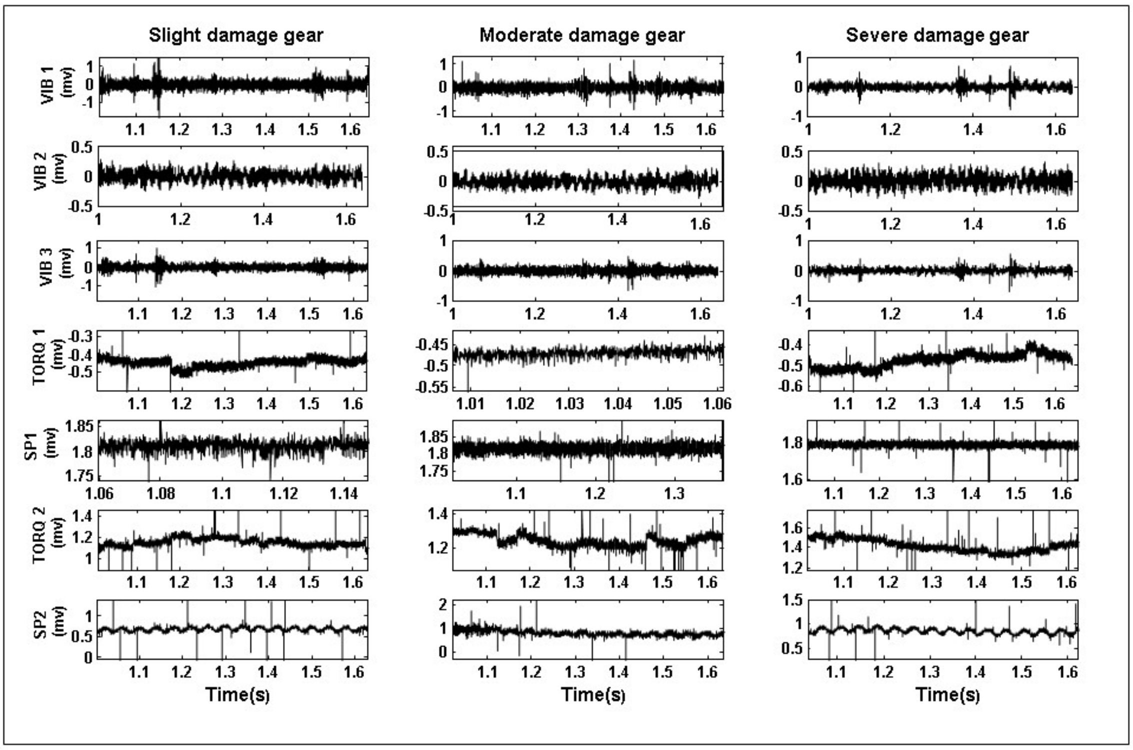


Figure 7.2: Example of the raw signals of damage gear for all sensors.

7.4 Signal Simplifications

As result of sensory signals complexity such as gearbox, the initial step is to convert raw signals from its complex shape into a set of simplified sensory signals named in this study as SCFs. For instance if the gear condition signals can be converted into a set of SCFs with less variation, so it is likely to be much easier to recover the significant information which offer the condition of gearbox based on the alteration in the level of the obtained SCFs as illustrated in Chapter 3, a sensitive SCF includes a significant amount of information regarding the state of the process. This should lead to better recognition. In this chapter, in order to compute the sensitivity of the SCFs based on gear damage, two statistical techniques and one computational intelligent technique are applied as following:

- Linear regression (slope)
- Principle component analysis
- Fuzzy inference system

Then the result from three techniques are evaluated in order to find the best technique to measure sensor sensitivity. All features are normalised based on Equation 7.1. Which means, all SCFs have values between 0.1 and 0.9. Therefore, it possible to compare all calculated SCFs relatively to each other. There is no precise purpose for using this formula of normalisation, so any other methods of normalisation could be applied. The only reason is that such values are expected to have better effect on the classification systems.Moreover, in order to compare the sensitivity values which are calculated using techniques mentioned early, these values are normalised as well using the same equation.

$$x = 0.1 + \frac{0.8}{max - min}(x_i - min) \tag{7.1}$$

where x is normalized value, max is the maximum value of SCF feature, min is the minimum value of SCF feature.

7.4.1 Selection of Linear Regression Method

Linear regression analysis is one of the most commonly used statistical technique to sum up or study a group of data. It is utilised to describe the degree of interdependence between two or more factors. Mathematically, it can be expressed as fitted a straight line through the centre of axis x, y of the data points in certain way which leads to the vertical distances between the data points and the fitted line as short as possible. The slope of fitted line can be considered as a correlation between the axis x and y adjusted by the ratio of STD of these parameters. Slope can be explained as the change in the mean of axis y for unit change in axis x. This means that there is a distribution of y values at each x and the variance of this distribution is the same at each x.

In this study, the slope of linear regression method is adapted to measure the relationship between the SCFs values and the damage gear distribution. It supposes that the effective sensor should be detects any tiny defect on gear may occur at any stage of process. Normally, gear damage starts with slight damage and then gradually increased to become severe damage after a period of time. Here, SCFs values of three conditions of gear damage such as slight, moderate and severe are tested. If the values of SCFs are progressively increased or declined from slight to severe damage status, this will lead to a change on slope value. When there is large variation in a positive or negative between SCF values of slight damage and severe damage. Therefore, this results in a massive deviation in slope line and this imply that SCF value is high sensitive to the damage. However if there is no change in SCFs values between slight damage and severe damage, this will lead to the fitted line become horizontal and slope to be zero. It infers that the SCF is low sensitive to the fault as illustrated in the Figure 7.3. it can be concluded that slope method is a useful technique which can be used to calculate sensors sensitivity.

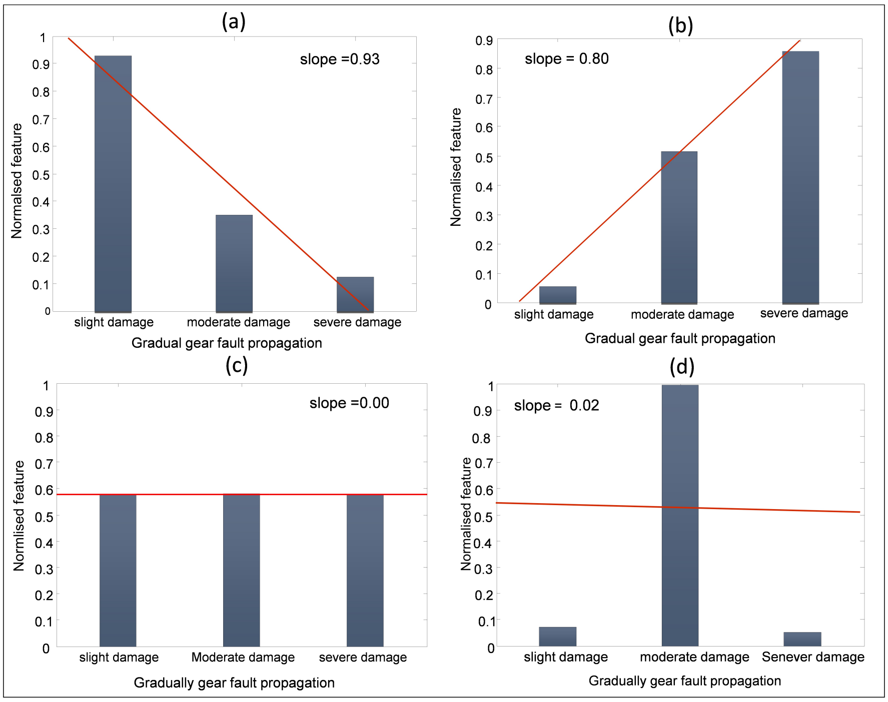


Figure 7.3: Examples of sensitivity SCF using slope of linear regression Method: a) High sensitivity, b) High sensitivity, c) Low sensitivity and d) Low sensitivity.

After calculating all SCFs for all sensors based on LR technique all SCFs are arranged in an ASM matrix. Figure 7.4 shows a graphical representation of ASM which contains the sensitivity of SCFs as implemented in this monitoring system. The ASM presents the sensitivity of each sensor and feature/signal processing methods to detect the gear faults. Where rows of the ASM matrix represent feature/signal processing methods and columns of ASM denote the sensors. Bright colour indicates high sensitivity of SCF which means high capability to detect the fault. While dark colour in the image represents no sensitivity which means sensor is ineffective. Therefore, it can be discarded to reduce the cost of a monitoring system. Gradation of colours from bright to dark is considered as medium sensitivity. From image, it can be noticed that $VIB3$, $VIB1$ and $TORQ1$ are the most sensitive to the gear damage while $VIB2$, $SP2$ and $SP1$ are the less sensitive to the fault. The most sensitive feature/signal processing is $TD2$, $TD3$, $TD5$ and $TD6$ while low sensitive features are $FD1$,$FD2$ and $FD4$.The other features can be considered as medium sensitivity to the fault .

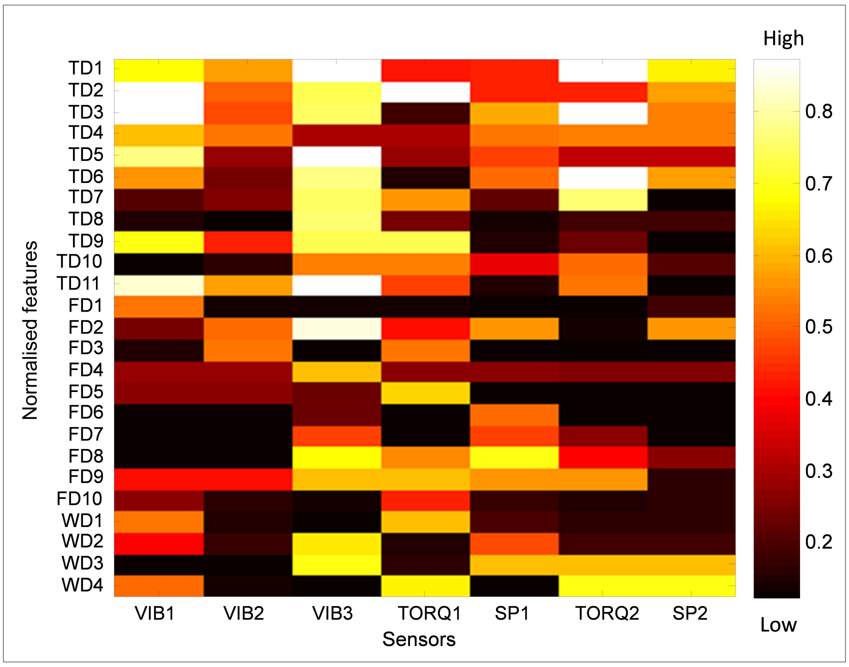


Figure 7.4: A graphical presentation of the sensitivity measurement using linear regression.

7.5 Selection of Fuzzy Rule Based System Method

In order to develop an automated monitoring system with high efficiency, multi-sensors and features extraction methods are required to select most sensitive sensors and associated features. Also, to reduce the budget of the monitoring system, the sensors with less contribution to the faults are need to be removed. Therefore, the measurement of sensor sensitivity is significant. In previous section a statistical technique (slope of LR) is conducted to measure the sensitivity and it gives clear presentation for the sensors that have been used in the study. In this section, a soft computing technique will be applied to evaluate the sensors and features sensitivity.

Fuzzy Rule-based System (FRBS) is implemented to estimate the SCFs sensitivity based on three gradual gear damage. FRBS has capability to transact vague or uncertain sensory signal with efficient way. And it can deal with raw data that has been captured from reveal sensors. it can express the gear damage conditions in terms of linguistic variables in place of the pre-processed sensory signals values. Moreover, it can provide clear explanations for these expressions to be more understandable to the sensor characteristic features. FRBS are employed in many applications such as Data mining, smart and intelligent environment image processing and pattern recognition. In this investigation, a group of FRBSs are used to evaluate and summarize sensitivity of SCFs features to faults in gear monitoring system. The following steps are used in developing FRBS.

For each SCF values, fuzzy rules are constructed based on values of the fuzzy inputs slight, moderate and severe. If all inputs slight, moderate and severe are the same reading: high or moderate or low than the fuzzy output is low that means there is no change in SCF values so the gear condition constant and sensor sensitivity is low as well. Also, if the first and third of fuzzy inputs are identical and the second fuzzy input is different from other fuzzy inputs. Therefore, the fuzzy output is low and the sensor sensitivity is low. As result of that the gear conditions are asymmetrical as shown in Figure 7.5.

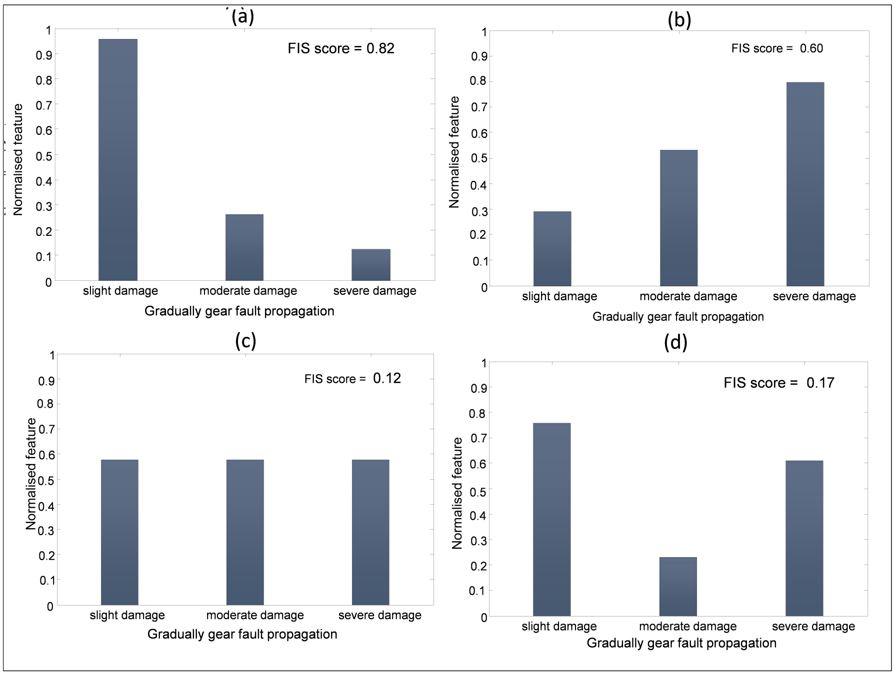


Figure 7.5: Examples of sensitive SCF using fuzzy inference system: a) High sensitivity, b) High sensitivity, c) Low sensitivity and d) Low sensitivity.

Fuzziffication

In this stage, SCFs set is transformed from its value into fuzzy value by appointing the membership degrees for each value of the input and output data set. SCF values arranged in SFM matrix which is explained in Section 3.6.3 are implemented to identify the degree of memberships of each SCF. These features are represented by three levels of gradual gear damage (slight damage, moderate damage and severe damage). These levels generate the input variables of FRBS where SCFs features are calculated based on statistical features for each sensory signals as illustrated in Table 6.3 in Chapter 7. For example, three $SCF(Vib1, TD2)$ values represents characteristic feature RMS of vibration1 in time domain, each value denotes level of gear damage.

Three input variables have three membership function μ: μ(Low), μ(moderate) and μ(High). They have different values based on SCF calculated from different level of gear damage. The output variable of the RBS named sensitivity of SCF which donate the rate of sensor contribution to the fault. The output fuzzy sets are converted their values to linguistic variable similar to input variables. Three membership functions are produced: μ(Low), μ(moderate) and μ(High). These membership functions are created for each SCF. The output variable ranges between $[0, 1]$. For example, the membership functions for the inputs and output to evaluate the sensor and feature sensitivity are illustrated in Figure 7.6.

Fuzzy rules and inference system

The form of IF-THEN expresses fuzzy rules where IF is placed in side of the rule is named the antecedent, while the THEN is placed in the side is named the consequent. the rules are constructed by using linguistic

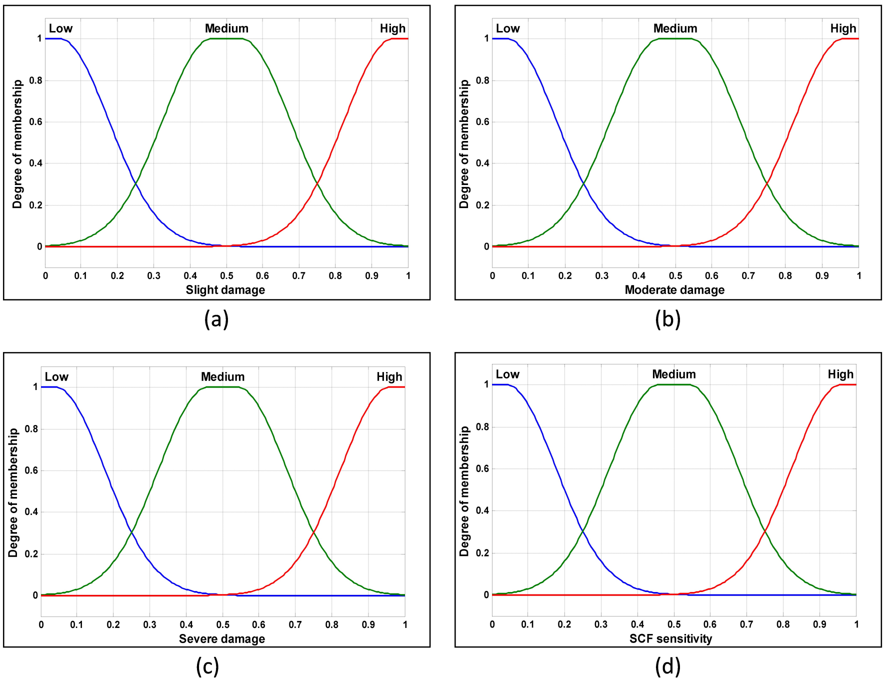


Figure 7.6: Membership labels for input and output variables for measuring sensitivity of sensors; a) Sight damage, b) Moderate damage, c) Severe damage and d) SCF sensitivity.

variables. The fuzzy inference system with fuzzy output is illustrated in Figure 7.7. The fuzzy system inputs can be used any of the options crisp or values, but the output has to be in fuzzy values. In this study, mamdani rule is used as fuzzy rule for the output of the inference system. The antecedents of the rules are slight, Moderate, Severe and CSF sensitivity respectively. For each FRBS, there are 27 rules with three membership for each inputs and three membership for each output ($m = 3$ and $n = 3$). The following configuration is employed:

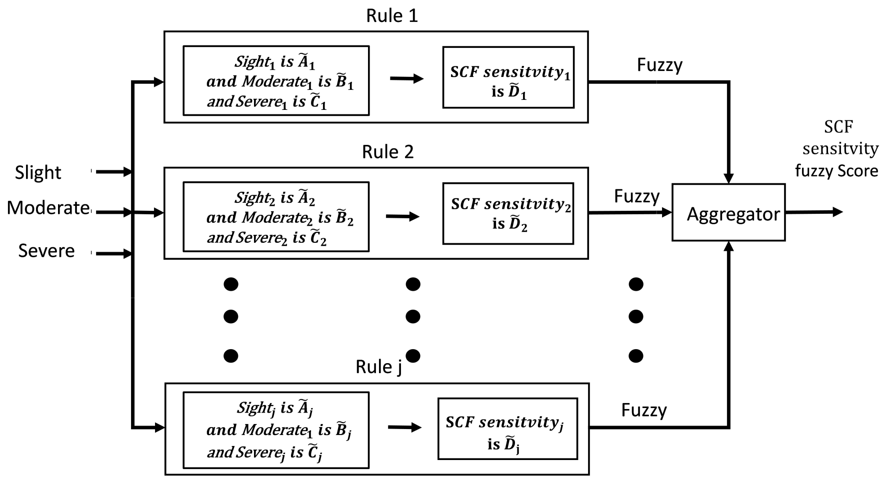


Figure 7.7: Fuzzy inference system with three inputs and one output.

$$R_i^j : If\ Sight_j\ is\ \tilde{A}_i^j\ and Moderate_j\ is\ \tilde{B}_i^j\ and\ Severe_j is \tilde{C}_i^j\ then\ SCF sensitivity_j\ is\ \tilde{D}_i^j \tag{7.2}$$

whereR_i^j is the label of i^{th} rule for the $SCFsj$. $Sight_j$, $Moderate_j$ and $Severe_j$ are the inputs for the sensor j. $SCFsensitivity_j$ is the output, $\tilde{A}_i^j$, $\tilde{B}_i^j$ and $\tilde{C}_i^j$ $(i = 1; 2; .....; m$ and $j = 1; 2; ....; p)$ are fuzzy labels (fuzzy values) for inputs and $\tilde{D}_i^j$ $(i = 1; 2; .....; n)$ is the label for outputs. p is the number of SCFs data set, m is the number of labels for input membership functions and n is the number of labels for output membership functions.

For each SCF values, fuzzy rules are constructed based on values of the fuzzy inputs slight, moderate and severe. If all inputs slight, moderate and severe are the same reading: high or moderate or low than the fuzzy output is low that means there is no change in SCF values so the gear condition constant and sensor sensitivity is low as well. Also, if the first and third of fuzzy inputs are identical and the second fuzzy input is different from other fuzzy inputs. Therefore, the fuzzy output is low and the sensor sensitivity is low. Because the gear conditions are asymmetrical.

Otherwise, the status of the process is considered as normal. It is also possible to reach other options if none of the above are satisfied. Therefore, to reach a decision based on the values of the indices, a fuzzy rule-based system is used to provide the decision. Sample of fuzzy rules for sensor sensitivity identification are defined as shown below:

R1: IF $Slight$ is $\mu(High)$ AND $Moderate$ is $\mu(High)$ AND $Severe$ is $\mu(High)$ THEN $SCFsensitivity$ is $\mu(Low)$

R2: IF $Slight$ is $\mu(Medium)$ AND $Moderate$ is $\mu(Medium)$ AND $Severe$ is $\mu(Medium)$ THEN $SCFsensitivity$ is $\mu(Low)$

R3: IF $Slight$ is $\mu(Low)$ AND $Moderate$ is $\mu(Low)$ AND $Severe$ is $\mu(Low)$ THEN $SCFsensitivity$ is $\mu Low)$

...

R23: IF $Slight$ is $\mu(Medium)$ AND $Moderate$ is $\mu(High)$ AND $Severe$ is $\mu(High)$ THEN $SCFsensitivity$ is $\mu(Medium)$

R24: IF $Slight$ is $\mu(low)$ AND $Moderate$ is $\mu(Medium)$ AND $Severe$ is $\mu(Medium)$ THEN $SCFsensitivity$ is $\mu(Medium)$

R25: IF $Slight$ is $\mu(low)$ AND $Moderate$ is $\mu(Low)$ AND $Severe$ is $\mu(High)$ THEN $SCFsensitivity$ is $\mu(High)$

R26: IF $Slight$ is $\mu(Low)$ AND $Moderate$ is $\mu(Medium)$ AND $Severe$ is

$\mu(High)$ THEN $SCFsensitivity$ is $\mu(High)$

R27: IF $Slight$ is $\mu(High)$ AND $Moderate$ is $\mu(Medium)$ AND $Severe$ is $\mu(Low)$ THEN $SCFsensitivity$ is $\mu(High)$

Figure 7.8 shows a graphical representation of ASM which contains the sensitivity of SCFs implemented in this monitoring system based on FRBS. The ASM shows the sensitivity of each sensor and feature/signal processing methods to detect the machining faults. Where rows of the ASM matrix represent feature/signal processing methods and columns of ASM denote the sensors. This matrix is similar to ASM matrix of LR. From the graphical image, it can be noticed that $VIB3$ and $VIB1$ are the most sensitive to the gear damage while $VIB2$ is less sensitive to the fault because it is placed away from the internal structure of gearbox. The most sensitive feature/signal processing is $TD2$, $TD3$, $TD5$ and $TD6$ while low sensitive features are $FD1$, $FD2$. The other features can considered they are as medium sensitivity to the fault. ASM of FRBS show that the fuzzy system is more powerful to detect the sensitivity of the sensors.

Based on stepwise procedure investigation, nine experiments with vary speed and load are tested to find the most sensitive sensors and features at each experiments and which is reliable speed and load for detecting fault. It can be noticed from Figures 7.10 and 7.11 that the reliable experiment is the experiment with speed1 and load3 as shown Figure 7.1 which gives high detection to the fault compared with other experiments. Load has positive impact for discovering the fault. Also, load has positive relationship with

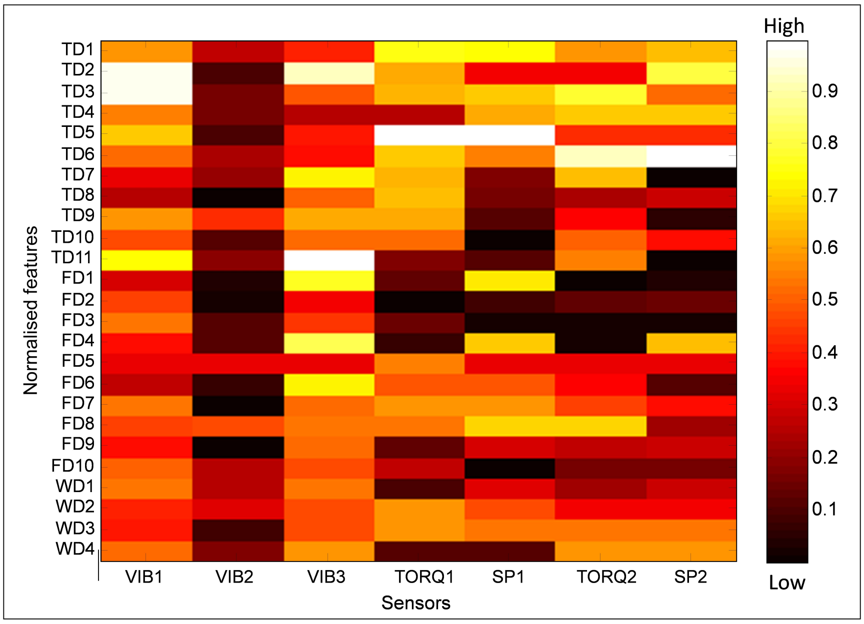


Figure 7.8: A graphical presentation of the sensitivity measurement using fuzzy inference system.

Table 7.1: Nine of experiment with rrange of speed and load.

Experiments	Load	Speed	Load (Nm)	Speed (RPM)	Aveage senstivity measurment
EXP1	Load 1	Speed 1	2	200	0.32
EXP2	Load 2	Speed 1	6	200	0.35
EXP3	Load 3	Speed 1	8	200	0.45
EXP4	Load 1	Speed 2	2	500	0.3
EXP5	Load 2	Speed 2	6	500	0.29
EXP6	Load 3	Speed 2	8	500	0.25
EXP7	Load 1	Speed 3	2	750	0.22
EXP8	Load 2	Speed 3	6	750	0.17
EXP9	Load 3	Speed3	8	750	0.15

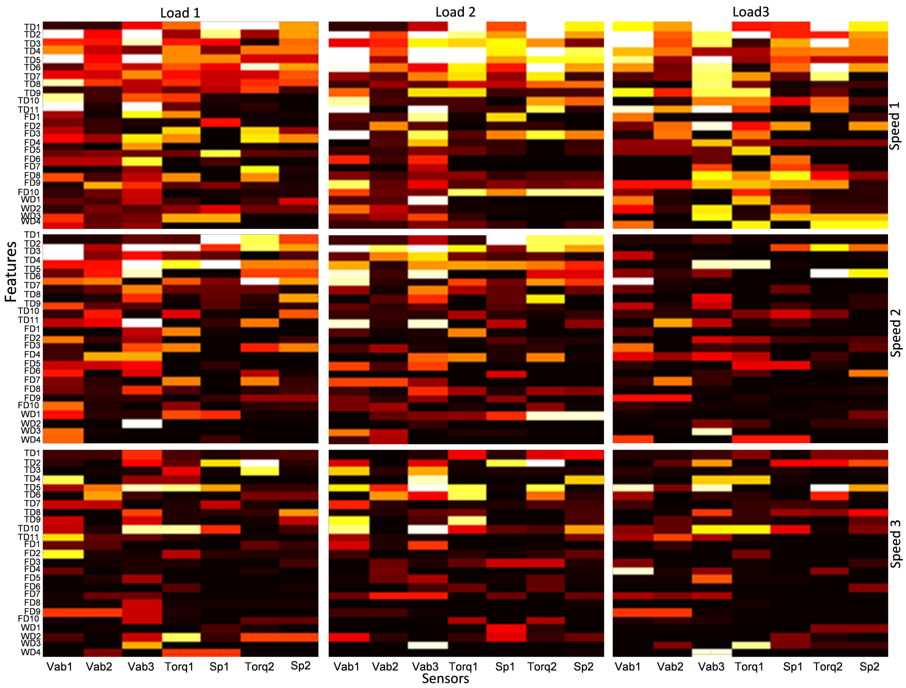


Figure 7.9: Images of nine experiments based of varying of speed and load.

fault identification, If the load increase the fault becomes clear to detect, taking into account speed should be low. However, speed has negative impact for identifying the fault. So, if the speed is increased the fault will disappear gradually. It can be observed from both figures 7.10 and 7.11 that vibration sensors ($VIB1$ and $VIB3$) is the most sensitive sensors and $VIB2$ is the less sensitive sensor to the fault all experiments. It can be concluded that gearbox driving parameters such as speed and load are very significant for detecting gear damage.

Figures 7.12 shows the relationship between nine experiments with varying speed and load and the average of sensors sensitivity. It can be observed from image that sensors in the first five experiments ($Exp1$ - $Exp5$) have high ability to discover defect while sensors in experiments ($Exp6$ - $Exp9$)

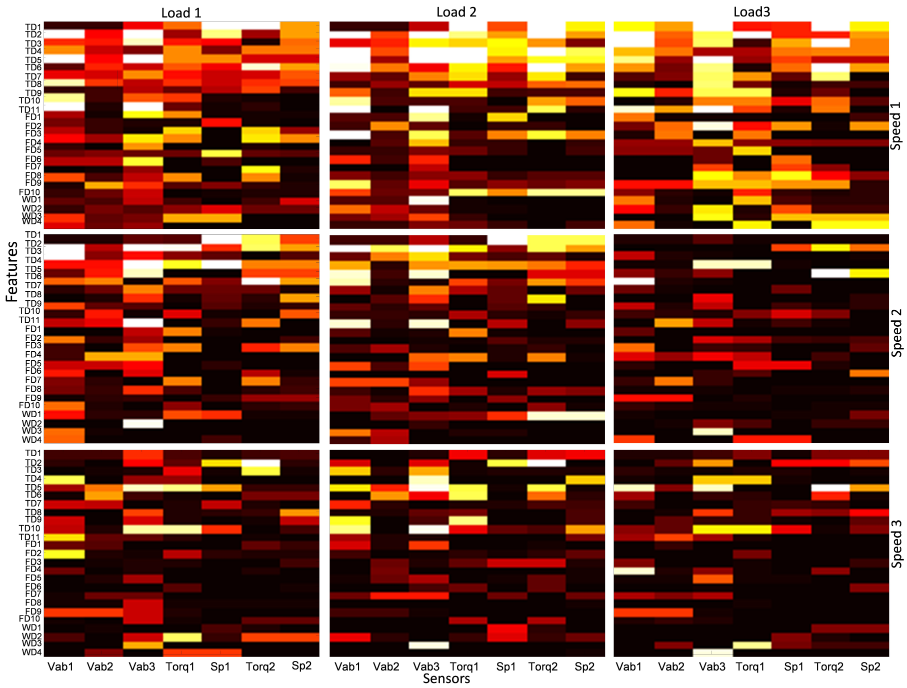


Figure 7.10: Images of nine experiments based of varying of speed and load.

are facing difficulty for determining the defect. Experiment 3 ($Exp3$) is the most reliable experiment which gives high reading for all sensors. From both figures, we can conclude that the sensors $VIB1$, VIB, $TORQ1$ and $TORQ2$ is the effective sensors and it can be used to develop a reliable gearbox condition monitoring for detecting gear damage. Also it can get rid of ineffective sensors, for example, $VIB2$, $SP1$ and $SP2$ in order to reduce the cost of gearbox monitoring system.

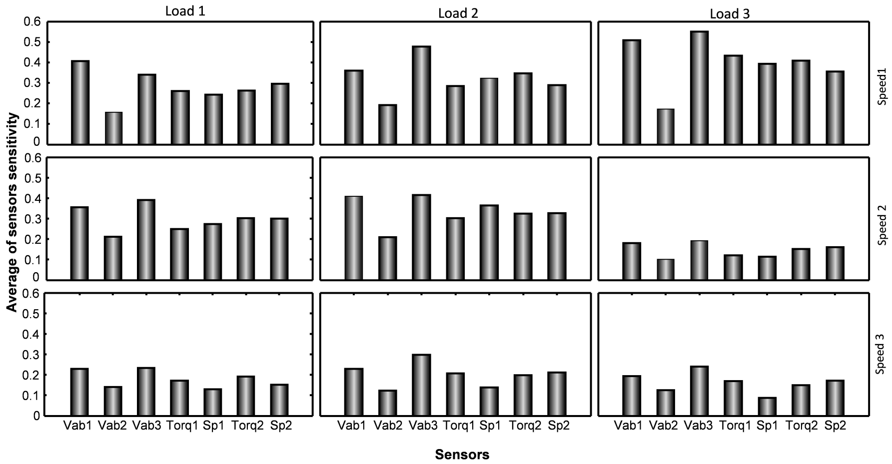


Figure 7.11: Nine graph measuring sensitivity based on varying of speed and load.

7.6 Selection of Principle Component Analysis Method

PCA is considered as one of the multivariate method which is used to reduce a number of variables. The purpose of PCA is to find how variables are associated to each other. PCA is valuable statistical technique used with more than one variables. As a result of the variables associated with each other are more likely to have a redundant data. Redundancy means that some of the variables are measuring data insignificant or repeated information. Therefore, this redundancy should be reduce which means reduce the observed variables into a smaller number of principal components with maintaining the significant information. Thus, it is appropriate to adopt PCA component in this research, due to the fact that it is essential to observe the impact of the variables (e.g sensors) on the data, this

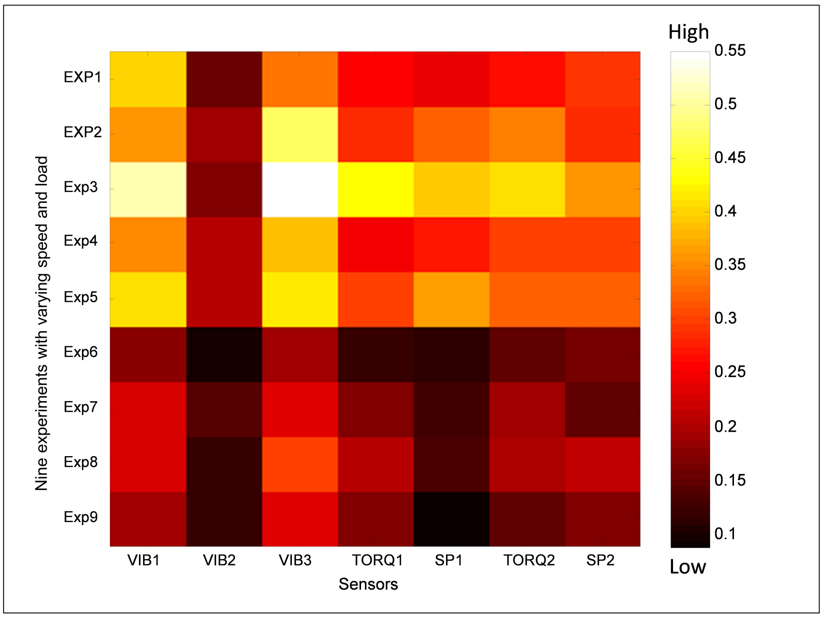


Figure 7.12: the relationship between sensors sensitivity and varying of speed and load.

will give clear picture to identify which variable is more effective to detect the abnormal condition in gearbox system. Here, PCA is applied in this research to identify the sensitive and insensitive sensors to the faults.

Figure 7.14 shows a graphical representation of ASM based on PCA calculation which contains the sensitivity of a few SCFs implemented in this monitoring system. The ASM presents for each sensor and signal processing method (SCF) the sensitivity to detect gear fault. PCA shows all SCFs have not sensitivity the fault, It can be noticed that all image has the same colour and whole image is dark. it can be conclude that PCA is not reliable technique to measure sensitivity in this case.

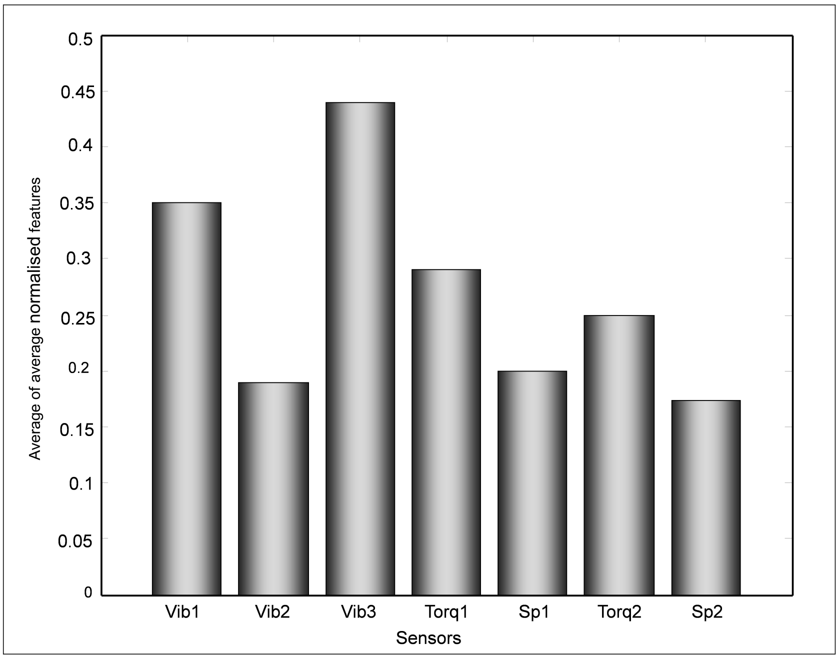


Figure 7.13: Example of the raw signals of damage gear for all sensors.

7.7 Comparison between sensitivity measurements techniques

In the current section, the (SFM) for this test has dimensions of $(7 \times 25 \times 9)$ thus presenting 7 sensory signals, signal processing methods and 9 runs of experiments. For every feature located in the SFM matrix. The sensors sensitivity to gear damage conditions is calculated and placed ASM matrix based on three techniques FRBS, LR and PCA. The 2175 SCFs are divided into 7 different groups/systems where each system contains 25 features. The features are arranged in a descending order so that system number 1 contains the features of maximum dependencies while system number 7 groups contains the features of minimum dependency. From the Figure,

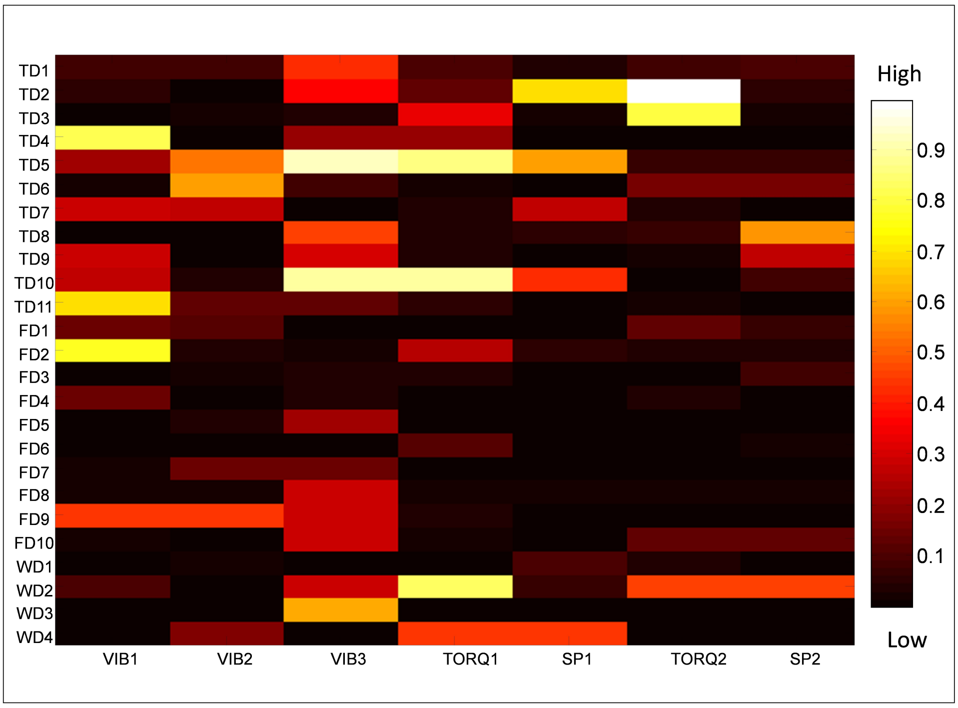
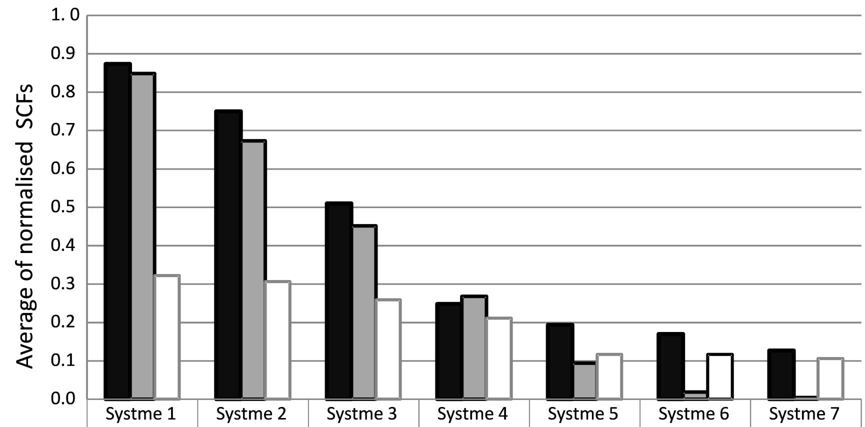


Figure 7.14: A graphical presentation of the sensitivity measurement using principle component analysis.

it can be noticed that FRBS and LR have found to be achieved higher sensitivity for all system in comparing with PCA. It can concluded that FRBS and LR are the best techniques to measure sensors sensitivity in gear conditions as illustrated in Figure 7.15.

7.8 Discussions

This chapter has investigated the capability of the ASPSG approach based on stepwise procedure. this approach provides a scientific methodology for selecting the optimal features and signal processing methods which in turn select a reliable sensors to the condition in gearbox system. In this chapter



	Systme 1	Systme 2	Systme 3	Systme 4	Systme 5	Systme 6	Systme 7
FRBS	0.874	0.750	0.510	0.248	0.194	0.170	0.127
LR	0.848	0.673	0.452	0.268	0.094	0.019	0.004
PCA	0.322	0.306	0.259	0.211	0.117	0.117	0.106

Figure 7.15: Comparison of the sensitivity measurement using three techniques.

three different faults are investigated slight, moderate and severe damage in gear tooth. Nine experiments with varying speed and load are tested. For each test; ASPSG approach based stepwise procedure has revealed the most sensitive sensors and insensitive sensors to the gear defect; also it illustrates which more useful than others in monitoring at specific type of faults. The result shows that vibration sensor $VIB1$ and $VIB3$ are significant to damaged gear. However, vibration sensor $VIB2$ is insignificant; because the accelerometer sensors $VIB1$ is mounted in the top of gearbox housing and close to bearing while accelerometer sensors $VIB2$ is installed at the side of gearbox housing and away from the structure components inside the gearbox. Also, speed and load values have significant impact on sensors measurements. The results confirm that only a partial number of the experimental tests are required in order to predict the gearbox condition for the full combinations of driving gearbox parameters and gear faults.

Chapter 8

Conclusions and Future Work

8.1 Introduction

This thesis addresses the application of several computational techniques for the diagnosing and predicting gearbox faults in rotating machines.This thesis has investigated and developed a reliable gearbox condition monitoring system and fault diagnosis using a novel approach named ASPSG, with reduce cost and experimental work. This section gives a clear picture of the overall structure of the thesis. Chapter 1 has presented an introduction to the research work. Chapters 2 and 3 has presented the background and gearbox condition monitoring domain which is under investigation in this thesis. In addition, the methods of signal processing and data analysis have been described. The methodology of the proposed approach ASPSG and the elements of the implemented condition monitoring systems, have been presented in Chapters 4. Chapter 5 described the general experimental set-up and the equipment details which have been used in this research. Chapters 6 has illustrated a new methodology of identifying the optimum sensor location. Chapters 7 and 8 have presented the implementation and evaluation of novel approach ASPSG based on two procures (holistic and stepwise) for developing effective gearbox condition monitoring system.

8.2 Summary

This thesis introduced a novel approach by answering the research questions from the theoretical and practical aspects. The study and the scientific analysis of the results found that the selection of sensory signals, its location and features/signal processing methods. This methods can play significant role to develop reliable condition monitoring for gearbox systems in terms of high performance, cost reduction and reduce the number of experiments. The main aim of this research work is to develop an effective gearbox condition monitoring system to detect the abnormal condition at a very early stage using a cost reduction methodology with reduced number of experiments have been conducted. This has been successfully achieved and examined by applying a systematic ASPSG approach. The ASPSG approach proposed automated way for selection the most sensitive sensor and its location and reliable feature/signal processing method to improve the reliability of conditions monitoring system gearbox. This approach is performed by using two methodologies (Holistic and stepwise) procedures. Both procedures will help in the design to find the most sensitive sensors and signal processing methods for use in a condition monitoring system.

The approach in developing the system and it is also combined with a new procedure to reduce the cost of the system without significantly affecting its prediction consistency and accuracy.

8.3 Concluding Remarks

This thesis has also provided an analysis of the identification and classification of sensory signals to design monitoring system of gearbox. Conclusions for different aspects of the project are presented below:

8.3.1 Automated Simplification Method

This thesis introduce scientific way to process and simplify all raw sensory signals that are collecting from test rig with three different unhealthy conditions. These signals are analysed using a wide range of statistical features and signal processing methods to produce an sufficient number of SCFs features automatically. The combination of features and signal processing techniques are considered as simplification techniques which are used to reduce the dimensionality and extract useful information about condition in the gearbox system.

The simplification process is effectively performed for all raw signals using the selected features and signal processing methods. Three-dimensional matrix SFM are produced where including all SCFs where x dimension represents sensors and y dimension represents features and z dimension denote number of experiments including all possible conditions need to be investigated. This step is very significant to identify the sensitivity of sensor and features. Also it has successfully converted the complex signals into more arranged and simplified SCFs Clarify important information about the condition monitoring system. For more information about the simplification method, see Section 7.3.

8.3.2 Automated Sensitivity Detection Method

The research also introduced an automated methods to measure sensitivity of SCFs using many statistical and computational intelligent techniques such as PCA factorial analysis, slope of LR and FRBS. These method are used to detect the sensitivity of the SCFs to the gradual gear tooth damage contained in the SFM matrix. It can be seen that the most sensitive SCFs which have significant change in their levels as result of gradual gear tooth damage. Also KNN technique has been conducted to evaluate an automated sensitivity measuring methods. Results shows that LR and FRBS are appropriate techniques for calculating sensitivity of SCFs and they give clear presentation for all SCFs features in terms of high and low sensitive to the faults while PCA technique provide results not clear compered to LR and FBrS.

8.3.3 The Selection of Sensors and Features Methods

Sensory signal and a feature/signal processing methods are employed to prove a SCF. If a SCF feature is discovered sensitive to a defect that means it is relevant sensor and signal processing method and it should be selected for the monitoring system. ASM matrix is contain the sensitivity coefficients were calculated using automated sensitivity detection method. The ASM is 2D matrix, comprises the sensitivity values of all the SCFs where columns represent sensors and rows represent features. This are arranged descendingly where the SCFs with high sensitivity should be at first rows and SCFs with low sensitivity at the end of matrix. After that ASM matrix is grouped every 20 SCFs so called systems. The most sensitive system is system 1 so that contains the first 20 SCFs where they can be selected to develop reliable condition monitoring system for gearbox. Therefore, the relevant sensors and features methods could be nominated as the most sensitive and suitable tools to design and develop the monitoring system.

8.3.4 Cost Reduction

The cost of condition monitoring systems are calculated depending on the earlier step. The cost are computed by adding the price of selected sensors and their conditioning devices. Cost reduction of reliable condition monitoring is performed by eliminating sensors which are less contribution and low sensitive to the faults progression. A limited number of SCFs was removed from the selected system of SCFs and exchanged with other sensitive SCFs from the sensors which were already in the system. The sensor utilisation factor is considered as very beneficial technique to identify the less used sensors within the monitoring system during process. The cost reduction is discovered as very useful step for all the experiments in order to minimise the cost of the monitoring system without affecting its efficiency.

8.4 Final Conclusion

The main aim of this research is to develop an reliable condition monitoring for gearbox system using a cost-effective methodology with reduced experimental work. The results has shown that this aim has been achieved and successfully tested. A systematic ASPSG approach, has been designed to develop an effective sensor-fusion model for gearbox system. This system will help to find the most sensitive sensors and features/signal processing methods for use in a gear condition monitoring system. The results demonstrate that the sensor location has significant impact on the information quality obtained from sensors and signal processing methods for the detection of tool condition. The approach is combined with a new procedure to reduce the cost of the system without significantly affecting its prediction consistency. The experimental results of this research work have shown, with clear consistency, that this approach has been successful in developing a condition monitoring system for gearbox system.

8.5 Directions for Future Works

Further investigation, in which future works could proceed, are listed below:

- To extend the work to develop automated monitoring system for gearbox condition using two dimensional sensing tool such as infrared camera rather than just using sensors which are considered one dimension sensing tool. It may bring now useful information for detecting gearbox condition with less cost and less experiments.

- The proposed methodology has been only examined and evaluated for one type of fault (gradual gear tooth damage). More experimental estimations of the approach for other industrial faults such as bearing damage, and shaft damage, could be done.

- More experimental work is needed to further evaluate the sensitivity and reliability of the proposed detection method on a different structure of gearbox system, (e.g. a two stage gearbox) to gain a better understanding of the effect of path transmission on the vibration signal.

- Limited numbers of pattern recognition systems are implemented and greater investigation on optimising pattern recognition systems and performance comparisons are still needed. This could lead to changing the proposed number of SCFs in the designed system.

Appendix A

Data Analysis and Classification Techniques

A.1 Introduction

This chapter describes various data analysis and processing techniques which are used to analyse the sensory signals based on condition of gearbox monitoring system. This chapter also describes pattern recognition techniques used in developing the model including neural networks and the novelty detection classification method. Used methods are briefly described here to give better understanding of the results applied in the following chapters of this thesis.

A.2 Design of Experiment

There are several published articles about performance of condition monitoring and fault detection system on machinery using different parameters such as vibration, speed, torque and acoustic emission to determine healthy and unhealthy conditions (He and Li, 2011; Guan et al., 2005; Wegerich et al., 2003b; Sait and Sharaf-Eldeen, 2011). However, there is still difficulty in determining the most effective parameters which can identify defect in early stages of the fault's development. While a machine is in operation, various signals are produced. These signals can give appropriate information on a machinery condition monitoring and diagnostic system and they usually contain a high ratio of noise. Also, the captured signals are measured arbitrary, thereby leading to redundant data and insignificant information. Therefore, an effective method of design of experiment that should be used to investigate the input signals which have significant impact on the efficiency of output signals.

Design of Experiment (DoE) is a statistical technique employed to investigate the effect of multiple variables simultaneously (Roy, 2001). It is a method used to explore output performance of machinery process. The input parameters are scheduled to levels in order to design a number of structured experiments. These levels have an impact on a predefined output which is then evaluated. The DoE method provides engineers with the ability to identify simultaneously and individually any of the input variables that could influence the output results in any design or plan. The DoE method also gives the extent of interdependence between design elements thereby helping to turn any standard design into a robust one. More so, the DoE method helps to identify the sensitivity of output parameters with respect to the input variables in designs.

For each input variable, a number of levels are defined which represents the range for which the effect of the desired variable is to be known. An experimental plan tells the user where to put each test variables for each run of the test. The output response is then measured for each run. The traditional method of designing experimental work is used to varying one factor and to hold other factors fixed and so on. This method gives unacceptable results in a wide range of experimental settings. If interaction exists between the factors, there is no guarantee that the final set of operating conditions will be at the optimum level. Mehrban et al. (2006) and Box and Meyer (1993) mentioned that the full factorial design methods are powerful tools for determining important factors to improve the system performance. Madu and Kuei (1993) applied the fractional factorial method to analyse the management of maintenance floats. They concluded that it is an efficient tool for analysing system performance.

A.3 Data Analysis Techniques

Signal processing techniques are mathematical methods to deal with the analysis of signals in order to enhance the understanding of information contained in received signals. There are many signal processing techniques and data analysis algorithms in the literature for the diagnostics and prognostics of machines. More investigations are required to choose suitable signal processing tools from a number of possibilities. The most common captured signals in condition monitoring systems are vibration signals and acoustic emissions (Al-Badour et al., 2011). There are three main categories of waveform analysis commonly used in gear condition monitoring systems. These are described in the following sections:

A.3.1 Time Domain Analysis

Time domain analysis is a method used to analyse the data over a given time period. It uses the amplitude of gear vibration signals as the source of time-based information to discover gear damage. 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 (Stevens et al., 2005). Time domain analysis can be considered as a suitable method if observed vibration signals are periodic and defects generate frequencies sideband as a result of periodic impulses. The waveform can be detected in the changes in the vibration signature developed by the defects, however, it is a challenge to identify the source of the defects.

Usually, when a signal is captured by suitable equipment, it is displayed in the time domain; where y axis represents amplitude and x axis represents time. Time-domain analysis is a way of representing or analysing the vibration signal as a function of time. Ordinary time domain analysis attempts to extract characteristic features from raw signals, using descriptive statistical features including Mean, Max, Min and Standard Deviation (STD), Skewness, the Peak Value (PV), RRMS, Kurtosis and CF etc. (Forrester, 1996b; Lebold et al., 2005). The simple statistical evaluation for signals measured can provide valuable information about potential defects. These features are simple to measure, however the disadvantage is that they are sometimes insensitive tools for fault detection. These features are usually called time-domain features (Yesilyurt, 1997).

Most mechanical devices produce high levels of vibrations when in operation. When these devices progressively generate defects, this leads to the level of vibration being raised consistently over time. However, the fault vibration development is often very small and is difficult to recognise. Therefore, if the proportion of this development is negligible, it may not be possible to identify a defect symptom from the differences in the waveform of the signal (Martin et al., 1990).

A.3.2 Frequency Domain Analysis

Frequency domain analysis is considered as common method for vibration analysis and it has been proved as a valuable method for detection and diagnosis of defects in machines (Forrester, 1996a). By applying this technique, the time-domain of sensory signals are converted into their equivalent of frequency components. The result of conversion has shown that the frequency components often contain more useful information about machine conditions than the time domain; because of the complex time-domain signal. Therefore, the signal in time domain can be simplified by disintegrating a signal into several frequency components. It can then be easily analysed and focus on specific frequencies which could be significant and related to fault diagnosis (Tom, 2010). There are different variations of frequency domain analysis most commonly used and these are covered in the following sections.

A.3.2.1 Fast Fourier Transform

Fast Fourier Transform (Fast Fourier Transform) is a common method applied to transfer the raw signal into the frequency domain. This method is widely used for measuring signal which do not fluctuate in spectral content over time (for example no variations in the rotating speed of the machine). When machine run with known and fixed velocity the frequency components of the vibrations generated by each parts in the machine can be expected. Hence, any alteration occurring in the vibration level within a specific frequency band can be associated with a specific part. Analysis of relative vibration levels at different frequency bands can provide some diagnostic information (Walker, 1996).

Variations in particular frequency amplitude of the pulse or sideband can be used as good indicator of possible gear damage. Essentially, the distance of the sidebands relies on periodic attributes of the loading and on the gearbox path. Therefore, it can be hard to obtain valuable features directly from vibration spectrum using only the FFT technique. When the interested signal is low compared to noise ratio and the vibration spectrum contains a large number of frequency components because of the system complexity, it becomes difficult to differentiate between the peaks generated by faults and peaks produced by other system parts. This is the most difficult issue related to the fault detection technique using FFT (Aherwar and Khalid, 2012).

The Fourier transform of a signal $x(t)$ is present as follows:

$$x(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}dt \tag{1}$$

where f is the frequency variable. The spectral density of a signal per unit frequency at a particular frequency f is $|x(f)|^2$, and the total signal energy in the frequency domain can be calculated by summing up the spectral density function over all frequencies. The total energy calculated in both the time and frequency domains is equal that is:

$$\int_{-\infty}^{\infty} |x(t)|^2 \, dt = \int_{-\infty}^{\infty} |x(f)|^2 \, df \tag{2}$$

A.3.2.2 Envelope Spectrum

Envelope spectrum analysis for signals is widely applied in many fields (Ho and Randall, 2000a). If the content of the signal to be extracted is not enough for representing signals of the physical trends a of interest, then the envelope spectrum method can be applied to select information that contains several complex components with different features. The main concept behind the envelope spectrum method is to demodulate low frequency oscillations from higher frequency signals. This method is used to observe the frequency component of the mechanical tools such as gear or bearing faults that have a periodical effect. The peak is produced each time the rolling element has a defect on another part in the bearing or as a damaged tooth in gear smashes with another tooth. This peak has an extremely short period of time compared to the time between two peaks. Using envelop analysis makes it possible to collect signal from the mechanical device with relatively low energy and it hides vibration signals from other mechanical parts (Yen and Lin, 2000). This technique is widely implemented so as to detect early the defects in rotating machinery elements such as gears.

A.3.3 Time-Frequency Domain Analysis

Analysing raw signals in the time and frequency domains offer some information about the characteristics of the signals for each domain separately. This means that, the time-domain signal does not include any spectral information and the time information of converted signal from time-domain to the frequency-domain is lost. So, both domains have their restrictions. Furthermore, it must be taken into account that the limitation of frequency-domain analysis is not able to deal with non-stationary signals, which are very common when machine defects occur.

Currently, widespread research has been performed on the analysis of raw signals in the time-frequency domain by combining both domains (time and frequency) to give a full picture of the signal (Peng and Chu, 2004b). Time-frequency domain are used to represent the energy of waveform signals in both dimensional functions of time and frequency in detail. It has been developed to study non-stationary signals, and an attempt to address the deficiency of time domain and frequency domain analysis. Recently, there have been many type of time-frequency domain such as Short-Time

Fourier Transform (STFT) also called (spectrogram) (Yen and Lin, 2000), Wigner-Ville Distribution (WVD) (Staszewski et al., 1997) and Wavelet Transform (WT). Generally, the main idea of this domain is to split the entire waveform of signal into sections with a short time window and then use a FT to each section.

The fundamental contrast between these techniques is their respective time and frequency resolutions. Wavelets analysis has been considered as the perfect method for diagnosing and monitoring the fault in machines. In comparison with, the STFT technique, the window size is fixed, while the wavelet transform allows flexible window sizes to analyse different frequency components within waveform signals (Forrester, 1989). Therefore, WT is a very reliable technique for analysing transient and non-stationary signals. Abnormal transients generated by early stage gear faults can be detected using discrete and continuous wavelet transformation (Diwakar et al., 2012).

A.3.3.1 Short-Time Fourier Transform

STFT uses a sliding window function $g(t)$ that is placed at the centre of time t. For every t, a time-localised Fourier transform is conducted on $x(t)$ waveform signal within the window. Then, the window is shifted by t along the path of the time, and another FFT step is conducted and so on. Through successive such processes, FFT of the whole waveform signal can be carried out. This assumes that the part of signal within the window function is roughly stationary. As a result, the STFT break down a signal in time domain into a two dimensional time-frequency representation, and the frequency components details of that signal within the window function are discovered. STFT is defined as follows:

$$STFT(\tau, f) = \int_{-\infty}^{\infty} g(t-\tau)x(t)e^{-j2\pi ft}dt \tag{3}$$

where $g(t) = e^{-(\frac{t}{\alpha})^2}$ and α is a constant that defines the width of the window used.

This equation develops the fourier transform of the function $F(t)$ windowed by $g(t)$ centered at time τ. By continuously performing the same analysis at multiple translated locations τs, it is possible to gain signal variations with time.

Time-frequency technique have been applied in many studies for gearbox fault detection. It gives better understanding for analysing signal compared to time and frequency domains. However, the drawback of the STFT method is that the window size remains constant during the entire analysis. This technique is ineffective especially when high resolution is needed to identify surprise changes over time. When the width of the window is chosen it cannot be adjusted during the transform.

In order to obtain a good resolution for both time and frequency domains which cannot be attained concurrently, the selection of window size is performed by a trade-off between the time resolution and the frequency resolution (Cohen, 1989).

Some gear defects can be discovered via checking the energy distribution of a signal $x(t)$ over a time-frequency space. Wang and McFadden (1993a) have demonstrated the application of combined STFT and the Gaussian window function for vibration signal analysis.

A.3.3.2 Wavelet Transform

Wavelet Transform (WT) is a mathematical tool used to decompose raw signals into a different shape, such as a chain of coefficients, in scale of time (Rioul and Duhamel, 1992). WT analyses are considered as appropriate signal processing method for monitoring system and diagnosing faults in machines. By converting a time domain signals into time-frequency space, so it is possible to identify frequency components in the signal and also the time duration of each individual frequency component (Staszewski and Tomlinson, 1994a; Peng and Chu, 2004c). Therefore, The WT is reliable method to examine vibration signals from faulty rotating machines, where either large or small scale changes in the vibration may occur if the defect is distributed or local (Sung et al., 2000). WT is usually utilised to determine all possible transients in vibration signals which are produced by faults in gearbox system. it possess multiple resolutions for localization of short time components, enabling all possible types of gear fault to be displayed by a single time-scale distribution resulting from the transform (Baydar and Ball, 2003). Generally, the wavelet transform can be classified into three techniques: Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT), and Wavelet Packet Transform (WPT).

A.4 Feature Selection Techniques

Feature selection is a very significant field in pattern recognition, statistics, and data mining. The major concept behind this topic is to select the optimal features that can achieve the highest precision results from input parameters whilst removing useless information which does not affect the characteristics of the input variable (Gharavian et al., 2013). Feature selection can considerably improve the accuracy of the resulting classification model. The feature selections mentioned below are used in our study.

A.4.1 Peak Value

Peak value is defined as the maximum vibration amplitude (Goh, 1995):

$$PV = x_{max}(t) \tag{4}$$

where $x_{max}(t)$ is maximum amplitude of the signal $x(t)$.

A.4.2 The Root Mean Square

The Root Mean Square (RMS) also known as the quadratic mean is the measurement of the power content in the vibration signal. The RMS considers features in time domain analysis. This feature is used to handle the overall noise level, however it will not give information on which element is deteriorating. It can be used effectively to detect some faults in rotating systems (Goh, 1995). Consider a signal $x = x_1, x_2, x_3, \cdots\cdots, x_M$ with length M, the following is the equation for calculating the root mean square:

$$RMS = \sqrt{\frac{1}{M}(x_1^2 + x_2^2 + x_3^2 + \cdots\cdots + x_M^2)} = \sqrt{\frac{1}{M}\sum_{i=1}^{M} x_i^2} \tag{5}$$

where; M is the number of samples ; $x(M)$ is the amplitude of the signal for the Mth sample; x is the mean value of the M samples.

RMS is the most common approach in vibration analysis for gearbox condition monitoring. Its working is based on the measurement of the overall intensity of a wide-band vibration, and calculates an averaging effect which reduces the influence of incidental impulse vibration.

A.4.3 Standard Deviation

Standard Deviation (STD), and variance are numerical measurements of distribution of the signal samples set from mean. A minimum STD shows that the data points are very close to the average, whereas high STD indicates that the data points are far apart from the average (Goh, 1995). The standard deviation is the RMS of the signal without the mean value component. The STD is defined as:

$$STD = \sigma^2 = \frac{1}{M}\sum_{i=1}^{M}(y_i - \bar{y})^2 \tag{6}$$

where $\bar{x}$ is the mean. To calculate the variance, we simply use the following expression.

$$\sigma = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(x_i - \bar{x})^2} \tag{7}$$

A.4.4 Crest Factor

The Crest Factor (CF) is computed by dividing the maximum positive peak value by the RMS value of signal. CF analysis is normally used on the raw vibration signal. It is suitable method to detect the alteration in the signal waveform pattern as result of impulsive vibration sources such as broken tooth in the gear (Goh, 1995).

$$CF = \frac{|x|_{peak}}{x_{RMS}} \tag{8}$$

A.4.5 Kurtosis

In the probability theory Kurtosis is known as a mathematical measurement, used to identify distributing data whether it is in its steady state or peaked relative to a natural distribution. Data with high kurtosis is distinguishable with a peak around the mean, and a rapid decrease to the normal. Data with a low Kurtosis is distinguished by a constant level close to the mean rather than a spike (Hadjileontiadis and Douka, 2007a). The normalised kurtosis for distribution $y(t)$ is given by its sample values

$x_i, \cdots, x_M$ is measured at times $t_i, \cdots, t_M$ and can be defined as:

$$Kurtosis = \frac{\frac{1}{M}\sum_{i=1}^{M}(x_i - \bar{x})^4}{(\frac{1}{M}\sum_{i=1}^{M}(x_i - \bar{x})^2)^2} \tag{9}$$

A.4.6 Spectral Kurtosis

Spectral Kurtosis (KS) was presented initially by Dwyer (1984), to detect transient signals in sonar applications (Antoni, 2006). Lately, it was reused as a new method in the signal processing for differentiating between different types of signals. It is defined as a statistical parameter which has the ability to show the spike of a signal with their positions with varying frequency. SK is the value showing how peak signals changes with frequency, and it is utilised as a signal characterisation in the spectrum. The fault pattern waveform changes and produces sequence of short spiked reactions when the mechanical part is deteriorating. Therefore, the SK can be used as a reliable method for detecting frequencies exposed by machine defects. Usually these frequency components contain useful fault information. This information is required to extract optimum frequency value using the SK method to obtain useful feature representing the nature of the fault. It can be revealed that the FFT spectrum of faulty bearings contains tiny diagnostic fault information, whereas the spectral components obtained by SK contain the required information about the impacts of repetition frequency (Hadjileontiadis and Douka, 2007b).

A.5 Automated Sensitivity Detection

A.5.1 Taguchi's Based Orthogonal Arrays

Taguchi's method is used in experimental work to minimise the number of experiments required to optimise process quality (Ranjit, 1990). Instead of using a full factorial experimental method where one factor is changing at each run, Taguchi's method uses a lower number of experiments to predict the best quality levels of each factor and to calculate the most significant factors in an experiment. The Taguchi method implements specially constructed tables known as Orthogonal Arrays (OAs). The use of these tables makes the design of experiments easy and consistent particularly when applied to experiments with a high number of variables (or factors in Taguchi's terms). A full factorial design will identify all possible combinations for a given set of factors. Since most industrial experiments usually involve a significant number of factors, a full factorial design results in a large number of experiments.

Taguchis approach complements two important areas. First, it defines a set of OAs, each of which can be used for many experiments. Second, it provides a standard method for analysis of the results.

A.5.2 Principal Component Analysis

Principal Component Analysis (PCA) is a multivariate statistical technique applied to reduce the number of variables in a data set into a smaller number of dimensions. In mathematical terms, from an initial set of n correlated variables, PCA creates uncorrelated indices or components, where each component is a linear weighted combination of the initial variables. For example, from a set of variables $x_1, x_1, x_1 \cdots\cdot, x_n$ Principal Component Analysis, and more specifically Factor Analysis groups together individual indicators which are collinear to form a composite indicator that captures as much as possible of the information common to individual indicators. Each factor (usually estimated using PCA) reveals the set of indicators with which it has the strongest association. The idea behind PCA and FA is to account for the highest possible variation in the indicator set using the smallest possible number of factors (He et al., 2007).

The formula for covariance can be defined as follows:

$$cov(x, y) = \frac{\sum_{i-1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{n-1} \tag{10}$$

The covariance matrix $cov(X, Y)$ is a squared matrix, therefore it is possible to calculate the eigenvalue and eigenvector as it will indicate the useful information about the effect of each variable on the data. Eigenvector, v, is a non-zero vector that after multiplying by the matrix, remain parallel to the original vector. For each eigenvector, there is corresponding eigenvalue, λ, which is a factor or real number to scale the eigenvector when multiplied by the matrix as shown on Equation 10. In other words, the eigenvalue will define the length of the variable of the raw data. It is possible to measure the eigenvalue by the following equation:

$$[cov(x,y)][v] = \lambda[v] \tag{11}$$

For the purpose of measuring the significance of the sensor in current research, eigenvalue will be used to evaluate the important of each sensor. The theory is based on the discussion represented in Section .

A.5.3 Linear Regression Analysis

Linear Regression (LR) is used to find the linear equation which best represents the linear relationship between two variables. The first variable is the independent variable which could be the degree of tool wear, etc. The second variable is the dependent variable which is a sensory characteristic feature that changes according to the change in the independent variable. The line is obtained by using the least squares straight line fitting. The least squares line is defined as (Gharavian et al., 2013):

$$y = \alpha x + \beta \tag{12}$$

where α and β are given by:

$$\alpha = \frac{M\sum_{i=1}^{M} x_i y_i - \sum_{i=1}^{MM} x_i \sum_{i=1}^{M} y_i}{M\sum_{i=1}^{M} x_i^2 - \left(\sum_{i=1}^{M} x_i\right)^2} \tag{13}$$

$$\beta = \frac{1}{M}\left(\sum_{i=1}^{M} y_i - \alpha \sum_{i=1}^{M} x_i\right) \tag{14}$$

A.6 Computational Intelligence Classifying Methods

Many researchers have introduced various computational intelligence techniques including FRBS and ANN models to classify the complex, non-linear data. The following sections a review of relevant techniques in classification are presented :

A.6.1 Fuzzy Rule Based System

Fuzzy Rule Based System (FRBS) is a particular area of concentration in the investigation of artificial intelligence and is constructed on the value of that data which is neither absolutely true nor false (Buragohain and Mahanta, 2008). The data which operators use in their everyday lives to base natural decisions and apply general rules of practical information can and should be applied to those control situations which demand them. Developed knowledge can be a great way to avoid the unwanted effects of the system reaction. In the current research, fuzzy logic will be used to implement the controlling of the sensitivity measuring method to select the most sensitive feature. A fuzzy logic model with its fundamental input-output relationship consists of four components namely, the fuzzifier, the inference engine, the defuzzifier, and a fuzzy rule base as In the fuzzifier, inputs are fuzzified into linguistic values to be associated to the input linguistic variables. After fuzzification, the inference engine refers to the fuzzy rule base containing fuzzy IF-THEN rules to derive the linguistic values for the intermediate and output linguistic variables (Khoo et al., 2000). Once the output linguistic values are available, the defuzzifier produces the final values from the output linguistic values.

A.6.2 Neural Networks

An Artificial Neural Network (ANN) is a soft computing methods that mimic the human neurons. It contains input, output and a number of hidden layers interconnected with each other. The layers consist of nodes (neurons) and weights. The model structure is somewhat a non-linear function with multiple input and output. The ANN learns the unidentified function by regulating its weights with monitoring of input and output. This procedure is usually named training stage of ANN. There are numerous neural network mode is, have produced based on required applications. The Feed Forward Neural Network (FFNN) is the most commonly applied ANN construction in machine fault diagnosis (Hajnayeb et al., 2011a; Saravanan and Ramachandran, 2010). An example of a general structure of feed forward neural network is shown in Figure A.1.

The application of ANNs in condition monitoring have received a great deal of attention from researchers. In one of condition monitoring system stages; ANN are dealing with huge information to define the status of machine. ANN can also be considered as an effective data analyser for pattern

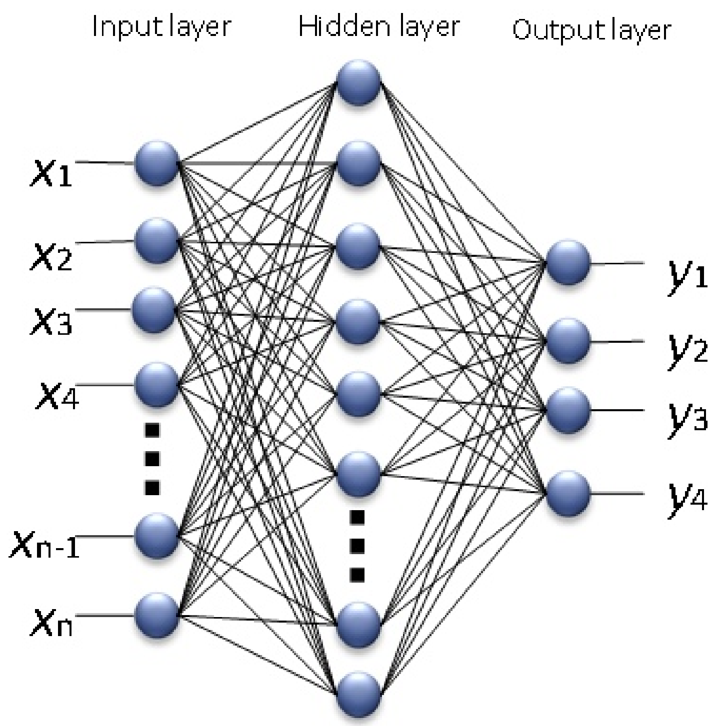


Figure A.1: Structure of feed forward neural networks.

recognition and classification method in condition monitoring systems (Li et al., 2011). The main advantage of using ANNs is the full automation of the learning and classification processes.

A.6.3 Structure of Applied Neural Networks

Many different neural networks structures have been established to achieve different learning and processing speed capabilities. Neural networks are categorised into groups supervised and unsupervised in terms of their learning characteristics. The decision is greatly dependent on the data obtainable from training the networks. If there is a target class or output for each pattern. Then a supervised neural networks can be used (Rojas et al., 2008). However, when the input data do not have target output specified previously, then unsupervised neural networks have to be implemented. Unsupervised neural networks such as competitive neural networks use a special algorithm to group similar patterns in the input data space into similar output classes. The reasons behind using unsupervised neural networks, is to compare the results obtained with other results obtained for the same system by using supervised neural networks.

In this thesis four types of neutral networks are used to test the proposed approach for more details see Chapter 7.

1. Back Propagation Neural networks (PB)(Supervised)
2. Radial Basis Neural Networks (RB)(Supervised)
3. Competitive Neural Networks (CN) (Unsupervised)
4. Learning Vector Quantisation (LVQ) (Unsupervised)

The neutral networks parameters are selected from experience to provide only an convenient performance to compare designed systems and not to assess the absolute performance of a system. A brief description of four neural networks have been used as presented in following section.

A.6.3.1 Back-Propagation Neural Networks

A back-propagation neural networks is a supervised neural networks which consist of n number of neurons connected together to form an input layers, hidden layers and an output layer. A basic back-propagation computational

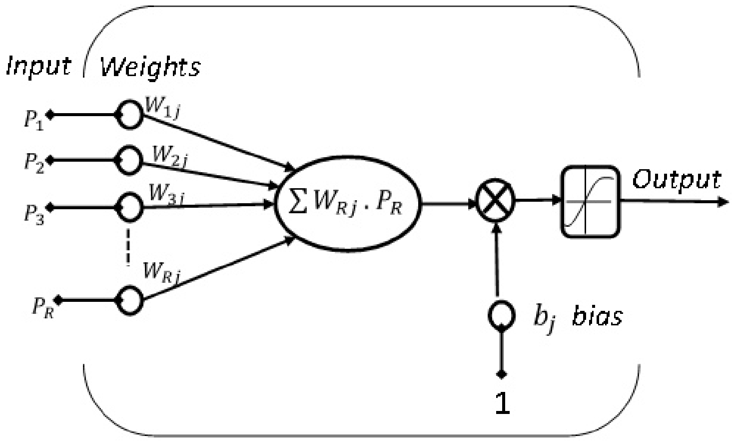


Figure A.2: The neuron of back propagation neural networks.

element is illustrated in Figure A.2. The node or neuron can have several inputs but only one output.

The back-propagation neural network used in this thesis uses a sigmoid function in the hidden layer and a liner function in the output layer respectively.

$$\mu(n_j) = \frac{1}{1 + e^{-n_j}} \tag{15}$$

The most important characteristic of neural networks is its ability to learn or to be trained. The training or learning process can be defined as a change in connection weight values that result in the capture of information that can later be called the supervised training which is done by iteratively adjusting the weights to minimise the error between the output and the target.

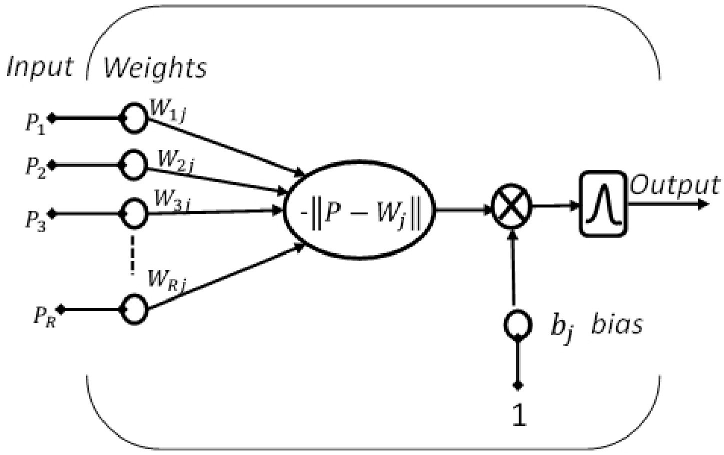


Figure A.3: The neuron of radial basis neural networks.

A.6.3.2 Radial Basis Neural Networks

A Radial Basis neural network is a supervised neural network which normally needs less time for training. The radial basis neural network consists of an input layer, a hidden radial basis layer and a linear output layer. The difference between the back propagation and the radial basis neural network is in the radial basis neuron structure shown in Figure A.3.

A.6.3.3 Competitive Neural Networks

A competitive neural is an unsupervised neural network which uses Associative Learning Rules which allow the network to learn the association between the inputs and outputs in response to the data presented to them. Competitive neural networks belongs to self-organising neural networks where such networks can learn to detect regularities and correlation in their inputs and adapt their future responses according to that input. A competitive neural network basically learns to recognise similar input

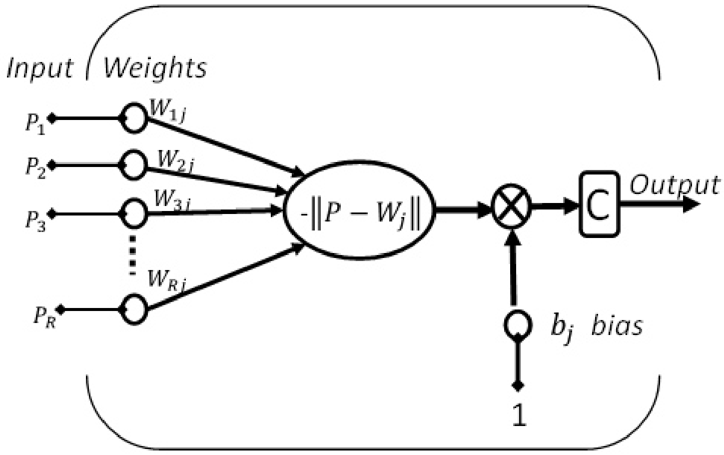


Figure A.4: The neuron of competitive neural networks.

vectors and to categorise in one group.

The neuron of a competitive neural networks in shown in Figure A.4. The input vector to the competitive layer is obtained by the negative distance between input vector p and the Weight vector w adding the bias b for any layer, the neurons are in competitive, all the output of the neuron will be zero, except the winner neuron, which its output will be one. When the weight w of a neuron is the closest to the input vector p, it will have least negative input and therefore it will win the competition and its output will equal to 1. The user has to choose the length of the input vector and the number of groups and then network will group the inputs according and to the required groups. The competitive neural networks used in this thesis has three groups and learning rate of 0.1 and 500 training iterations. More details about competitive neural networks can be found in (Hajnayeb et al., 2011b),

A.6.3.4 Learning Vector Quantisation

The advantage of using Learning Vector Quantisation (LVQ) is that it learns to classify input vectors into target classes chosen by the user. However, the learning rules are done according to the competitive layers depending on the distance between the input vectors and the weight and not according to the error between the output and target dissimilar to back propagation neural networks. Hence, there is no mechanism in the network to dictate whether or not any two input vector belong to the same category. The LVQ has an input layer, a competitive layer, and a linear output layer. The competitive layer learns to classify the input vectors to subclasses while the output linear layer transforms the competitive subclasses into the desired target classes . More information about LVQ can be found in (Saravanan and Ramachandran, 2010).

A.7 Discussions

This chapter explained the theoretical basis of conventional diagnostic methods based on gear condition and sensory signals to assist the understanding of results presented in the following chapters. Briefly, it has discussed the state-of-the-art data processing techniques that are commonly used in the area of gear fault detection and diagnosis which includes, time domain, frequency domain and time-frequency domain. The use of time-frequency analysis such as wavelet transformation was established when analysing sensory data from complex machines such as gearbox as this domain provides better results for non-stationary signals as vibrations generated by gear impacts. Moreover, brief theoretical of feature selection techniques are discussed. Finally a overview of pattern recognition and classification models were discussed which will be employed in this research study.

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