DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

SMART MONITORING OF WORM GEARS

by
Berkan HIZARCI

August, 2016
İZMİR

SMART MONITORING OF WORM GEARS

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by
Berkan HIZARCI

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M. Sc THESIS EXAMINATION RESULT FORM

We have read the thesis entitled "**SMART MONITORING OF WORM GEARS**" completed by **BERKAN HIZARCI** under supervision of **PROF.DR. ZEKİ KIRAL** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

....

Prof. Dr. Zeki KIRAL

Supervisor

....

Assoc.Prof.Dr. Hasan ÖZTÜRK

Jury Member

Asist.Prof.Dr. Savaş ŞAHİN

Jury Member

Prof. Dr. Ayşe OKUR

Director

Graduate School of Natural and Applied Science

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SMART MONITORING OF WORM GEARS

ABSTRACT

Worm gearboxes are commonly used in many various fields of industrial applications such as escalators, presses, conveyors etc. However, heavy industries face important problems about this type of gears due to unexpected failures. These failures, for instance pitting, wear and tooth breakage, cause so many problems such as waste of time, outages and damages on human health. The vibration signal of a gearbox carries the signature of the fault. Hence, vibration measurement and its graphical representation play an important role for analysis of physical conditions of gearboxes. Although there are many options for vibration measurement systems, cost effective and portable microcontrollers based monitoring system is a good option.

This thesis focuses on monitoring condition of worm gearbox via a developed smart device and the detection of pitting damages which have been realistically simulated on a few tooth surfaces. For this purpose, smart monitoring device has been developed via STM32 platform with ARM Cortex M4 microcontroller. Data acquisition system, various vibration analysis techniques, fault detection and visualization have been investigated and integrated in one system. Measurement of angular velocity of shaft, real time monitoring of vibration signal, time synchronous average, fast Fourier transform and statistical metric analysis have been carried out with developed monitoring device. The results of vibration analysis have been visualized on the screen and vibration data has been transferred into memory stick.

Moreover, dynamic squared error, image processing based fault detection and support vector machine based pattern recognition method have been applied on vibration data acquired from worm gearbox for better explanation of effects of pitting failures.

Keywords: Worm gear, vibration, smart monitoring, microcontroller, fault detection.

SONSUZ DİŞLİLERİN AKILLI İZLEMESİ

ÖZ

Sonsuz dişli kutuları yürüyen merdivenler, presler, konveyörler v.b. gibi endüstriyel uygulamaların çok değişik alanlarında yaygın olarak kullanılmaktadır. Ancak, ağır sanayi bu tür dişli kutuları hakkında beklenmeyen hatalar yüzünden önemli problemler ile karşı karşıya kalmaktadır. Bu hatalar, örneğin çukurlaşma, aşınma ve dişli kırılması, zaman kaybı, zafiyat ve insan sağlığında hasarlar gibi pek çok sorunlara neden olmaktadır. Bir dişli kutusunun titreşim sinyali arızanın imzasını taşır. Bu nedenle, titreşim ölçümü ve grafiksel gösterimi dişli kutularının fiziksel durum analizinde önemli bir rol oynar. Titreşim ölçüm sistemleri için birçok seçenek olmasına rağmen, maliyet olarak efektif ve taşınabilir mikrodenetleyici tabanlı izleme sistemi iyi bir seçenektir.

Bu tez geliştirilen akıllı cihaz aracılığıyla sonsuz dişli kutularının durumunun izlenmesi ve bir kaç diş yüzeyinde gerçekçi olarak benzeri yapılan çukurlaşma hatalarının tespiti üzerine odaklanmaktadır. Bu amaçla, akıllı izleme cihazı ARM Cortex M4 mikrodenetleyici ile STM32 platformu üzerinden geliştirilmiştir. Veri toplama sistemi, çeşitli titreşim analiz teknikleri, arıza tespit ve görüntüleme konuları incelenmiş ve bir sistemde birleştirilmiştir. Milin açısal hız ölçümü, titreşim sinyalin gerçek zamanlı izlenmesi, zamanla senkron ortalama, hızlı Fourier dönüşümü, ve istatistiksel metrik analizi geliştirilmiş izleme cihazı ile yapılmıştır. Titreşim analizi sonuçları ekran üzerinden görselleştirilmiş ve titreşim verisi hafıza ünitesine transfer edilmiştir.

Ayrıca, çukurlaşma hatalarının etkilerini daha iyi açıklamak için dinamik karesel hata, görüntü işleme tabanlı arıza tespiti ve destekçi vektör makineleri tabanlı örüntü tanıma metodu sonsuz dişli kutusundan alınan titreşim verilerine uygulanmıştır.

Anahtar kelimeler: Sonsuz dişli, titreşim, akıllı izleme, mikrodenetleyici, hata tespiti.

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CHAPTER ONE
INTRODUCTION

1.1 Introduction

Gears are the vital parts of many machines and systems. They help to increase or decrease output torque and the velocity of machines. They also change the direction of rotation. One of the types of gears is worm gear, which is used in case of a large reduction of speed between driving and driven shafts with a proportional increase in the torque of the driven shaft. Worm gears can be found in devices from home to heavy machinery. For instance, they are used in many systems such as guitars, presses, rolling mills, conveyors, elevators, mining industry machines, escalators, helicopters, wind turbines and so on. Thus, their unexpected failures cause many problems such as waste of time, outages, damages on human health etc. Moreover, industrial companies face important problems about this type of gears due to undetected failures.

Predictive maintenance (PdM) helps to determine the condition of equipment. In this type of maintenance, deterioration of equipment is detected before a significant degradation occurs in component. A large amount of research has been carried out into the condition monitoring of gearboxes, but it is a fact that study of worm gearboxes has not been studied in depth. Most of the researchers investigate condition monitoring of other gearbox types, bearing faults or vibration of motors. There is limited number of publications about the condition monitoring of worm gearboxes because of difficulties in analysis of worm gear vibration. Unlike the other type of gearboxes where defects cause periodic impacts around the gear mesh frequencies (Rao, 1996; Alan, 1998), such distinctive symptom is not obvious for worm gearbox because of sliding interactions between worm and wheel gears (Vahaoja, Lahdelma & Leinonen, 2006). Briefly, the geometrical properties of worm thread profile cause difficulties about fault diagnosis of worm gearboxes.

Vibration signals measured at the external surface of a gearbox provide information about the performance, efficiency, reliability and life of machine. By diagnosing the health of a worm gearbox, unscheduled machinery outages and costly damaged can be avoided. The vibration signal of a gearbox carries the signature of the fault. Hence, vibration measurement and graphical representation plays an important role for analysis of physical conditions of gearboxes. This kind of fault diagnosis system generally adopts PC as processing platform. Vibration signal acquisition by using PC requires expert knowledge, manual operation and complex data transmission equipments. Although this type of vibration measurement system are used more often, cost effective and portable microcontroller based monitoring system is a better option. This thesis aims to develop a kind of worm gearbox fault detection system based on low cost microcontroller. It can be run independent of a PC.

The main contribution of this study is development of vibration data acquisition and gearbox fault detection system based on the STM32 platform with ARM technology. Data acquisition, signal processing, analysis, and visualization of results are integrated in one system. In present work, analog vibration signal is acquired from the worm gearbox and convert into analog voltage signal by means of accelerometer sensor. This voltage level is normally in millivolt, which has to be isolated and amplified before inputting to the analog to digital converter unit. The signal conditioning unit isolates and amplifies the m-volts signal from accelerometer sensor. Sensor’s output signal has both positive and also negative voltages. It changes with direction of acceleration. Thus, to measure positive-negative voltages, external bipolar analog to digital converter (ADC) has to be used. The vibration signal is then converted from continuous time analog signal to discrete time digital signal by ADC for subsequent signal processing. STM32F429ZI series high performance ARM Cortex 32 bit RISC core microcontroller is used here for implementation of advanced signal analysis methods, such as Time Synchronous Average (TSA), statistical indexes, Fast Fourier Transformation (FFT). After the signal analysis is completed, the chosen characteristics of measured signal are compared with those of reference healthy model of worm gearbox's signal. Results of vibration analysis are displayed by TFT screen and stored in USB memory stick.

Finally, fault detection methods and pattern recognition techniques are applied with using vibration data which is acquired by developed smart condition monitoring device.

1.2 Problem Statement

The worm gears consist of two components called worm screw gear and wheel gear. The wheel gear is similar to helical gear, with the only difference being that the top of the teeth curves inwards to envelope the worm screw gear. As a result, the worm screw slides rather than rolls. Moreover, the surface of the wheel gear is generally softer than that of the worm screw gear (Black, 2014). That's why; the wheel gear can be wear during the sliding process. Furthermore, failures on wheel gear tend to occur when a gear is working under high stress conditions, lack of lubrication, contaminated lubrication, long operation at high load, higher temperature, etc. If they aren't detected at early stage, there can be dramatic consequences such as pitting, wear, tooth breakage etc.

1.3 Motivation

Gears are used in almost all power transmission systems. Besides, condition monitoring based on vibration signal analysis have been developed dramatically so far. A large amount of research has been carried out on the condition monitoring of gearboxes, but it is a fact that there is seldom published research for condition assessment of worm gearbox due to the challenges of analysis of worm gearbox vibration. The vibration analysis has difficulties to apply to worm gearboxes. Distinctive defect symptoms such as peak at gear mesh frequencies on the frequency spectrum are not obvious for the worm gearbox because of the sliding motion. Thus, the choice of study with worm gearbox was deliberate for this thesis.

1.4 Literature Survey

Today, vibration measurement and its analysis are often required for assessment of physical conditions of gearboxes. Gear failures such as inadequate lubrication, fatigue pitting, heat cracking, higher loading etc. cause vibration of mechanical equipment that is interpreted absolutely not good. These harmful vibrations are the symptoms of the failure. Vibrations caused by failures need to be identified and corrected.

For this purpose, many researchers have been studied on this topic. They implement various vibration analysis techniques in order to detect and diagnose faults within mechanical equipments. For instance, time domain analysis such as peak to peak value, root mean square, kurtosis, crest factor etc., frequency domain analysis such as fast Fourier transform, envelope analysis etc., time frequency analysis such as wavelet, atomic decomposition etc. are the most common vibration analysis methods that have been studied. Worm gearboxes are generally used for many important applications, but due to their unique property, that is sliding contact between worm and wheel, fault diagnosis of worm gearboxes is a challenging issue. Consequently, the literature on this topic is relatively scarce.

Smart condition monitoring of machinery equipment are widely used in almost all industries with applications in automation and predictive maintenance. The real time monitoring of machinery is an advanced technique that determine the conditions of failure. Over the past few years, there has been a major technological developments related to digital system, including hardware and software. These innovations enable to design new smart systems that are used in condition monitoring field. Embedded systems, microcontroller, FPGA, DSP etc. are devoted to vibration analysis for fault detection and diagnosis in rotating machines.

In this literature review, research in worm gearboxes, analysis techniques of vibration signals, smart data acquisition systems and pattern recognition techniques have been mentioned.

Jamaludin, Mba & Bannister (2001) summarized the limitations in applying vibration analysis to slow rotating machines. For slow speeds, the energy generated from the machines might have not showed as an obvious change in vibration. Thus, it causes undetectable failure using conventional vibration analysis.

Peng & Kessissoglou (2003) diagnosed faults in a worm gearbox using combined the oil and vibration analysis. The focus on the study was to develop an integrated approach to fault diagnosis using both wear debris analysis of gear oil and vibration analysis. By comparing the results of two techniques, more reliable assessment of the condition of worm gearboxes tried to make. Peng et al. concluded that oil analysis is a useful method for the detection of gear wear. They also remarked that the vibration analysis of worm gearbox is more appropriate for identifying bearing failures. It was shown that, for increasing wear, the velocity-frequency spectrum is offset from the baseline. This interpreted as an indication of wear failure in worm gearbox.

Acoustic emission analysis for worm gearbox was implemented by Elforjani, Mba, Muhammad & Sire (2012). In this work, they investigated condition of worm gearbox under different shaft speeds and load conditions using acoustic emission and vibration root mean square (R.M.S.) value. They stated that there was no increase in vibration levels for either the large or small defect, but acoustic emission technique is well suited for detecting small energy release rates.

Elasha, Ruiz-Carcel, Mba, Kiat, Nze & Yebra (2014) studied about pitting detection in worm gearboxes with vibration analysis. Gearbox vibration measurements were undertaken on three operational escalator worm gearboxes. They used statistical metrics, FM4, envelope analysis and spectral kurtosis for vibration analysis techniques. To aid diagnosis, vibration measurement was taken all three directions and all characteristic vibration frequencies were determined. Elasha et al. specified that parallel to wheel shaft axis is most sensitive direction of vibration measurement for fault diagnosis of worm gearbox. In this study, distinctive harmonics of worm shaft frequency were observed in the frequency spectrum. It was interpreted the presence of pitting damage.

Vahaoja, Lahdelma & Leionen (2006) experimented on worm gearboxes in cover machines worked for cable manufacturing and talc production. Four similar machines, some of which had failures, were compared with each other in order to point out similarities and dissimilarity. They examined failures in worm gearboxes by means of vibration analysis and wear metal analysis of oil. They measured vibration signal though one direction which was the contact point of the worm gear and the wheel gear. They stated that the impacts caused by gear faults occurred occasionally. There were no periodic impacts in the time domain signals as usual other types of gears. These impacts also were slightly damped because of the behavior of these gearboxes. Thus, they concluded that it was not easy, but not impossible, to determine faults in worm gearboxes via vibration analysis.

Flores, Cardoso & Carvalho (2008) developed a predictive maintenance system using motor current signature analysis (MCSA), to diagnose mechanical faults in a worm gearbox of building elevator system. For safer people transportation, elevator failures must be detected as soon as possible. Results of their experimental study showed that this technique can contribute to an effective predictive maintenance for safety transportation with elevators.

Researchers have applied various vibration analysis techniques in order to diagnose faults within gearboxes.

Baydar & Ball (2001) are used Wigner-Ville distribution method in order to detect gear failures. They investigated acoustic and vibration signals of a gearbox for detection of three types of progressive local faults, broken tooth, gear crack and localized wear. The results show that the Wigner-Ville distribution method is powerful technique to detect faults in gearbox.

Baydar, Chen, Ball & Kruger (2001) investigated detection of incipient tooth defect in helical gears using multivariate statistics. Multivariate statistics techniques detect disturbances and provide diagnostic information. This study bases on principal component analysis (PCA), squared prediction error (SPE), Q and T^2 statistics. They detect abnormalities on gear tooth with multivariate statistics.

Baydar & Ball (2003) were applied wavelet transform for both acoustic and vibration signals in order to detect of gear failures. The difference from other studies is that this study examines both acoustic and vibrations signals using the wavelet transform. In this study, they emphasized success of wavelet transform for detection of failure in gearboxes. They stated that the wavelet is more efficient technique for both vibration and acoustic signals. Even though both the acoustic and vibration signals provided reliable diagnostic information, the vibration signals seemed to outperform in terms of early fault detection.

Feng & Chu (2007) applied atomic decomposition to gear damage detection. This method can represent arbitrary signals very well. Atomic decomposition methods, including method of frames (MOF), best orthogonal basis (BOB), matching pursuit (MP) and basis pursuit (BP), were used in the analysis of vibration signals from both healthy and faulty gearbox in order to extract the transient features of gear vibration. The gear tooth damage is detected easily according to the periodic impulses. They found that atomic decomposition is more effective method by comparing with traditional signal analysis methods such as Fourier transform, continuous wavelet transform and so on.

For smart condition monitoring systems for vibration analysis, researchers benefit from high speed microcontrollers. But, this type of solution requires adapting complex signal processing algorithms to the limited computing resources of microcontroller. For this purpose, up to date, they have used DSP, FPGA, etc.

Zhang & Chen (2008) studied in condition monitoring of CNC milling machine tool subject. Their aims were to enhance the quality, productivity of machined products and reduce the machining cost by detecting tool failures. For this purpose, Zhang et al. used signal conditioning circuit, microcontroller board and PC. The tool vibration signals came from three axes accelerometers was amplified by signal conditioning unit, and then measured by data acquisition board. This data sent from board to PC because of decision making and visualization of results.

Betta, Liguori, Paolillo & Pietrosanto (2002) developed measurement and diagnosis system for detection faults of asynchronous AC motor using DSP. They used two concurrent DSP to be analyzed vibration signals in real time. The implementation consists of a pattern matching procedure, which detects the faults by comparing faulty and good condition machine. Betta et al. analyzed vibration signals in the frequency domain, evaluated the characteristics of its spectrum.

Saraf & Holmukhe (2012) designed low cost and effective system based microcontroller for real monitoring vibrations of D.C. motor. Their study involves circuit design of signal conditioning unit, hardware modifications, PCB fabrications and software design. They used AT89C51 microcontroller. Personal computer was used to display and store results.

Merendino, Pieracci, Lanzoni & Ricco (2011) presented a new microcontroller-based embedded system devoted to vibration analysis for fault diagnosis in rotating machine. The developed system was based on advanced spectra methods, such as Wavelet and Fourier Transform. Suitable algorithms developed to run on a microcontroller for such complex methods in spite of limited computing resources. Merendino et al. used ARM9 STR912F44 microcontroller with a suitable MEMS accelerometers. Their study is shown that the microcontroller based vibration measurement system is capable of real time operational for effective fault detection and diagnosis.

Kashiwagi, Costa & Mathias (2012) developed of diagnostic system for rolling bearing faults based on FPGA. A real time measurement, analysis, modeling and simulation based in FPGA were presented. FPGA provides high DSP performance for analysis of vibration. The study includes MATLAB/SIMULINK simulation software.

Djajadi, Azasi, Rusyadi & Sinaga (2011) studied about monitoring vibration of a model of rotating machine. They attempted to detect unbalance condition of rotating machine. The Memsic 2125 accelerometer and Atmega 8535 microcontroller are used as a data acquired system. The acceleration data sent to personal computer in order to visualize on screen.

Zhang & Kang (2013) designed the data acquisition system based on STM32. They gave the whole design scheme of system and the multi-channel vibration signal in axis X, Y and Z of the rotary shaft, acquired rapidly and displayed in real-time.

The pattern recognition and classification of mechanical faults are commonly applied techniques for understanding condition of machine. There are many studies about this subject.

Jack & Nandi (2000) examined support vector machine (SVM) for detection and characterization of rolling element bearing faults. They found that the SVM algorithm shows good performance for fault diagnosis of rolling element bearings with limited training data.

Samanta & Al-Balushi (2003) presented artificial neural networks (ANN) based fault diagnosis of rolling element bearings using time domain features. They used the characteristic features of time domain vibrations signals of the rotating machinery with normal and faulty bearings as an ANN inputs. Their results showed the effectiveness of the ANN in diagnosis of the machine condition. They achieved significant performance results, more than 80%, in separation of healthy and normal condition of rolling bearing.

Samanta, Al-Balushi & Al-Araimi (2003) introduced ANN and SVM with genetic algorithm for bearing fault detection. In this study, they used two different classifiers, ANN and SVM, for bearing fault detection. For the feature extraction, the time domain vibration signals of rotating machine were used. Classifiers were trained with some part of experimental data for known machine conditions, and testing using the remaining set of data. The results of two classifiers methods were compared with regard to performance. The performance of SVM had been found to be better than ANN.

Samanta (2004) investigated gear fault detection using ANN and SVM with genetic algorithms. In this study, Samanta attempted to detect faulty gear condition by extracting features of time domain vibration signals with normal and defective gears. The roles of different vibration signals, obtained under both normal and light loads and at low and high sampling rates, had been investigated. For SVM with six features, 100% classification success was achieved in all test cases.

1.5 Objective of Thesis

This study attempts to identify presence of defects within the worm gearboxes with smart monitoring and also find to the most appropriate vibration signal processing technique for this.

The work plan and objectives for this research are:

- Review the literature about fault diagnosis of worm gearboxes. Assessment of commonly used suitable vibration analysis techniques in terms of gearbox fault detection.
- Review the literature about smart condition monitoring. Investigation of smart condition monitoring techniques and devices.
- Learning structure of worm gearboxes: their types and applications. Specification of forces acting on it between worm gear and wheel gear to help understand the vibration signal characteristics.
- Decision on the equipments of experimental setup and their features
- Design of solid modeling of experimental setup and manufacture.
- Making a decision of suitable smart condition devices for detection of worm gearbox faults via vibration analysis.

- Decision of suitable vibration analysis techniques for detection and diagnostic of worm gearbox faults.
- Development and electronic design of data acquisition system and PCB design.
- Measurement the rotating velocity of worm gearbox, vibration data acquisition and implementation of vibration analysis techniques on proposed smart condition monitoring device.
- Implementation of simulated pits on wheel gear for pitting faults of worm gearbox.
- Vibration data acquisition and analysis with faulty worm gearbox.
- Comparison results of healthy and faulty cases and visualization of results.
- The various fault detection techniques are employed on vibration data acquired by developed smart condition device.
- Pattern recognition and classification of faulty and healthy gearbox.

CHAPTER TWO
WORM GEARBOXES

2.1 Worm Gearbox

Worm gears are very old gear type. Its history begins with the First Punic Wars, 264 BC. The first worm gear used for lifting giant warships in shipyards. Archimedes developed a revolutionary crane that made lifting possible (Dudas, 2005). He was the first inventor of worm drive, which can be seen in Figure 2.1.

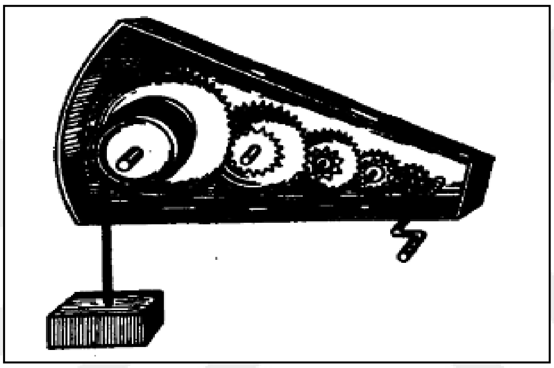


Figure 2.1The first worm gear, Archimedian barulkon (Dudas, 2005)

The first technical worm gear drawings were made by Leonardo da Vinci, can be shown in Figure 2.2. In early application, the Boulton and Watt factory in England manufactured worm gear drive with wooden teeth. After that, the wooden teeth were replaced by iron ones because of mechanical requirements (Dudas, 2005).

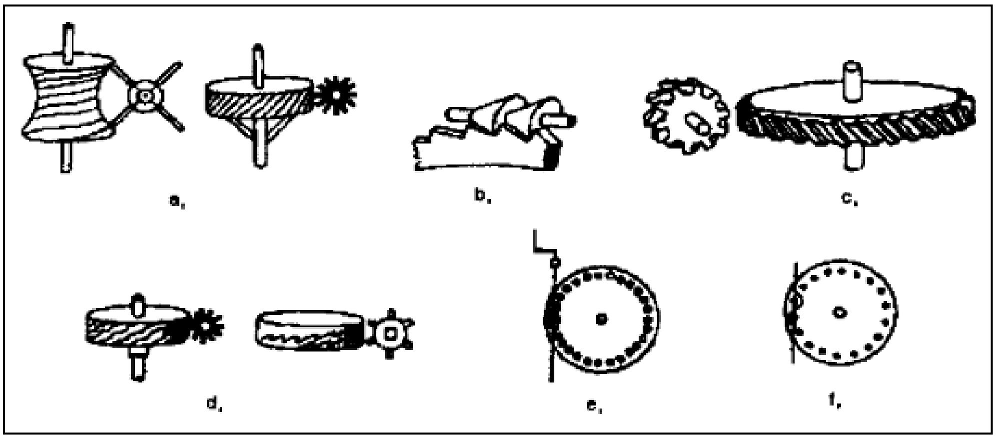


Figure 2.2 Sketches of worm gear drives made by Leonardo da Vinci (Dudas, 2005)

A worm gearbox consists of a worm; which is a gear in the form of a screw; meshes with a wheel; which is similar in appearance to a spur gear. The two parts are also called the worm screw and worm wheel. Basically, the geometry of a worm is similar to a power screw. The worm is generally made of steel, while the wheel is made of bronze. The geometry of a wheel gear is similar to a spur gear, except that the wheel gear teeth are curved in order to envelope worm teeth. In Figure 2.3, an example of worm, wheel gears and their contact pattern can be seen.

Worm gears can be found in most devices from home to heavy machinery. For instance, this type of drive is used in presses, rolling mills, conveyors, mining industry machines, escalators and also guitars etc.

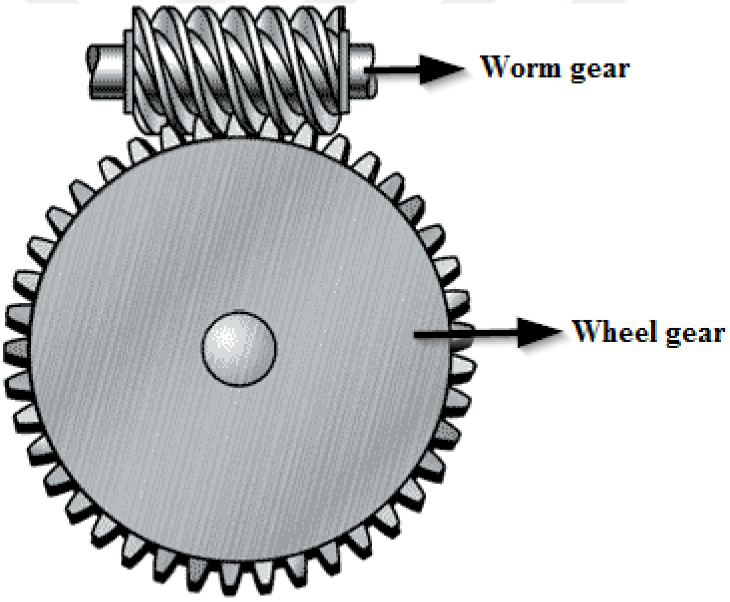


Figure 2.3 Example of the worm and wheel gears

Worm gearboxes have many advantages. The reason of using worm gearboxes in mechanical system is given below:

- The worm gearboxes can reduce speed ratios as high as 300:1.
- The worm gearboxes can increase torque ratios as high as 1:300.
- The worm gearboxes transmit power perpendicularly.
- The operation of worm gearboxes is smooth and silent.

- The volume of worm gearboxes is small compared with equivalent other gearbox types for the same reduction ratios.
- They have self locking effect, low backlash and damage tolerance.
- The worm gearboxes are irreversible.

On the other hand, the worm gearboxes also have many disadvantages, which are given below:

- They are expensive.
- As sliding motion between two gears, they generate high friction.
- Due to the high friction, the amount of heat generation is quite high.
- The efficiency is low compared with other types of gearboxes.
- The capacity of power transmitting of worm gearboxes is low (up to 100 kW).

The modern worm gearbox and their parts can be seen in Figure 2.4.

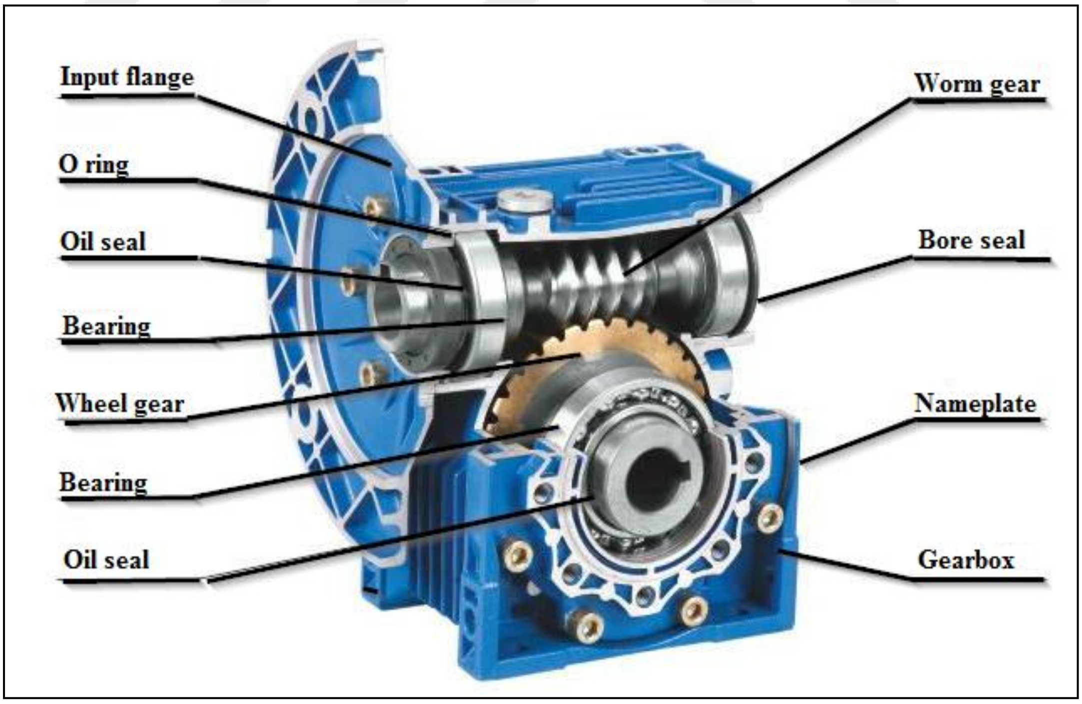


Figure 2.4 Modern worm gearbox and their parts (Zhejiang Evergear Drive Machine, n.d.)

One of the most important advantages of worm gearboxes is an enormous reduction ratio. Thus, they generally used for greatly increase the torque or decrease the speed. There is one more important reason that worm gearboxes are used in industrial system. Transmission direction of worm gearboxes is irreversible, when using large reduction ratios. This advantage is not valid for the other gear types. As the greater friction involved between the worm gear and wheel gear, the motion cannot be transferred from wheel gear to worm gear. That means, when a worm gear revolves, the meshing worm wheel also turns, but revolving the worm wheel will not turn the worm gear. Thus, worm gearboxes can tolerate large loads. They can be used in high load applications like cranes, lifts and so on.

Another important feature of worm gearbox is changing the rotational movement by 90 degree. They have non-intersecting shafts. For most of the worm gearbox, worm and wheel shafts are perpendicular. Their movement pattern can be seen in Figure 2.5.

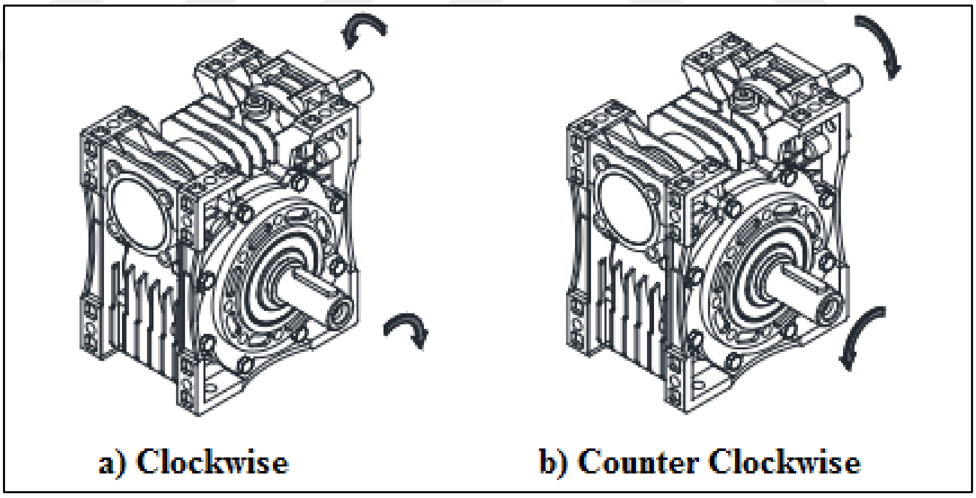


Figure 2.5 Perpendicular movement of worm gearbox (Yılmaz redüktör, n.d.)

There is one particularly reason why one would not choose a worm gear over a standard gear: lubrication. The movement between the worm and the wheel gear faces is entirely sliding. There is no rolling component to the tooth contact or interaction. This makes them relatively difficult to lubricate (Black, 2007).

2.2 Types of Worm Gearbox

There are three different types of worm gearing: non-throated, single-throated, and double-throated, seen in Figure 2.6.

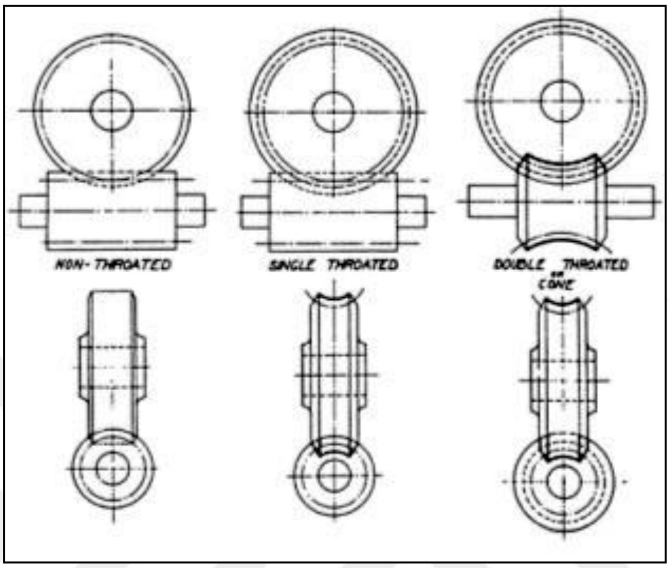


Figure 2.6 Three worm gear design (Double enveloping technology, n.d.)

In non-throated worm gearing, neither the worm nor the wheel gear is throated. They do not have concave features. Their contact pattern is straight between gears. Tooth contact is a single moving point. This leads to high unit loads and wear. In single-throated worm gearing, one gear (usually the wheel) is throated. This leads to line contact, permitting higher loads without excessive wear. A wheel gear with a concave tooth width allows the worm drive to nestle into the gear and increasing efficiency. In double-throated worm gearing, both the wheel gear and the worm are throated. Worm and wheel gear have both a concave tooth width profile. This increases from line contact area permitting increased loading and lower wear. This design maximizes efficiency (Lubrication of worm gears, n.d.).

2.2.1 Types of Worm Gears

The following are the two types of worms:

- Straight or cylindrical worm
- Double Enveloping or cone worm

The cylindrical or straight worm, as shown in Figure 2.7 (a), is most commonly used. The cone or double enveloping worm, as shown in Figure 2.7 (b), is used to some extent.

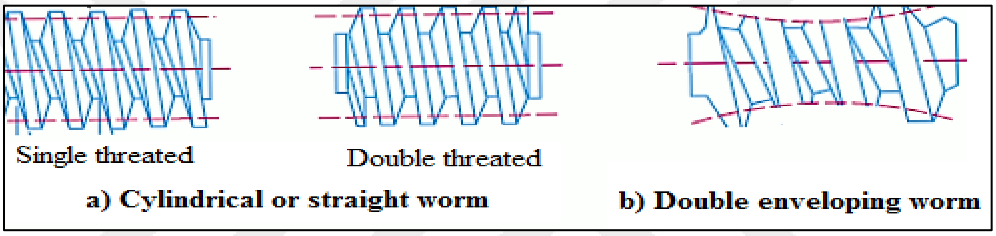


Figure 2.7 Types of worm gears (Khurmi & Gupta, 2005)

2.2.2 Types of Wheel Gears

The following three types of wheel gears are important from the subject point of view:

- Straight face wheel gear, as shown in Figure 2.8 (a),
- Hobbed straight face wheel gear, as shown in Figure 2.8 (b),
- Concave face wheel gear, as shown in Figure 2.8 (c).

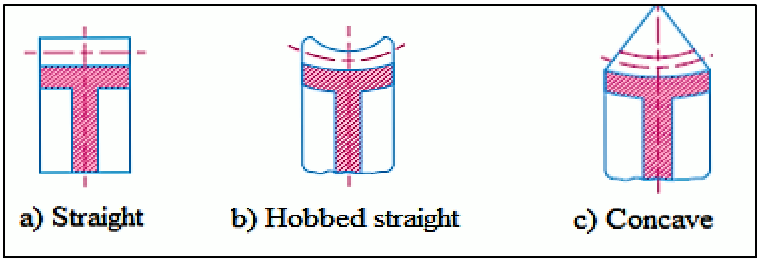


Figure 2.8 Types of wheel gears (Khurmi & Gupta, 2005)

The straight face wheel gear is like a helical gear in which the straight teeth are cut with a form cutter. Thus, it has only contact point with the worm. The hobbed straight face wheel gear's teeth are cut with a hob. The concave face wheel gear is the standard form and is used for all general industrial uses. The teeth of this gear have more contact area (Khurmi & Gupta, 2005).

2.3 Terms Used in Worm Gearboxes

Straight (cylindrical) worm and hobbed face wheel gear can be seen with more detailed view in Figure 2.9. The important terms, corresponding with the worm gearbox, are given in below:

2.3.1 Axial Pitch

It is also known as linear pitch of a worm. It is the distance measured parallel to the axis of worm from a point on one thread to the corresponding point on the adjacent thread on the worm, as shown in Figure 2.9 with p_a. It may be noted that for the only worm gearboxes, the axial pitch (p_a) of a worm is equal to the circular pitch (p_c) of the wheel gear, when the shafts are at right angles (which is most common).

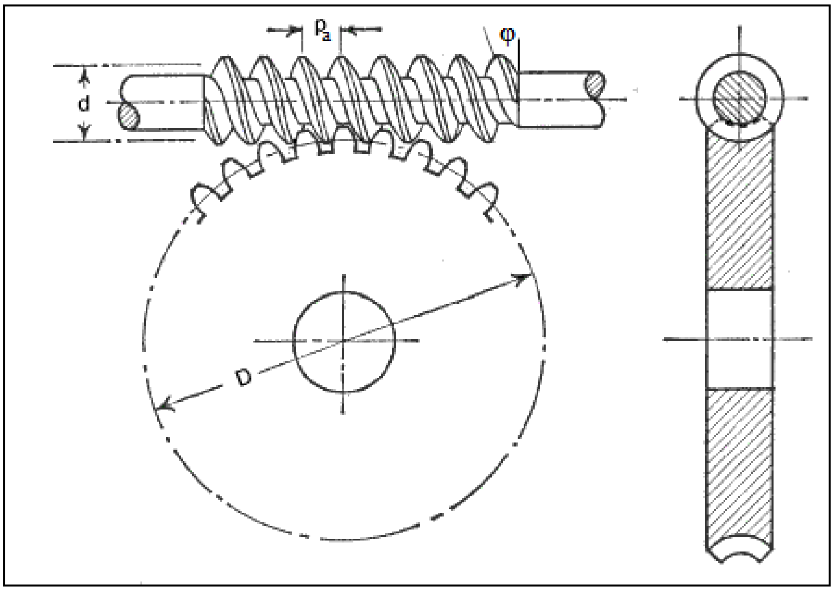


Figure 2.9 More detailed view a straight worm and hobbed wheel gear (Beardmore, 2013)

2.3.2 Normal Pitch

It is the distance measured along the normal to the threads between two corresponding points on two adjacent threads of the worm. Mathematically,

$$p_n = p_a * \cos\lambda \tag{2.1}$$

2.3.3 Lead

It is the linear distance (ℓ) through which a point on a thread moves ahead in one revolution of the worm. For single start threads, lead is equal to the axial pitch. For multiple start threads, lead is equal to the product of axial pitch and number of threads. Mathematically,

$$\ell = p_a * n \tag{2.2}$$

where p_a denotes axial pitch, n denotes the number of threads, and λ denotes lead angle.

2.3.4 Lead Angle

It is the angle between the tangent to the thread helix on the pitch cylinder and the plane normal to the axis of the worm, as shown in Figure 2.10. It is denoted by λ.

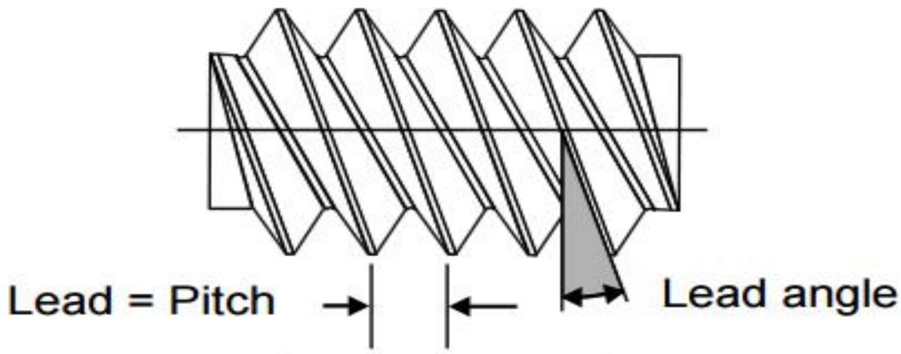


Figure 2.10 Pitch and lead angle

For one completion turn of a worm thread, it will form an inclined plane whose base is equal to the pitch circumference of the worm and altitude equal to the worm lead, as shown in Figure 2.11.

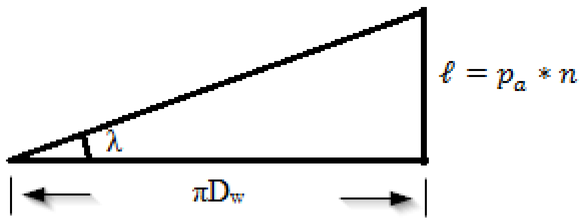


Figure 2.11 Development of lead angle

From the geometry of the figure, we find that,

$$\tan\lambda = \frac{\text{Lead of the worm}}{\text{Pitch circumference of the worm}} = \frac{\ell}{\pi * D_1} \tag{2.3}$$

$$= \frac{p_a * n}{\pi * D_1} = \frac{p_c * n}{\pi * D_1} = \frac{\pi * m * n}{\pi * D_1} = \frac{m * n}{\pi * D_1} \tag{2.4}$$

where m = module, D_1 = Pitch circle diameter of worm and l = p_a*n, p_a = p_c, p_c = π*m. For a compact design of worm gear, the lead angle may be chosen by the following equation 2.4. Lead angle generally vary from 9˚ to 45˚.

$$\tan\lambda = \left(\frac{N_2}{N_1}\right)^{1/3} \tag{2.5}$$

where N_2 is speed of wheel gear, N_1 is speed of worm gear.

2.3.5 Tooth Pressure Angle

It is measured in a plane containing the axis of the worm and is equal to one-half the thread profile angle, shown in Figure 2.9. The following Table 2.1 shows the recommended values of lead angle (λ) and tooth pressure angle (φ).

Table 2.1 Recommended values of lead angle and pressure angle for gearboxes

Lead Angle (λ) in degrees	0-16	16-25	25-35	35-45
Tooth pressure angle (φ) in degrees	14.5	20	25	30

2.3.6 Helix Angle

It is the angle between thread helix on the circular cylinder and axial line of worm gear. It is denoted by α_W, in Figure 2.12.

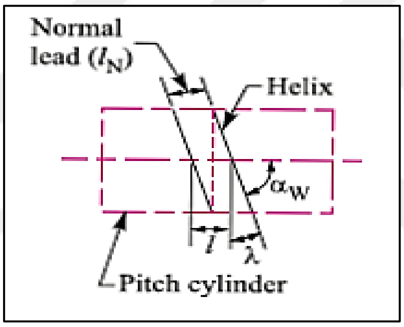


Figure 2.12 Helix, helix angle, lead angle, axial pitch, normal pitch (Khurmi & Gupta, 2005)

The worm helix angle is the complement of worm lead angle,

$$\alpha_W + \lambda = 90^\circ \tag{2.6}$$

2.3.7 Velocity Ratio

It is the ratio of the speed of worm (N_1) and the speed of the wheel gear (N_2). Mathematically,

$$\text{V.R.} = \frac{N_1}{N_2} \tag{2.7}$$

Let l = lead of the worm and D_2 = Diameter of wheel gear; we know that linear velocity of worm,

$$v_1 = \frac{\ell * N_1}{60} \tag{2.8}$$

and linear velocity of wheel gear,

$$v_2 = \frac{\pi * D_2 * N2}{60} \tag{2.9}$$

The linear velocities of the worm and wheel gear are equal, therefore

$$\frac{\ell * N_1}{60} = \frac{\pi * D_2 * N_2}{60} \quad \text{or} \quad \frac{N_1}{N_2} = \frac{\pi * D_2}{\ell} \tag{2.10}$$

We know that diameter of the wheel gear,

$$D_2 = m * T_2 \tag{2.11}$$

where m is the module and T_2 is the number of teeth on wheel gear.

$$V.R = \frac{N_1}{N_2} = \frac{\pi * D_2}{\ell} = \frac{\pi * m * T_2}{\ell} \tag{2.12}$$

$$= \frac{p_c * T_2}{\ell} = \frac{p_a * T_2}{p_a * n} = \frac{T_2}{n} \tag{2.12}$$

where n = number of starts of the worm gear.

From the above, we see that velocity ratio may also the ratio of the number of teeth on the wheel gear and the number of thread of the worm.

2.4 Tooth Forces Acting on Worm Gearboxes

When the worm gearboxes are transmitting power, the tangential, axial and radial forces acting on it can be shown in Figure 2.13. It is assumed that the driving member is a clockwise rotating right hand worm gear. It may be noted that the forces on a wheel gear are equal in magnitude to that of worm, but opposite in direction.

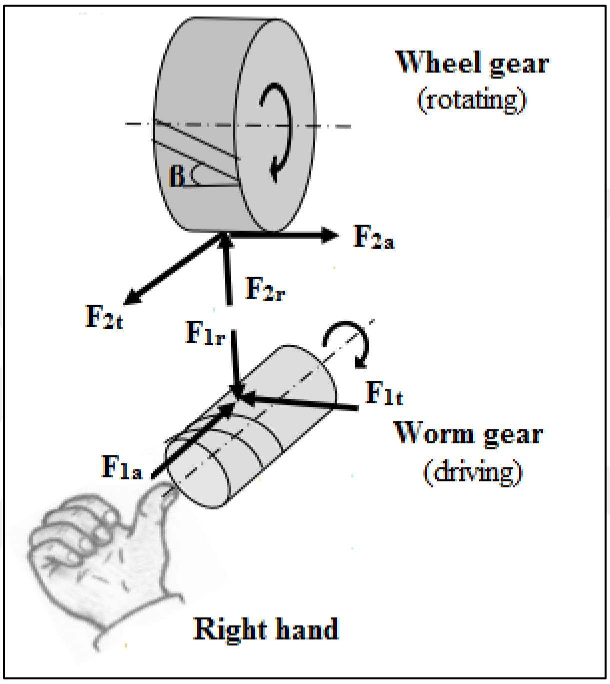


Figure 2.13 Tooth forces acting on worm gearbox (Dündar, 2013)

For the usual 90° shaft angle, the worm tangential force is equal to the wheel axial force in magnitude and vice versa.

$$|F_{1t}| = |F_{2a}| \quad (2.13)$$

$$|F_{1a}| = |F_{2t}| \quad (2.14)$$

The worm and wheel radial forces are also equal in magnitude.

$$|F_{1r}| = |F_{2r}| \quad (2.15)$$

The worm lead angle λ of a screw thread corresponds to the pressure angle φ of the worm. The worm tooth number is Z_1, wheel tooth number is Z_2, torque on the worm is M_1, diameter of worm is D_1 and efficiency of worm gearbox is η. These equations are derived below with reference to the worm and wheel geometry.

The reduction ratio of a worm gear (N);

$$N = \frac{Z_2}{Z_1} \tag{2.16}$$

Tangential force on the worm (F_{1t}) = Axial force on the wheel (F_{2a});

$$|F_{1t}| = |F_{2a}| = \frac{2 * \text{Torque on worm}}{\text{Pitch circle diameter on the worm}} = \frac{2 * M_1}{D_1} \tag{2.17}$$

The tangential force (F_{1t}) on the worm produces a twisting moment of magnitude (F_{1t}*D_1/2) and bends the worm in the horizontal plane.

Axial force on the worm (F_{1a}) = Tangential force on the wheel (F_{2t});

$$F_{1a} = F_{2t} = F_{1t} * \tan(\lambda) = \frac{2 * \text{Torque on the wheel}}{\text{Pitch circle diameter of wheel}} \tag{2.18}$$

The axial force on the worm tends to move the worm axially, induces an axial load on the bearings and bends the worm in a vertical plane with a bending moment. Radial force on the worm (F_{1r}) = Radial force on the wheel (F_{2r});

$$F_{1r} = F_{2r} = F_{1a} * \tan(\varphi) \tag{2.19}$$

The radial force or separating force tends to force the worm and wheel out of mesh. This force also bends the worm in the vertical plane.

2.5 Worm Gearbox Failures

Gear failures tend to occur when a gear is working under high stress conditions, lack of lubrication, contaminated lubrication, long operation at high load, higher temperature, etc. When failures occur, gears can no longer do their job for which they designed. If they aren’t detected early stage, there can be dramatic consequences. In this section, the most common faults of worm gearbox are illustrated.

2.5.1 Wear

Moderate wear is most commonly caused by an inadequate lubrication film, with the film thickness being too thin for the load. Dirt in the lubrication can also cause this type of wear. This type of wear takes place over a relatively long period time (Shipley, 1967). Moreover; foreign particles in the lubrication system causes abrasive wear in the meshing area. The particles can be metallic debris from the gear and bearing system, rust, sand etc. An example of abrasive wear can be seen in Figure 2.14.

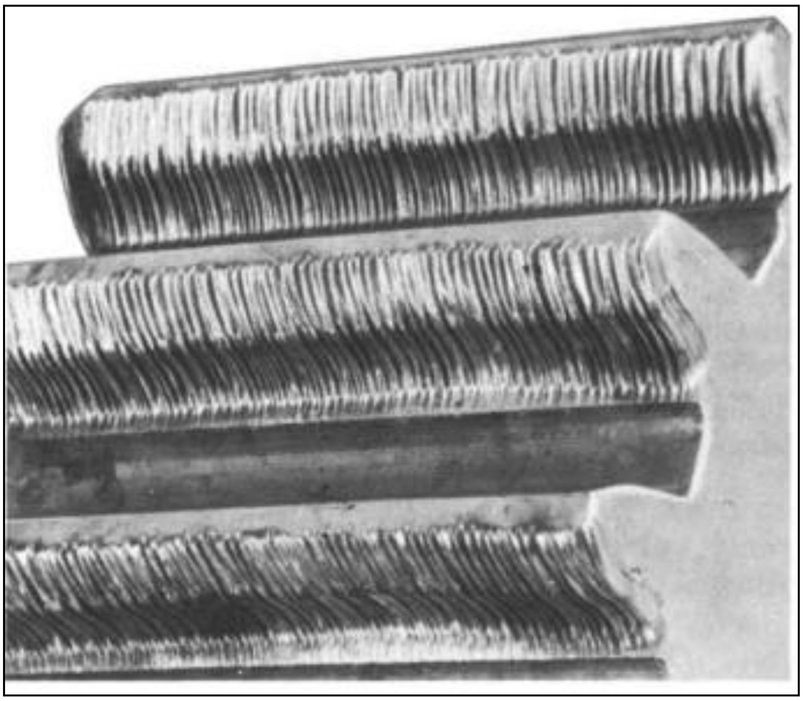


Figure 2.14 Wear (Shipley, 1967)

2.5.2 Pitting

Pitting is a tooth surface fatigue failure which occurs when the stress on the tooth is greater than endurance limit of gear tooth. Typical tooth pitting damage is shown in Figure 2.15. Development of this failure depends on surface contact stress and number of stress cycle. Initial pitting is generally caused by gear tooth surfaces not fitting properly. With small pits, pitting begin on the outside of the gear. This type of pitting can be avoided by providing smooth gear tooth surfaces.

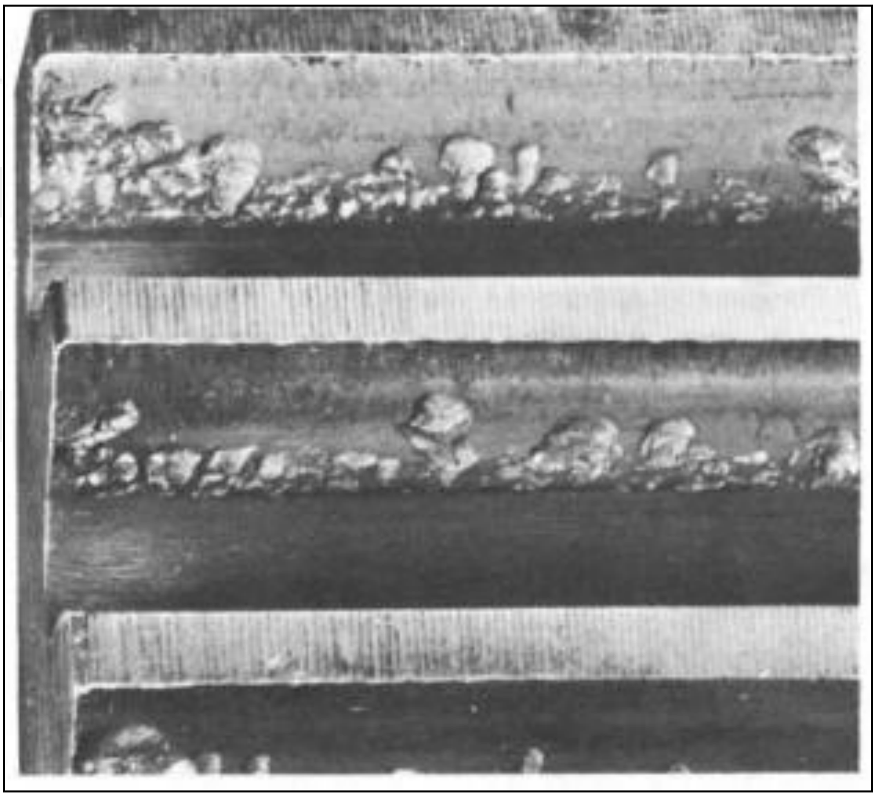


Figure 2.15 Typical tooth pitting (Shipley, 1967)

When the load is not proper distributed on the gear tooth surface, destructive pitting can happen. In this type of pitting, the surface pits have usually larger diameter than those of initial pitting. After a certain period of operation with repeated variation of the load, some small areas of metal on gear tooth surfaces can fatigue. When pitting has occurred, it tends to spread over neighboring teeth because the non-pitting areas of teeth must support the extra load formerly carried by the damaged area. The destructive pitting can usually progress to other teeth surfaces. All pitting on teeth surfaces can develop with various shapes and sizes. Once enough stress can be build up, pitting can continue until the all surfaces are completely destroyed. Pitting can be inhibited with increasing hardness of material of gear tooth. This research will emphasize the progression of a pitting fault.

2.5.3 Scoring

Inadequate or unsuitable lubrication, overloading and misalignment permit breaking down lubrication film and increasing metal-metal contact between two gears. This metal-metal contact cause overheating than excepted and local welding and tearing of metal surfaces in gearboxes. This process ends up with removing metal areas rapidly from the surfaces. These faults tend to progress slowly, thus the gear can still transmit power although the scoring fault develops. An example of scoring fault can be seen in Figure 2.16.

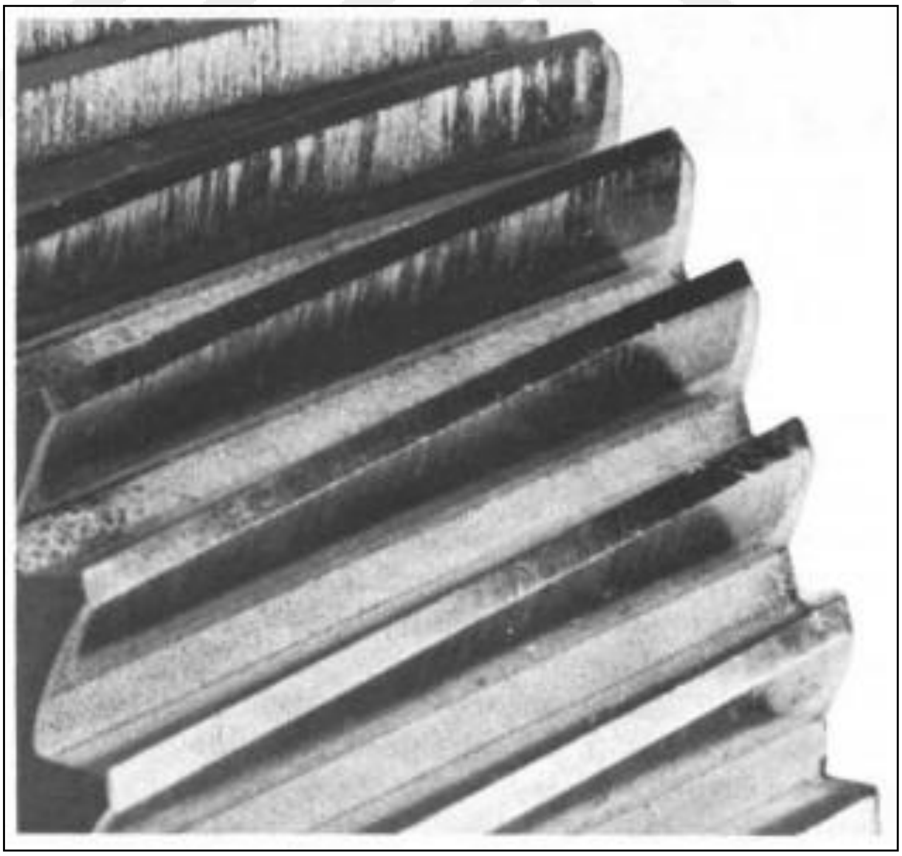


Figure 2.16 Scoring (Shipley, 1967)

2.5.4 Plastic Flow (Rippling)

Cold working on gearboxes can cause high friction and contact stress between gears. During transmission of power between two gears, gear tooth tends to push or pull the other gear tooth in the direction of motion. Plastic flow is a deformation of on the tooth surfaces resulting from yielding of the surface material due to cold working. It is usually associated with softer gear material, although it can occurs on hardened gears in heavily loaded case. In this type of failure, the surfaces of gear which contact each other show evidence of metal gear. An example of plastic flow fault can be seen in Figure 2.17.

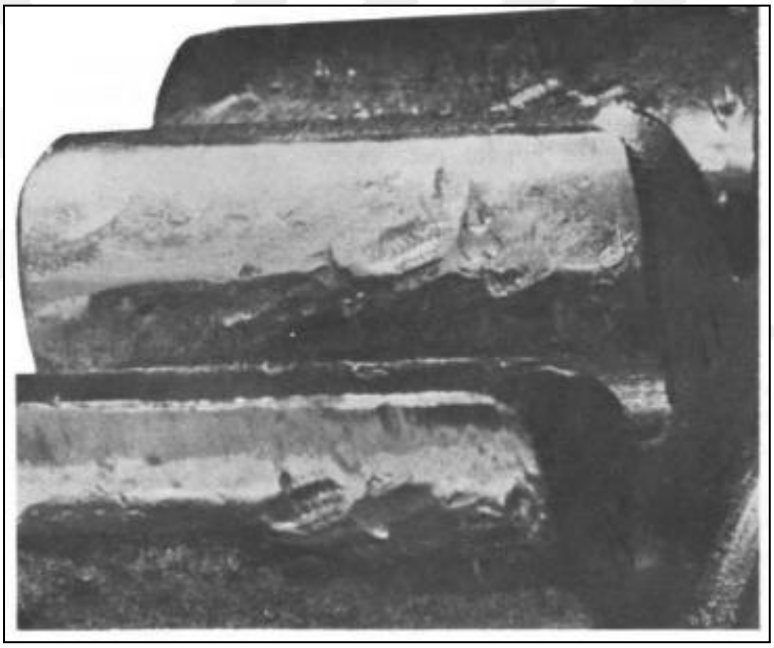


Figure 2.17 Plastic flow (Shipley, 1967)

2.5.5 Ridging

Ridging is caused by the plastic flow of surface due to high contact stresses during sliding motion between gears. It shows definite peaks and valleys or ridges across the tooth surface in the direction of sliding. It is often present on heavily loaded worm gearboxes. This type of fault can generally exist on low hardness gears but, when the contact stress is very high, it may also present on high hardness materials. An example of ridging fault can be seen in Figure 2.18.

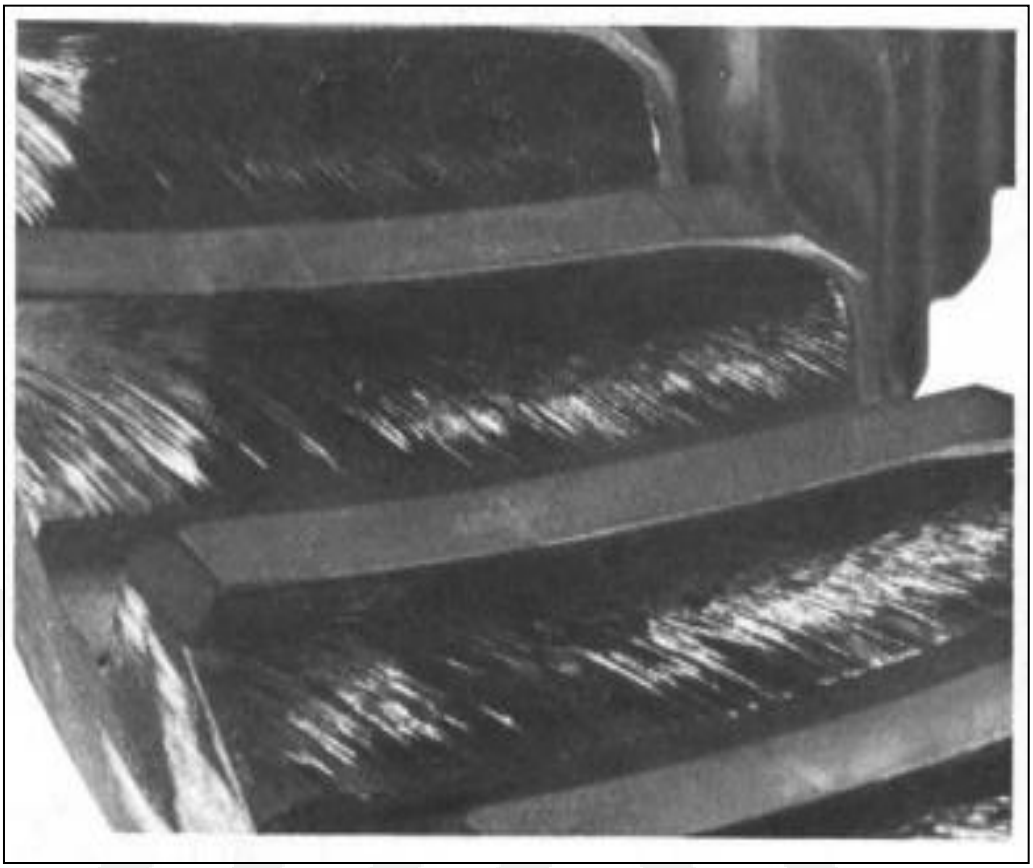


Figure 2.18 Ridging (Shipley, 1967)

2.5.6 Tooth Breakage

Tooth breakage is a most destructive gear failure caused by breakage of whole tooth or a substantial part of a tooth. This failure results from excessive load, bending fatigue and stress of the gear tooth beyond the endurance limit. Tooth breakage is the most dangerous type of gear failure and leads to disability of the gearbox. This failure often damages of other gearbox components such as the shaft, bearing, etc. Before it happens, there is evidence of fatigue or local point of break. It usually begins with a small break, which tends to develop until part or entire tooth breaks away. The remaining tooth will have bigger impact loading, thus the gearbox can be disabled. An example of tooth breakage fault can be seen in Figure 2.19.

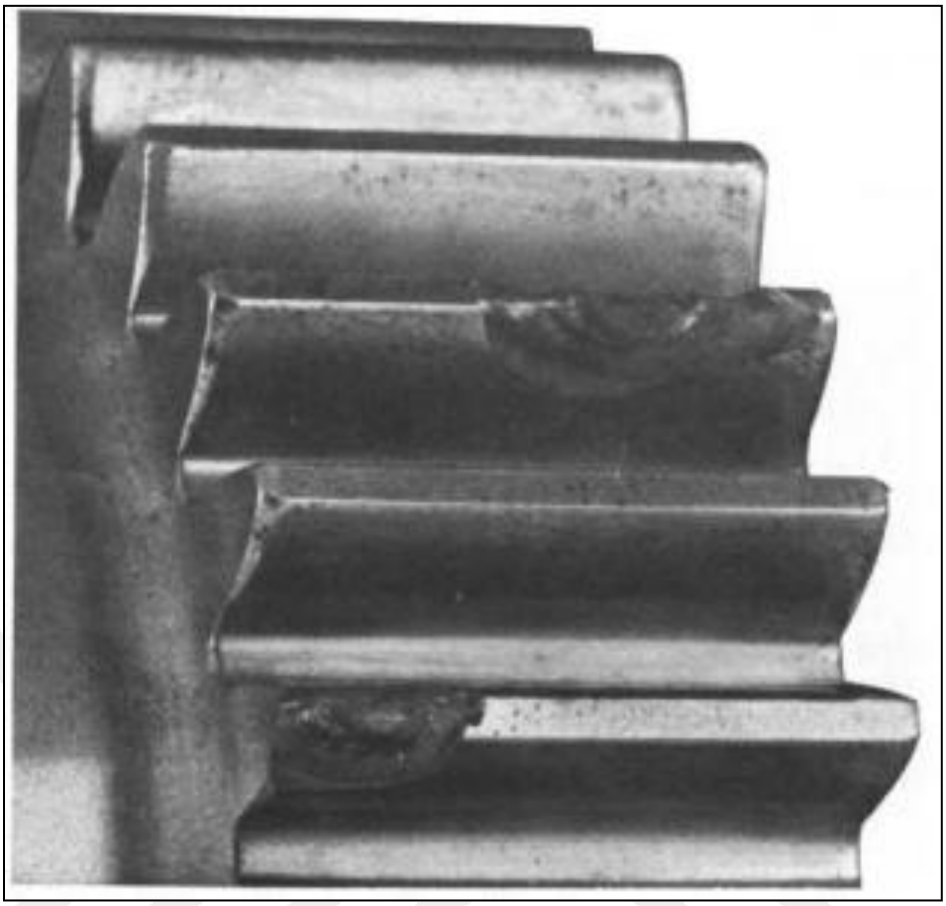


Figure 2.19 Tooth breakage (Shipley, 1967)

CHAPTER THREE
CONDITION MONITORING TECHNIQUES

3.1 Predictive Maintenance

Predictive maintenance (PdM) helps to determine the condition of machine in order to predict when maintenance should be performed. It attempts to detect deterioration of equipment in advance before significant degradation in component resulting with failure happens. Predictive maintenance performs continuously or at intervals according to the requirements for diagnosis and monitoring a condition or a system. There are three types of maintenance;

- Reactive maintenance (RM)
- Preventive maintenance (PM)
- Predictive maintenance (PdM)

In the past, industrial machine was maintained when it developed a fault (reactive). However, developments of computer technology have provided implementation of periodic time-based preventive maintenance strategies. By the 1990s, the diagnostic capabilities of predictive maintenance technologies have increased. Advances in electronic and sensor technologies enabled the development of cost-effective instrumentation for predictive maintenance, and this allows the identification of machine problems by measuring the condition of the machine.

Failures can cause severe interruption to work schedules, increase costs, lower product quality and increase risk of health to machine operators. During production, machinery failure cause downtime and halt the production process. This downtime cost often exceeds maintenance costs by many times. Condition based predictive maintenance provides the detection of the faults in early stage, increasing machinery performance and life, reducing significant damage and important outcome in terms of cost. Common predictive technologies and their applications can be shown in Table 3.1.

Table 3.1 Common predictive technologies and their typical applications (NASA, 2000)

		Applications						
		Pumps	Electric Motors	Heavy Equipment	Valves	Heat Exchangers	Electrical Systems	Mechanical Systems
Technologies	Vibration Monitoring	✔	✔	✔				✔
	Lubricant Analysis	✔	✔	✔				✔
	Wear Particle Analysis	✔	✔	✔				✔
	Temperature Analysis	✔	✔	✔				✔
	Performance Monitoring	✔	✔			✔		✔
	Ultrasonic Noise Detection	✔	✔		✔	✔		✔
	Ultrasonic Flow	✔			✔	✔		✔
	Infrared Thermography	✔	✔	✔	✔	✔	✔	✔
	Visual Inspection	✔	✔	✔	✔	✔	✔	✔
	Motor Current Signature Analysis		✔					✔
	Motor Circuit Analysis		✔				✔	
	Electrical Monitoring		✔				✔	
	Polarization Index		✔				✔	
	Non-destructive Testing					✔		
	Insulation Resistance		✔				✔	

In the world, predictive maintenance is last in application of maintenance techniques with 12 percent, although predictive maintenance can provide lots of benefits for industrial companies. These favors are briefly;

- Increase in performance, efficiency and life time of machine
- Increase in quality of product
- Reduction in number and severity of failures
- Changing failed equipments before machine breakdown
- Decrease in downtime of machine
- Decrease in unplanned maintenance
- Decrease in cost of maintenance and employee
- More stabilization for process
- Decrease in energy consumption caused by inefficient machine working condition.

The most important advantage of using predictive maintenance for industrial companies is process reliability. The notions such as product competition, reliability, security and cost optimization affect maintenance departments of companies positively. Maintenance costs are 4% – 25% of total costs of industrial companies, thus importance of predictive maintenance gradually increase. According to independent research surveys, companies which used predictive maintenance have benefited, such as;

- Return on Investment Amount: 10 times
- Reduction in maintenance activities: 25% - 30%
- Reduction in breakdown: 35% - 45%
- Increase in production: 20% - 25%

There are two samples scenarios, which emphasize how predictive maintenance is important.

- Without predictive maintenance: “It seems rough. Something doesn’t sound right. We need to overhaul it before winter. It won’t last another season.”
- With predictive maintenance: “The vibration level has remained steady for 3 years, but began rising 2 months ago. According to its present rates of increase, it will probably fail in 4 months. The spectrum indicates that an imbalance has developed. We should overhaul during next month’s outage.”

The first scenario will be more expensive because everything replaced with a new one, in the hopes of changing deterioration part. Money and time would have been wasted. The second scenario provides more information about the failure of machine. It also suggests the specific actions to be taken to overcome the problem (Wowk, 1991). This example shows us importance of condition based predictive maintenance. In this thesis, condition based predictive maintenance is studied and researched deeply.

3.2 Condition Based Predictive Maintenance

Condition based predictive maintenance provide adequate maintenance properly with acquisition condition information from system before significant failure happens. When certain equipment is critical to performance of the system, site inspections may not be sufficient. Condition based maintenance can eliminate machinery breakdown by evaluating the condition of the machine thanks to suitable sensors. With this technique, it can be possible monitoring of machines or systems continuously or very frequently and assessment of working condition of them quickly. An example of condition monitoring of wind turbines, can be seen in Figure 3.1.

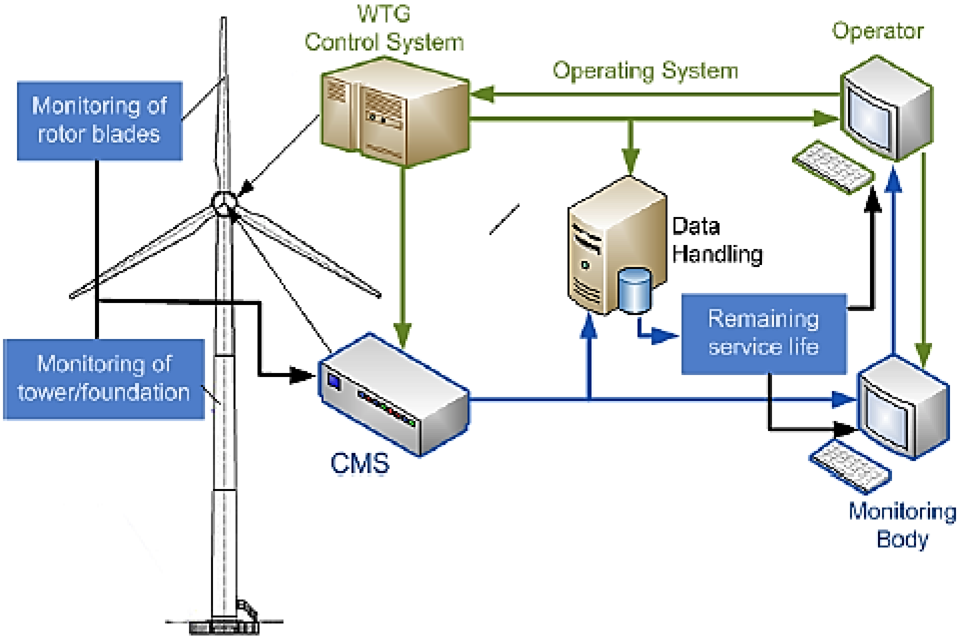


Figure 3.1 Example of condition monitoring of wind turbines (LeBlanc & Graves, n.d.)

The key factor of condition monitoring is the accumulation of data which involves information about system. This information can be taken either at regular intervals (periodic monitoring) or continuously (continuous monitoring). For measurements, suitable sensors should be used in order to analyze condition of system correctly. Measurements are taken by data collectors and then analyze for assessment of condition by means of complex analysis algorithms. However, without knowing the value of a parameter in normal condition, it is not possible to figure out abnormal value in an abnormal condition.

3.3 Condition Monitoring Techniques

Vibration monitoring, temperature monitoring, lubricant analysis, motor current signature analysis, etc. are the main technologies for machinery condition monitoring. Some of these technologies can be shown in Figure 3.2, briefly.

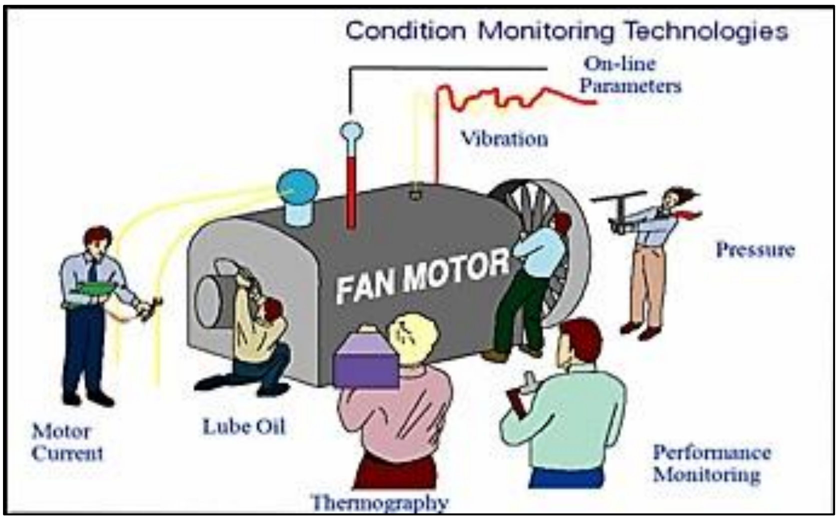


Figure 3.2 Examples of condition monitoring techniques (Industrial manufacturing condition monitoring, n.d.)

Condition monitoring techniques can be grouped into six categories.

- Aural, Tactile and Visual Inspection: There are basic techniques of condition monitoring involving human instincts to aid monitoring.

- Performance Trending Monitoring: In performance trending monitoring, operational parameters affecting the performance of a machine such as force, torque, speed etc. are monitored to detect any failure. Any significant deviation from normal operational condition is considered as an indicator of deterioration. For example, gas usage of car, oil usage of engine etc.

- Thermal Monitoring: This monitoring technique involves checking working temperature of a system and identification of sources of heat generation due to any fault. Temperature can be measured by a variety of thermal sensors such as thermometers, thermocouples, and infrared thermal cameras. Infrared (IR) thermography can be defined as the process of generating visual images that represent variations in IR radiance of surfaces of objects. An example of infrared thermography can be shown in Figure 3.4.

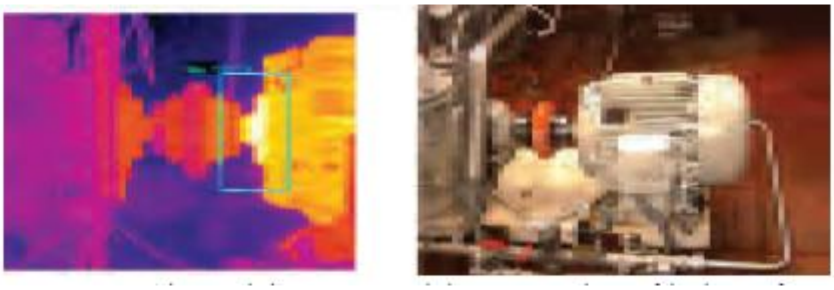


Figure 3.3 Example infrared thermography (Predictive maintenance technologies, n.d.)

- Wear Debris Monitoring (Oil analysis): Wear is removal of material due to mechanical process under conditions of sliding, rolling, or repeated impact. Wear occurs in case of excessive loading, inadequate lubrication etc. Material removed from contacting surfaces contaminates lubrication. Thus, wear debris monitoring uses lubrication analysis. One of the oldest predictive maintenance technologies still in use today is that of oil analysis. The most common oil analysis tests are used to determine the condition of the lubricant and the presence of contamination. Oil condition is easily determined by measuring viscosity, acid number, and base number. Component wear can be determined by measuring the amount of wear metals such as iron, copper, chromium, aluminum, lead, tin, and nickel.

- Vibration Monitoring: In all condition monitoring techniques, vibration monitoring is most widely used for condition monitoring. For condition monitoring of a structure, analysis of vibration signals is appropriate technique, because for any change in the condition of the system, there will be most likely an effect in vibration signal. That means defects on system will change the amplitude and phase modulations of the system's vibrations signal. A variety of faults such as bent or eccentric shaft, misaligned components, resonance problem, mechanical looseness, unbalanced components, faulty bearings and gears etc. can be detect with vibration monitoring.

- Motor Current Monitoring: Over the past several years, motor condition analysis techniques have evolved from simple testing into testing techniques that more accurately define a motor's condition.

Compared with other monitoring techniques, vibration monitoring is more suited technique to detect gearbox failures. Thus, this research work has concentrated upon the use of vibration analysis for gearbox condition monitoring.

3.4 Sensors for Condition Monitoring

Many sensors detect changes in equipment components. They are often critical equipment in condition monitoring for detecting abnormalities. The mechanical deterioration time graph and signs of failure are shown in Figure 3.4.

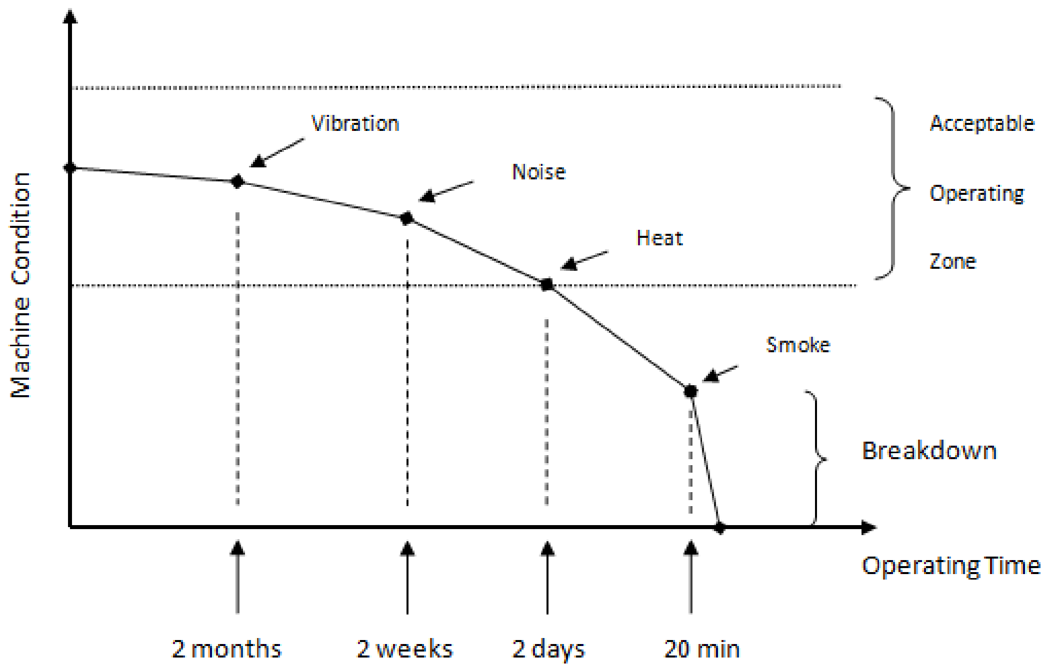


Figure 3.4 Machine condition-time diagram

As shown in Figure 3.4, the first sign of failure is vibrations of mechanical equipment. This signs can provide detection of failure prior to 2 months. There are more signs of failure such as noise, heat, and smoke before the system is breakdown. Thus, using suitable sensor is an important issue for detection of failure. Some of sensing technologies used in condition monitoring are listed in Table 3.2. The table includes the types of condition monitoring, suitable sensors for each type, their necessary frequency range and signal condition needs.

Table 3.2 Some sensing technologies used in condition monitoring

Measurement	**Sensor**	**Frequency Range**	**Possible Signal Conditioning Needs**
Vibration	Accelerometer	>100 Hz	AC/DC coupling, ±24 V input, Anti-alias filter.
Vibration	Velocity	>20 Hz to <2 kHz	AC/DC coupling, ±24 V input, Anti-alias filter.
Vibration	Proximity Probe (Displacement)	<300 Hz	Modulator/demodulator, Anti-alias filter, ±30 V input range.
Speed	Proximity Probe	<300 Hz	Modulator/demodulator, Anti-alias filter, ±30 V input range.
Motor Current	Current Shunt Current Clamp	Up to 50 kHz	±333 mV or ±5 V
Temperature	RTD Thermocouple	Up to 10 Hz	Noise rejection, cold-junction compensation
Temperature	Infrared Camera	Multiple frames per sec	User Interface Visualization
Oil Quality	Viscosity Contamination Particulates	Up to 10 Hz	mA current input, ±10 V input, 50/60 Hz noise rejection

CHAPTER FOUR
VIBRATION BASED GEARBOX FAULT DETECTION TECHNIQUES

4.1 Introduction

Vibration analysis has been used widely as predictive maintenance techniques until this time. In industrial applications, vibration analysis based techniques are the most frequently applied method to detect rotating machinery failure comparing to the other techniques such as wear debris, temperature, motor current and acoustic emission and so on. Since unusual conditions, such as gear fault, cause abnormal vibration on gearbox, vibration analysis is widely employed in industry. By measuring and analyzing vibration of a gearbox, it is possible to determine severity of the defect and type of failure, and hence predict the machine's condition (Ismon, 2013).

Rotating machine faults can be generally classified as distributed faults such as wear, and localized faults such as pitting, tooth loss etc. The distributed faults increase the transmission errors, while the localized faults not only affect the transmission accuracy but also cause catastrophic failure of the transmission system (Li, 2012). In this thesis, the research was carried out only localized faults (pitting) of worm gearbox.

The vibration fault detection techniques were developed for two main purposes. The first purpose is to separate the vibration signal from other components such as noises in order to minimize the noise effects which may mask the vibration signal. The second purpose is to determine the condition of machine and distinguish the healthy and faulty machine.

In real applications, the fault symptoms are masked by the background noises and irrelevant vibration signals generated by other machine components. Because of these signals, the distinctive defect symptoms cannot be detected. Therefore, some techniques were developed to increase signal to noise ratio (SNR). Time synchronous average (TSA) technique increases the SNR by separating the vibration signal of the relevant component from other machine components and suppressing the background noise. TSA is a powerful method and is the most popular pre-processing technique in gear fault detection.

In general, there are three main categories of vibration based signal processing methods for rotating machinery fault detection and diagnostics. They are time domain methods, frequency domain methods, and time-frequency domain methods. The first researchers studied on time domain analysis based gear fault detection. They attempted to determine distinctive defect symptoms by using time analysis method while the severity of faults increased. Furthermore, the development of the Fast Fourier Transform (FFT) algorithm and the computational capability of the digital processor made the real-time spectral analyze possible. It is known that mechanical faults produce characteristic vibrations at different frequencies. Thus, following researches about fault detection was carried on by analysing the time and frequency spectrums. These analysis techniques are widely applied to the rotational machinery for fault detection with successful applications. However, the spectral analysis assumes that the signal is stationary. The machine condition signals may show non-stationary property due to the fact that some defects and incipient failures often reveal themselves in the form of changes in the spectrum of a measured signal (Zhan & Jardine, 2005). Hence, more recently, a new technique called joint time-frequency analysis methods are developed for rotational machinery fault detection and diagnostics. The fundamental idea of joint time-frequency analysis techniques is to represent the energy density of a signal in time and frequency domain simultaneously (Baydar & Ball, 2001). For time-frequency analysis, wavelet Transform (WT) is the one of the most used methods of joint time-frequency analysis.

In this thesis, time domain and frequency domain analysis are carried out. Furthermore, for better fault detection; time domain and frequency domain analysis are combined and a frequency component based statistical analysis is developed. In this section, these analysis techniques are described.

4.2 Time Synchronous Average

Time Synchronous Average (TSA) is an essential pre-processing algorithm technique for determining reliable condition of rotating equipment. Gear failure occurs synchronously with shaft rotation, but distinctive symptoms of failure may disappear because of the irrelevant noises. Time synchronous averaging (TSA), or synchronous averaging, is a method that removes of this noise component from a vibration signal (Bechhoefer & Kingsley, 2009). Thus; in this thesis, this method is used in order to eliminate effects of signal components that are not related to considered gearbox.

Signal to noise ratio (SNR or S/N) is a measure that compares the level of a desired signal to the level of background noise. It is defined as a ratio of signal power to the noise power, often expressed in decibels. The desired is low level random noise vibration and thus, higher signal to noise ratio because of improving reality of vibration measurement. For this purpose, the TSA method was suited for gearbox analysis. Vibrations which are synchronous with gear shaft will repeat periodically with shaft rotation. Other vibrations are evaluated as irrelevant noise which affects the vibration analysis badly. The method eliminates this random noise from all vibration and extract essential vibration signal which are related to gearbox. Hence, it significantly improves the signal to noise ratio. The averaged signal can be obtained using the formula;

$$x_{av} = \frac{1}{N}\sum_{n=1}^{N} x(t + nT) \tag{4.1}$$

where T is the period of time which the signal is averaged and N is the number of samples.

For implementation, TSA method first begins with measurement the velocity of gear shaft. This information gives us duration in one revolution of a gear in a machine. This duration is multiplied by sampling frequency in order to determine the number of vibration samples which are taken in one revolution of gear shaft. The samples are synchronized in that they all begin at the same exact point. Hence, the signal coming from accelerometers is averaged in time, employing periodicity with gear shaft rotating speed. After performing a sufficient number of averages, peaks which are synchronous with the gear rotating speed will remain, while non-synchronous peaks will be averaged and disappeared. The SNR will be reduced by a factor of $1/\sqrt{n}$, where n is the number of averages. A simplified block diagram of TSA for worm gearboxes is shown in Figure 4.1.

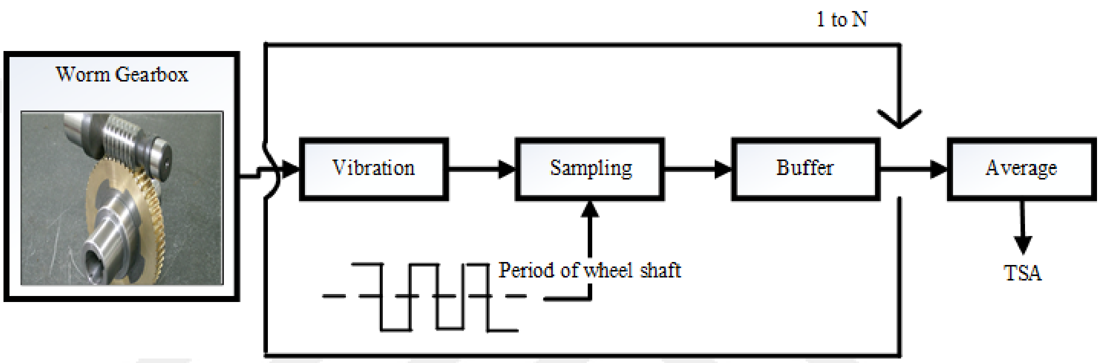


Figure 4.1 Simplified block diagram of TSA

4.3 Time Domain Analysis

Time domain analysis of vibration signals is one of the simplest and easiest methods of interpreting rotating machine condition. It can give qualitative information about the machine condition. These statistical properties of signal (i.e. Kurtosis, crest factor, RMS, peak to peak value etc...) have been used to detect faults in gearboxes.

Time domain analysis uses the amplitude information of the vibration time signal in order to detect gear faults. Time domain analysis are appropriate when periodic vibration is observed (Al-Arbi, 2012). Time waveform of vibrations shows changes caused by faults, but it is difficult to diagnose the source of faults by using time domain analysis. Figure 4.2 shows an example of time waveform of worm gearbox vibration.

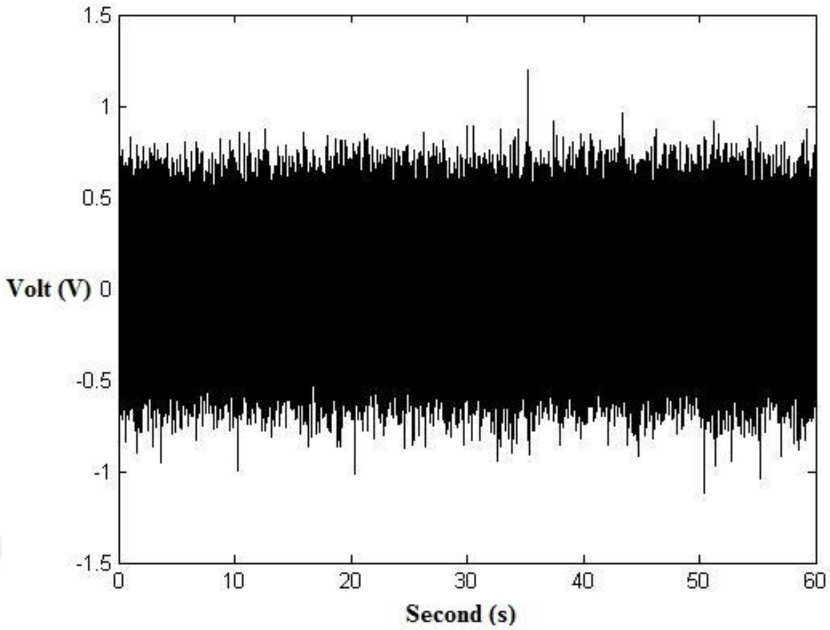


Figure 4.2 Example of worm gearbox vibration time waveform

A time waveform observation can also be useful in identifying vibration that are unusual impacts. By studying the time domain waveform using equipment such as oscilloscopes, it is possible to detect changes in the vibration signal caused by faults. Time waveform analysis provides determination of the abnormal behaviour of the gearbox. However, diagnosis of faults is a difficult task. This type of fault diagnosis is only valid for huge impacts in time domain. For vibration signal x(), the statistical parameters which are widely used in condition monitoring are given below.

4.3.1 Mean Value

The mean (or "arithmetic average") value of a set of numbers is the ratio of sum of the values to the number of values. Mean is denoted by μ. Its formula is given as;

$$\mu = \frac{1}{N}\sum_{n.=1}^{N} x(n) \tag{4.2}$$

where; N is the number of samples taken in signal, x(n) is the amplitude of the signal for the n^{th} sample, and μ is the mean value of N samples.

4.3.2 Peak Value

Peak value (PV) is the maximum vibration amplitude, defined as;

$$PV = x_{max} \tag{4.3}$$

where; x_{max} is maximum value of the signal.

4.3.3 Peak to Peak Value

Peak-to-peak value is the difference between the highest amplitude value to the lowest amplitude value, which can be negative. Its formula is defined as;

$$PTP = x_{max} - x_{min} \tag{4.4}$$

where; x_{max} is maximum value of the signal, x_{min} is minimum value of the signal.

4.3.4 Root Mean Square Value

Root mean square (RMS) is used in order to illustrate the power content of the signal. It measures the effective magnitude of the signal. The presence of defects causes the increase in the vibration signal amplitude, thus increasing of power of the vibration signal. This statistical parameter is widely used in all vibration monitoring techniques, because it is a very effective parameter that provides symptoms about existence of failure. However, it does not give meaningful information to identify which component has failure. RMS can be defined as;

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(x(n))^2} \tag{4.5}$$

RMS is not a sensitive parameter for sudden short peaks in the vibration signal; hence it is often not sensitive enough to detect incipient failure. RMS becomes more useful when overall vibration level of the system is measured. It is therefore considered a very good descriptor of the overall condition of gearboxes. However, it is susceptible to changes in operational conditions such as load and speed (Vecer, Kreidl & Smid, 2005)

The first discover on vibration based fault detection for rotating machine in time domain is root mean square (RMS) value. Researchers observed that the RMS value increases as the severity of faults grows. The RMS magnitude of vibration velocity is standardized according to machine type by International Organization for Standardization (ISO). DIN ISO 10816 (2372; formerly) is a procedure and general guide outlining evaluation of mechanical vibration taken from the non-rotating parts of industrial machinery. This standard gives information about the critical machinery vibrations. Moreover, it informs the operators about machine condition. Machine manufacturer product their machines according to this standard and test their production for efficiency works. It is also a relevant quality indicator for efficient working.

10816 Standard provide guidance for evaluating vibration severity in machines operating in the 10 to 200Hz (600 to 12,000 RPM) frequency range. Examples of these types of machines are electric motors and pumps, production motors, medium-sized motors, generators, steam and gas turbines, turbo-compressors, turbo-pumps and fans. Some of these machines can be coupled rigidly or flexibly. First, the general classification of the machine has to be identified. The application, mounting technique, and operational conditions must also be specified. Measurement should be taken on the bearings, bearing support housing, or other structural parts which significantly respond the dynamic forces and characterize the overall vibration of the machine (ISO 10816-3:2009, 2009). According to ISO 10816, velocity measurement can be categorized as follows:

- Class I is for small machines approximately up to 15 kW.

- Class II is for medium machines from 15 kW to 75 kW.
- Class III is large movers and other large machine with large rotating assemblies mounted on rigid and heavy foundations.
- Class IV is huge machines such as turbine generators and gas turbines greater than 10 MW.

Typical vibration velocity RMS boundaries are outlined as in Figure 4.3.

VIBRATION SEVERITY PER ISO 10816-1					
Machine		Class I	Class II	Class III	Class IV
in/s	mm/s	Small Machines	Medium Machines	Large Rigid Foundation	Large Soft Foundation
0.01	0.28				
0.02	0.45				
0.03	0.71		GOOD		
0.04	1.12				
0.07	1.80				
0.11	2.80		SATISFACTORY		
0.18	4.50				
0.28	7.10		UNSATISFACTORY		
0.44	11.20				
0.70	18.00				
1.10	28.00		UNACCEPTABLE		
1.77	45.90				

Vibration Velocity Vrms

Figure 4.3 Typical vibration boundaries limits (ISO 10816-3:2009, 2009)

4.3.5 Crest Factor

Crest Factor is the ratio of the peak value to RMS value of the input signal, as illustrated in Figure 4.4. It determines how extreme the peaks are in the waveform. Higher crest factor indicates the existence more peaks, however crest factor 1 indicates no peaks. The CF value is obtained by using following formula;

$$CF = \frac{|x_{peak}|}{x_{rms}} \qquad (4.6)$$

Some failure cause impulsive impacts on vibration signal of rotating machine. For detection of these failures, the examination of behaviour of the signal can be better indicator. As crest factor uses peak value of vibration, it is useful parameter in order to detect these impulsive failures such as gear tooth breakage. The peak value of the impulsive signal will increase as the damage grows while the RMS level of the overall vibration will change only slightly (Swanson & Favaloro, 1984).

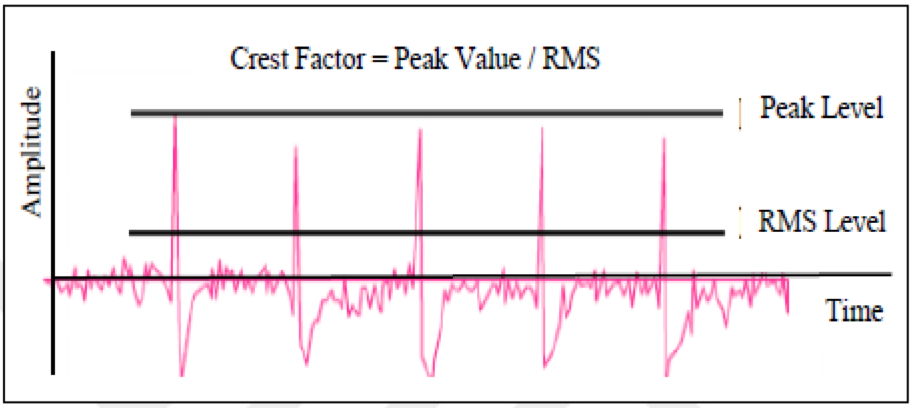


Figure 4.4 Crest Factor (Öztürk, 2006)

4.3.6 Kurtosis

Kurtosis measures the smoothness and heaviness of distribution in signal. It is a non-dimensional quantity used to detect the presence of significant peaks in the time-domain of the vibration signal. Kurtosis is the 4th order statistical moment of the given signal (Hahn & Shapiro, 1967). The normalized kurtosis formula for a vibration signal x(t) is given as follows;

$$\text{Kurt}[X] = \frac{\mu_4}{\sigma^4} = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^4}{\left[\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2\right]^2} \tag{4.7}$$

where; μ_4 is the fourth moment about the mean, μ is the mean of signal, σ is the standard deviation of input signal.

4.3.7 Skewness

Skewness measures the asymmetry of the signal about its mean value. It is the ratio of the average cubed deviation from the mean divided by the cube of the standard deviation. It is the 3th order statistical moment of the given signal. The skewness value can be positive or negative. The skewness formula is given,

$$\mathrm{Skew}[X] = \frac{\mu_3}{\sigma^3} = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^3}{\left[\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}\right]^3} \tag{4.8}$$

4.4 Frequency Domain Analysis

Frequency domain analysis is widely used as a powerful technique for machinery vibration analysis. The faults on rotating machine shows themselves in vibration signal with specified frequencies. These several frequencies are distinctive for each fault. In order to illustrate frequencies in vibration signal, time domain of the vibration signal is transformed into its frequency domain. Frequency domain analysis is a useful tool for detection and diagnosis faults in rotating machines. Moreover, it has been evaluated that the frequency domain analysis is much more useful than the time domain analysis for fault detection of rotating machine; because every change in the frequency domain of a vibration signal produced by a machine can be interpreted. Frequency domain analysis provides harmonic contents in vibration signal. Such properties cannot be determined in the time domain analysis.

For transformation from time to frequency domain, Fast Fourier Transform (FFT) algorithm is applied. FFT is a mathematical computation, which is used widely for many applications in engineering, science etc. For vibration analysis, FFT algorithm has lots of applications; because it shows amplitude of vibration for all frequencies. This transformation algorithm computes the discrete time Fourier transform (DTFT) of a sequence by converting a signal from its original domain (often time) to frequency domain and vice versa. The vibration signal and Fourier transform, denoted by x(t) and X(f), respectively, are expressed as follows:

$$X(f) = \int_{-\infty}^{+\infty} x(t) e^{-i2\pi ft} dt \tag{4.9}$$

In many applications; the input data are purely real and discrete, in which case the outputs of FFT is symmetric about the half of sampling frequency. Because the input data is finite discrete time functions, discrete time Fourier transform (DTFT) is used, as follows;

$$X_k = \sum_{n=0}^{N-1} x_n e^{-2\pi kn/N} \tag{4.10}$$

where k = 0, 1 ,2 , ..., N-1

An FFT and a DTFT produces exactly the same result. Although FFT needs more memory than DFT, most important difference is that an FFT is much faster. As the output of DTFT is N periodic sequence of complex numbers, the magnitude of output is computed in order to display frequency spectrum, as given below:

$$|X_k| = \sqrt{\mathrm{Re}(X_k)^2 + \mathrm{Im}(X_k)^2} \tag{4.11}$$

Frequency domain analysis is appropriate if the operation condition of machine doesn’t change (i.e. changing in the rotational speed of the machine). If machine specifications and operation conditions are known, the vibration distinctive frequencies of each component can be estimated. Analysis of amplitude of these vibration frequencies can provide detection and diagnosis of fault. In figure 4.5, there is an example of frequency spectrum of a healthy worm gearbox.

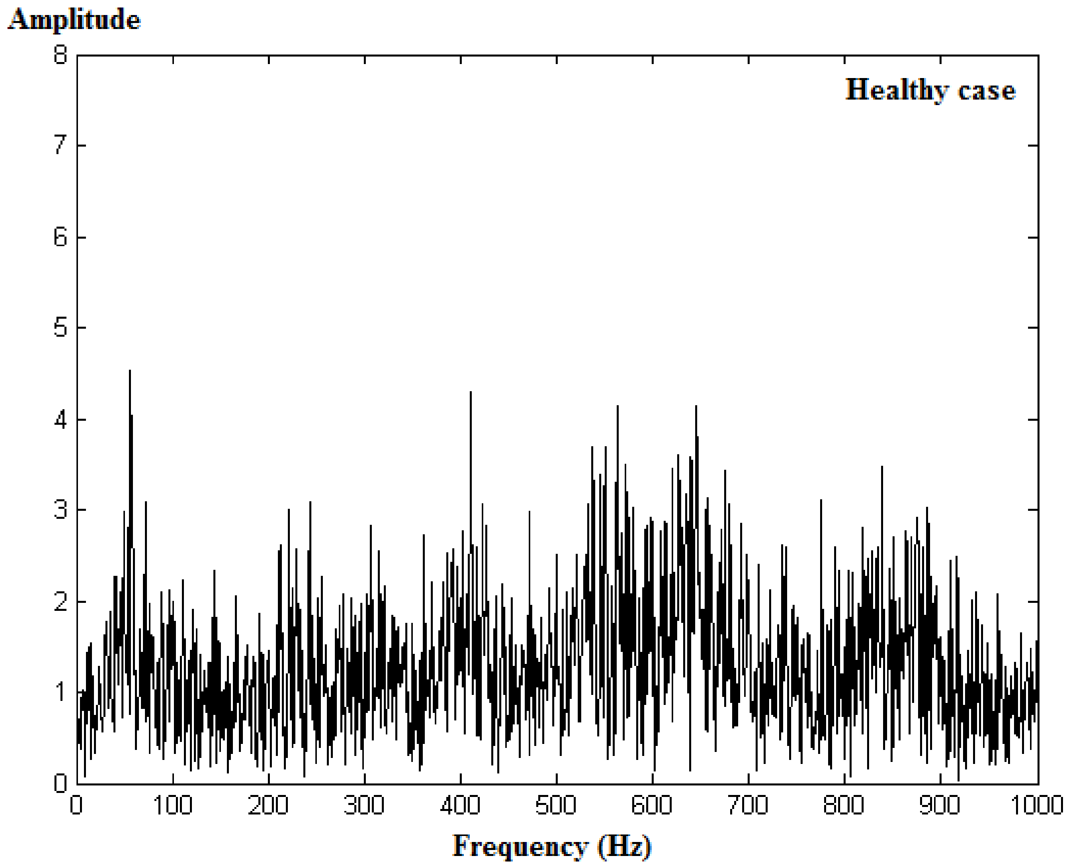


Figure 4.5 Example of frequency spectrum of a healthy worm gearbox

4.5 Joint Time Frequency Analysis

For vibration analysis, one method is visualization of vibration signal in time domain. Another useful method is representation of vibration signal in frequency domain. Time frequency analysis comprises those two techniques that study a signal in both time and frequency domains simultaneously. This technique provides changes in frequency with time. JTFA transforms a one-dimensional time domain signal into a two-dimensional representation of energy versus time and frequency. JTFA have numerous applications such as speech analysis, telecommunications, underwater acoustics, bioacoustics, geophysics, and structural analysis. This technique is applied in order to follow the dynamics of the signal such as non-stationary, transient, etc whose parameters change with time. There are various methods for JTFA, as follows:

- Short time frequency domain
- Wavelet transform
- Wigner distribution
- Gabor spectrogram
- Cohen class transforms and so on.

In recent years, there has been an increasing interest in the research of joint time frequency domain analysis. However; in this thesis, joint time frequency analysis is considered for further research. Thus, this section is given just for information.

4.6 Frequency Component Based Statistical Analysis

Frequency component based statistical analysis is used for more reliable assessment of condition of gearboxes. This method has commonly used recently in order to detect failures on gearboxes. The condition monitoring companies such as SPM Instrument AB, Bearing Man Group (BMG) etc. have studies about this method. This method combines vibration time domain analysis and frequency domain analysis in order to understand machine condition data. It is known that the RMS value of vibration increases in case of existence of failure. Moreover; in frequency domain, the distinctive gear frequencies are shown in case of gear failure. These frequencies are analyzed with fast Fourier transform (FFT). Gear mesh frequency, their harmonics, input shaft rotating frequency and output shaft rotating frequency are important frequencies for gear failure. In the event of failure, amplitude of these vital frequencies increases. In frequency component based statistical analysis, time domain analysis and frequency domain analysis are combined. RMS value of these distinctive frequencies is calculated in a specified bandwidth. The implementation of this method can be illustrated in Figure 4.6.

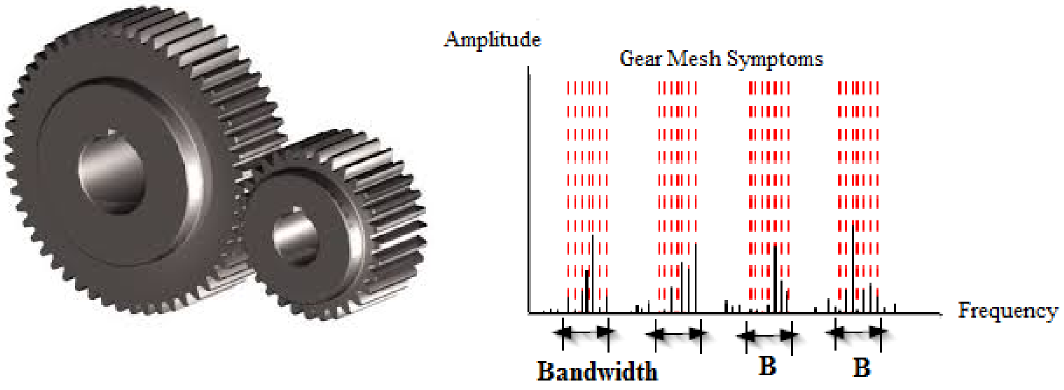


Figure 4.6 Frequency component based statistical analysis

The formula of frequency component based statistical analysis is given below.

$$\mathrm{FCSA} = \sqrt{\mathrm{RMS}_{B_1} + \mathrm{RMS}_{B_2} + \ldots + \mathrm{RMS}_{B_N}} \tag{4.12}$$

where B_1, B_2, …., B_N stand for the considered frequency bands.

CHAPTER FIVE
SMART CONDITION MONITORING

5.1 Smart Condition Monitoring

The condition monitoring of complex systems requires crucial algorithms and intensive calculations. Therefore, most of work about condition monitoring was carried out by using PCs, data acquisition cards, signal condition kits and other helpful devices. Vibration signal acquisition by using PC requires expert knowledge, manual operation, hardwired long signal cables, complex data transmission equipments. Thus, this type of maintenance is expensive. In traditional data acquisition systems, the data measured from acquisition card are generally send into the computer, and specific software analyzes the data. But, over the past few years, there has been major technological developments related to digital system. As a result, smart monitoring technologies, a new concept of condition monitoring, start to be used for effective monitoring. These technologies have some advantages such as portability, easy to relocate, reduction in system size, quick start up, wireless communication, on-line monitoring, simplicity, etc. A portable smart condition monitoring system, its operator who measures the parameter of a fan and sample results can be seen in Figure 5.1.

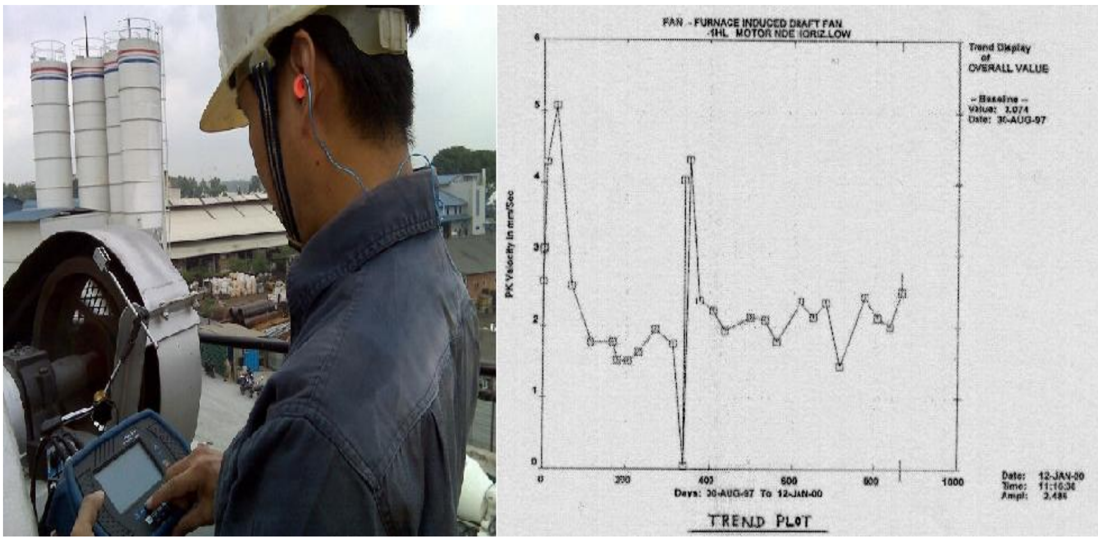


Figure 5.1 Example of a portable smart condition monitoring system (Condition monitoring, n.d.)

Comparison of different systems for condition monitoring can be seen in Table 5.1. In smart condition monitoring systems, companies generally benefit from high speed microcontrollers. On the other hand, this type of solution requires adapting complex signal processing algorithms to the limited computing resources of microcontrollers. For this purpose, up to date, they have used DSP, microcontrollers, embedded systems, FPGA, etc.

Table 5.1 Comparison of condition monitoring devices

Features	**Smart monitoring**	**Standard monitoring**
Cost	Low<100$	High > 500$
Hardware	One integrated system	More electronic devices
Software	Fundamental analysis	More complex analysis
Advantage	Fast results Portable Simple	Accurate results More analysis Continuous monitoring
Disadvantages	Limited computing resources	Requirement expert knowledge Manual operation

Implementing smart condition monitoring represents a certain challenge. First of all, to be able to collect reliable monitoring data, system parameters must be known and synchronously associated with the measurement data. For example, varying load condition and rotating speed changes measured data. Without information on these parameters, interpretation of condition of system is not reliable. Second; for failure-critical instruments, condition parameters should be recorded without delay and almost in real time. Moreover, for dependable results, multiplexer scanning, which means taking measurement more than one, has to be done. Last but not least; the trustworthy analysis of the monitoring data requires capable diagnosis techniques and permanent monitoring. Permanent monitoring generates vast amounts of data, thus smart condition monitoring systems needs computing powers and data storages.

The use of modern technology makes measurement and signal conditioning fast, accurate and repeatable. One of the examples of new designed smart condition monitoring system, Prüftechnik - Vibxpert 2, is shown in Figure 5.2.

Figure 5.2 Prüftechnik, Vibxpert 2 (Vibxpert ii, n.d.)

The last technology Vibxpert 2 is very talented smart condition monitoring system. Vibxpert 2 is an all-in-one data collector, vibration analyzer and field balancer. These are a few of their good specifications:

- Fastest measurements using trending spectra, advanced processor technology
- User-friendly interface and intuitive operation
- Powerful analysis and diagnostic tools for machine trouble shooting such as time waveform of vibration, narrowband and broadband frequency spectrum, resonance tests, modal analysis, ODS analysis, orbit measurements etc.
- Automatic switchbox support
- Long-lived battery

For smart monitoring of gearboxes, analysis of vibration signals is appropriate technique, because for any change in the gearbox condition, there will be most likely an effect in vibration signal. Thus; in this thesis, vibration based smart condition monitoring of worm gearbox is described. Data acquisition and signal processing system is developed.

5.2 Developed Smart Condition Monitoring Device

In the scope of this thesis, a new high-performance online system for condition-monitoring of worm gearboxes is developed. The aim of this thesis is production of smart condition monitoring system which can measure and analyze vibration signal and also detect failures on worm gearbox. Developed system provides measurement of rotating shaft velocity, representation vibration in time waveform and analysis of vibration using time based indicators and frequency spectrum. It is carefully designed and developed to fit the needs of machinery applications.

Developed smart condition monitoring device (SCM) uses condition-based information to acquire and store real-time plant vibration data. Developed SCM device uses this data in order to determine equipment condition and sends a message to operator when maintenance is actually necessary. The use of modern technology in the SCM device makes measurement and analysis of vibration data fast, precise and stable.

The developed system comprises a sensor, signal conditioning, commander unit, analog vibration measuring unit and visualization screen. Measurement results can be transferred to a USB memory stick. Band alarms enable alarm management, which is used for warning of failure. Developed smart condition board is an electronic device designed to acquire data from vibration sensor, analyze data with suitable algorithms and monitor parameters. The developed SCM device has been examined in two aspects: hardware system development and software system development.

5.2.1 Hardware System Development

Smart condition monitoring system in this experimental research includes acceleration sensor, amplifiers, speed measurement module, analog digital converter, data acquisition, signal processing unit, visualization and storage device. The hardware parts of this vibration monitoring system are shown in Figure 5.3.

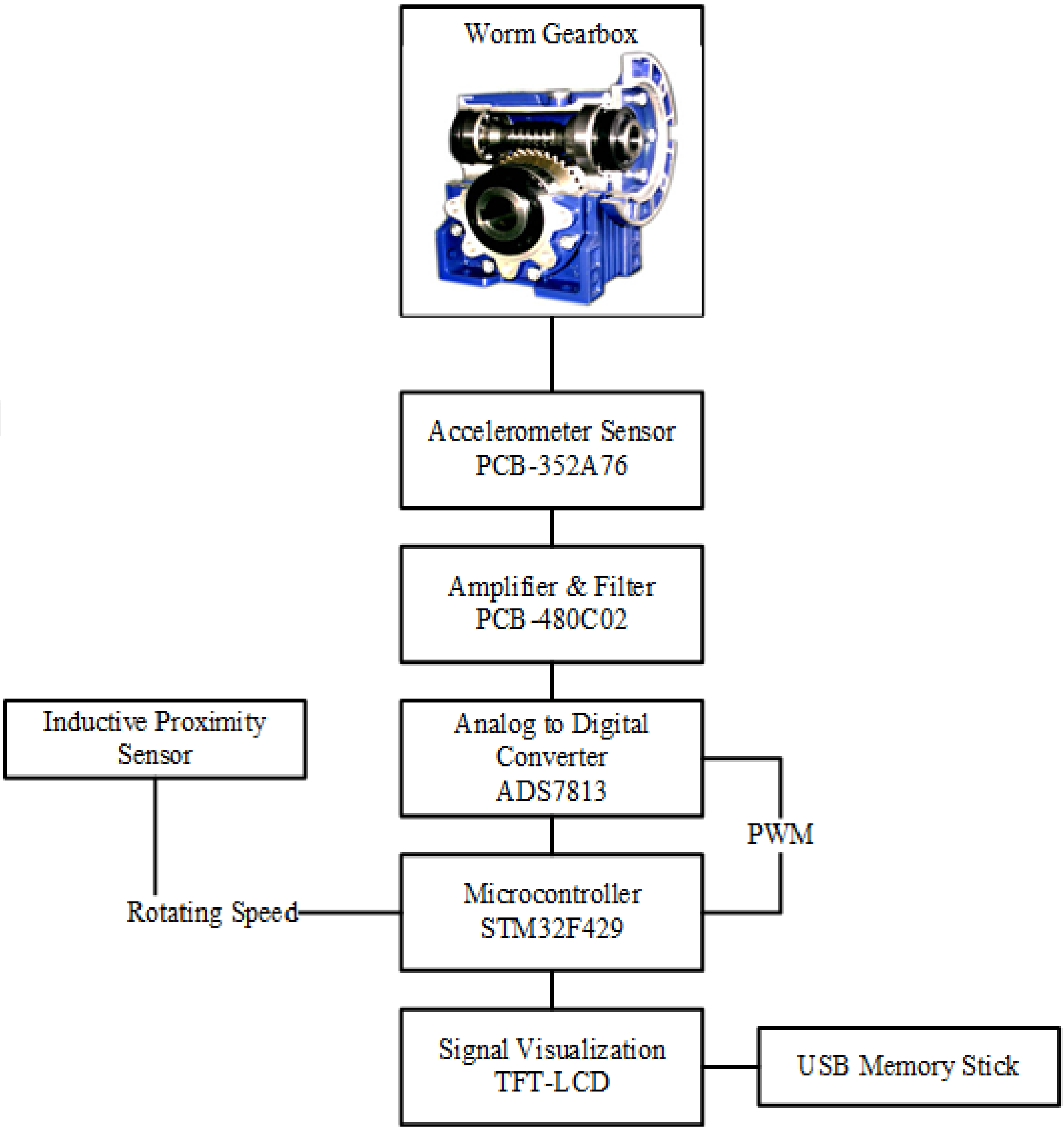


Figure 5.3 Hardware parts of developed vibration smart monitoring system

5.2.1.1 Acceleration Sensor

Effective vibration analysis first begins with acquiring an accurate signal from vibration sensors such as accelerometer. According to requirement, suitable sensors are chosen to acquire vibration signal. Piezoelectric or MEMS acceleration sensors are used in order to measure vibration. These sensors convert vibrations into analog voltage signals. The most commonly used transducer for vibration measurement is the piezoelectric accelerometer. The piezoelectric accelerometer has wide frequency range and high sensitivity for measuring low amplitude signals. They have also relatively small-sized, highly durable, stability and measurement linearity.

Accelerometers consist of a piezoelectric crystal and a small mass normally enclosed in a protective metal case. When the accelerometer is subjected to vibration, the mass exerts a varying force on the piezoelectric crystal, which is directly proportional to the vibratory acceleration. The charge produced by the piezoelectric crystal is proportional to the varying vibratory force. The charge amplifier converts the charged output of the crystal to a proportional voltage output in mV/g (Sheffer, 2004).

Sensor output voltage, sensitivity, bias level and frequency bandwidth have to be specified according to system necessity. In this study, PCB Piezotronics brand 352A76 series accelerometer sensor whose sensitivity is 9.77 $mV/m/s^2$ and frequency bandwidth range 5-10000 Hz is preferred. The accelerometer sensor used in this research can be shown in Figure 5.4.

Figure 5.4 PCB Piezotronics brand 352A76 series accelerometer sensor

5.2.1.2 Signal Conditioner

Important components of the signal conditioning unit are anti-aliasing filters and amplifiers. First of all, as the vibration travels from the point of generation to the accelerometer on the gear, it will be contaminated by vibrations from other sources. Thus, the detected signal will usually need pre-processing and, possibly, filtering. Filter provides recovering the desired signal from the accelerometer signal. The analog vibration signal is passed through a low-pass filter before the signal is sampled and recorded. Thus, high frequencies coming from noise are eliminated.

Electronic components (capacitors, resistors, amplifiers) are built to amplify sensor output voltages and filter in order to capture the real vibration signal. These products provide conditioning of vibration sensor signals for transmission to data acquisition system. Charge converters and amplifiers convert high impedance signals to low impedance voltage signals. Signal conditioners can have AC or DC coupling and provide additional conditioning including gain, filtering and integration. For this purpose, PCB Piezotronics brand 480C02 series signal conditioner is chosen in this research, seen in Figure 5.5. This model with its 27 Volts supply will allow the positive side of the signal to go to +14 Volts. The negative side of the signal is capable of -8 Volts.

Figure 5.5 PCB Piezotronics brand 480C02 series signal conditioner

5.2.1.3 Speed Measurements

Since there are many kinds of working conditions in different speed situations, the fault model of worm gearbox is also different. According to rotating speed, distinctive frequencies of gear will change. In order to realize the fault diagnosis of different conditions, it is necessary that the rotation speed of gear should be known. In order to measure the angular speed and find shaft position for calibration vibration frequencies, an inductive proximity sensor is used. MEFA brand proximity sensor (supply voltage 5V and when metal detected, output voltage is 4.2V approximately) is used in experiments, as shown in Figure 5.6.

Figure 5.6 MEFA brand, inductive proximity sensor

The velocity of wheel gear shaft was measured by this sensor which is a non-contact device. It produces a square pulse output for every complete revolution of the wheel shaft. The output of the sensor is directly connected to the smart condition monitoring system. This sensor information is also used in time synchronous average (TSA) method. The vibration measurement starts when the proximity sensor detects metal component.

5.2.1.4 Analog to Digital Converter

In real world, we encounter with both analog and digital signals. Digital signals are particularly robust to noise, and extremely efficient. On the other hand, in certain situations analog signals are sometimes more appropriate or even necessary. Microcontrollers are capable of detecting binary signals, 1 or 0. Thus, real world signals must be converted into digital, using a circuit called ADC (Analog to Digital

Converter), before they can be manipulated by digital equipment. For example, a modem will convert signals from digital to analog before transmitting them over telephone lines that carry only analog signals. These signals are then converted back into digital form at the receiving end so that the computer can interpret the data in digital format.

Briefly, since signals are interpreted by a microprocessor, analog signals have to be converted into discrete digital numbers. ADC has been built in order to digitize the vibration signals and send the signals to the digital signal processor. For this purpose; Texas Instruments brand ADS7813 series featuring SAR, low power, 16 bit resolution, 40 kHz maximum sampling frequency, SPI communication, ±10V input range bipolar analog digital converter was chosen. ADS7813 and its basic operation circuit can be shown in Figure 5.7. Although microcontrollers have analog to digital converter unit, an external ADC is necessary because microcontroller internal ADC generally operates only in range from 0 to 5 input volts.

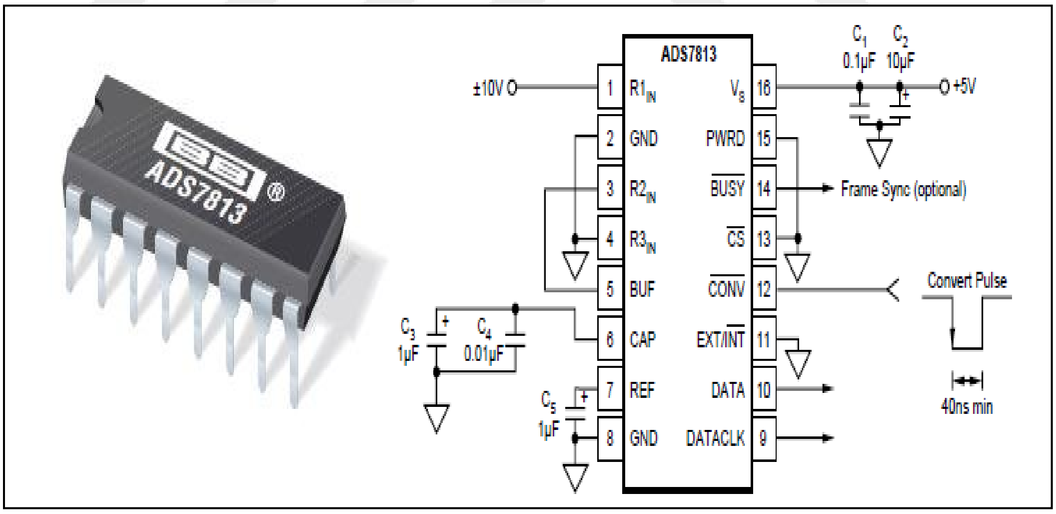


Figure 5.7 ADS7813 and its basic operation circuit (Texas instruments-ADS7813, n.d.)

Important parameters of the data acquisition system such as quantization and sampling frequency involved in the ADC process are outlined below:

- Quantization: Quantization is a process of digitizing the range. This process is completed by dividing the amplitude range of the system (-10V to 10V in this study) into a number of discrete levels. For example, an n-bit ADC has the ability to produce 2^n quantized levels. Therefore, a 16-bit device will produce 2^{16} or 65536 levels. A system with a selected input range of -10V to 10V, and divided into 65536 levels results in a resolution of (20/65536) ≈ 305µV.

- Sampling: Sampling is an essential process that the continuous analog signal is converted to a discrete signal. Sampling is performed by measuring the value of the continuous signal at equal sampling intervals (Δt seconds). The sampling signal y[n] is given by:

$$y[n] = y[n\Delta_t] \quad n = 1,2... \tag{5.1}$$

and sampling frequency, f_s is defined as:

$$f_s = \frac{1}{\Delta_t} \text{ (Hz)} \tag{5.2}$$

where Δ_t is the time interval between samples.

The sampling frequency or sampling rate, f_s, is the average number of samples obtained in one second. A suitable sampling frequency plays a major role in the acquisition of data. It determines whether the signal characteristics will be correctly recorded. The sampling frequency should be set high enough to capture the maximum frequency components of interest in the signal. According to the Nyquist frequency theorem, the sampling rate must be equal to or greater than the two times highest frequency (f_{max}) in order to properly reproduce the analytic signal.

$$f_s \geq 2f_{max} \tag{5.3}$$

The serial peripheral interface (SPI) is used as a communication method between connecting the ADS7813 and SPI-equipped microcontrollers.

5.2.1.5 Signal Processing Unit

For this research, the tasks greatly restrict the number of development platforms that can be used. First, the platform that works with the 8-bit or 16-bit core is not good enough. Moreover, the platforms must do digital signal processing (DSP) instructions in order to find FFT. The Table 5.2 gives an overview of three platforms which are examined very closely for this work.

Table 5.2 Overview of three platforms which are examined

Specifications	**TMS320C6713 DSP**	**STM32F429 Discovery**	**Raspberry Pi Model B**
Kernel	32/64 Bit	32 Bit	32 Bit
Architecture	TMS320C67x DSP Core	ARM Cortex M4	ARM1176
Clock Rate (Max)	225 MHz	180 MHz	700 MHz
Storage	512 Mb	2 Mb	SD-Card
RAM	256 Kb	256 Kb	512 Mb
USB	✔	✔	✔
SPI	✔	✔	✔
USART	✕	✔	✔
I2C	✔	✔	✔
ADC	✕	✔	✕
RTC	✕	✔	✔
Operating system	-	-	Linux
Debugger	✔	✔	✔
Programming language	C/C++	C/C++	C++, Java, Python
Visualization	✕	✔	✔
Cost	$ 415	$ 35	$ 40

Microcontroller based data acquisition device was selected as analysis, diagnosis and visualization hub. For this purpose, STM32F429 Discovery development board from ST was preferred. This board has STM32F429ZIT6 high performance ARM Cortex M4 core microcontroller featuring 2 Mbytes of Flash Memory, 256 Kbytes of RAM, 32 bit, frequency up to 180 MHz. This microprocessor is very powerful, well equipped and very suitable for digital signal processing instructions. It also comes with the SW Debugger. With this, it is possible to program on the microcontroller and also debug it. Discovery board has also 2.4" TFT LCD on board which is useful for graphical user interface and visualization of gear condition. The STM32F429 Discovery microcontroller can be seen in the Figure 5.8

Figure 5.8 STM32F429 Discovery board (ST-STM32F429 Discovery Board, n.d.)

This microcontroller also supports DSP instructions with aid of the Cortex Microcontroller Software Interface Standard (CMSIS). CMSIS is an independent hardware abstraction layer for the Cortex-M processor series and defines generic tool interfaces. It has DSP library collection with over 60 functions for various data types; fix-point (fractional q7, q15, q31) and single precision floating-point (f32). The library is available for all Cortex-M cores. The Cortex-M4 and Cortex-M7 implementations are optimized for the SIMD instruction set. This signal processing unit is chosen, because it is more equipped, easier for coding and lower priced than others.

Commander unit cooperate with ADC module via SPI communication. SPI is a synchronous serial communication interface specification used for short distance communication, primarily in embedded systems. SPI communication bus is shown in Figure 5.9. SPI devices communicate in full duplex mode using master-slave architecture with a single master. Multiple slave devices are supported through selection with individual slave select (SS) lines. The SPI bus specifies four logic signals:

- SCLK: Serial Clock (output from master).
- MOSI: Master Output, Slave Input (output from master).
- MISO: Master Input, Slave Output (output from slave).
- SS: Slave Select (active low, output from master).

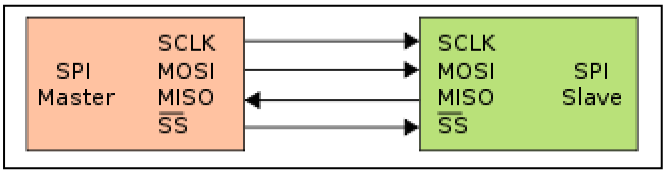


Figure 5.9 SPI bus, single master and single slave (Serial peripheral interface bus, n.d.)

ADS7813 works in master mode and sent digital data to Discovery kit, working in slave mode with own master clock via SPI communication. To start conversion analog to digital signal in ADS7813, the input CONV pin should be pulled low. It is a falling down trigger for starting conversion. When the conversion is finished, the

ADC pulls the output BUSY pin low. The developed SCM device is monitoring the status of this pin, and once it is HIGH, it is waiting to get digital data from the ADS7813 via SPI. ADC sends out a clocking signal with SCLK pin for reading the data from SCM device synchronously. SCM device is getting digital data from ADS7813 thanks to this clock. The AD7813 sends out one bit of the conversion for each low to high transition of SCLK. The data appears on the SPI MISO pin in SCM device. Then, SPI communication finish and ADC is starting to wait new trigger. Conversion timing sequence for ADS7813 can be seen in Figure 5.10.

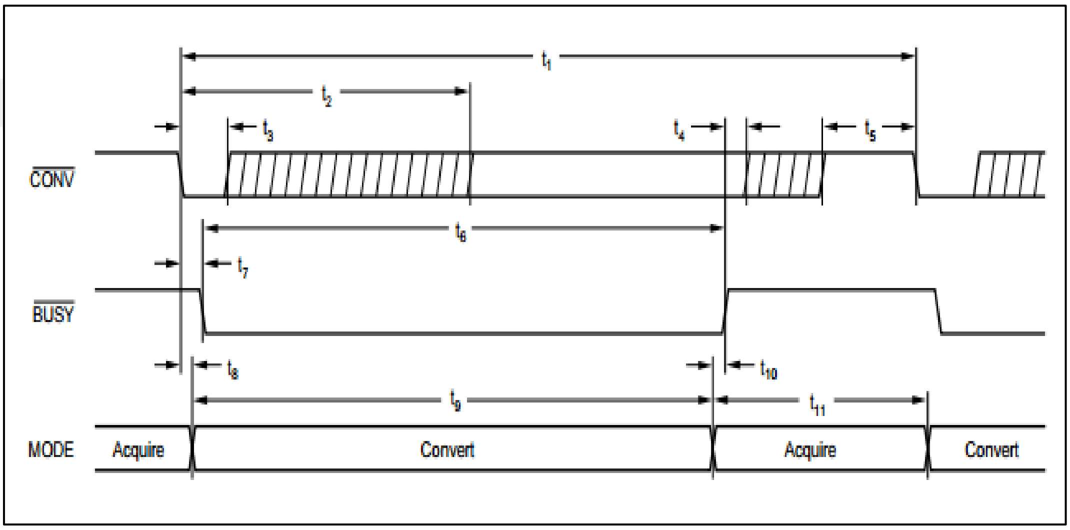


Figure 5.10 Conversion timing sequence of ADS7813 (Texas instruments-ADS7813, n.d.)

Developed SCM device sends a Pulse Width Modulation (PWM) code to ADS7813 in order to get vibration signal at every sampling time. PWM is a modulation technique used to encode a message into a pulsing signal. It is also used for switching the power to a device or triggering at a given frequency. PWM output pin from device trigger ADC CONV pin with falling edge at every sampling time. Between each trigger, the last conversion result of ADC is taken by SCM device.

Speed measurement unit is used inductive proximity sensor, which is a metal detector. There is a metal component on the wheel gear that sensor detect it when it is really nearby. Normally, sensor output voltage is 0 V approximately, but sensor produce 5V (logic 1) when the metal object is detected. Thus, for every complete revolution of the wheel shaft, it produces a square pulse output. The output of the sensor is directly connected to input external interrupt pin of SCM device. The general scheme of smart condition monitoring can be seen in Figure 5.11.

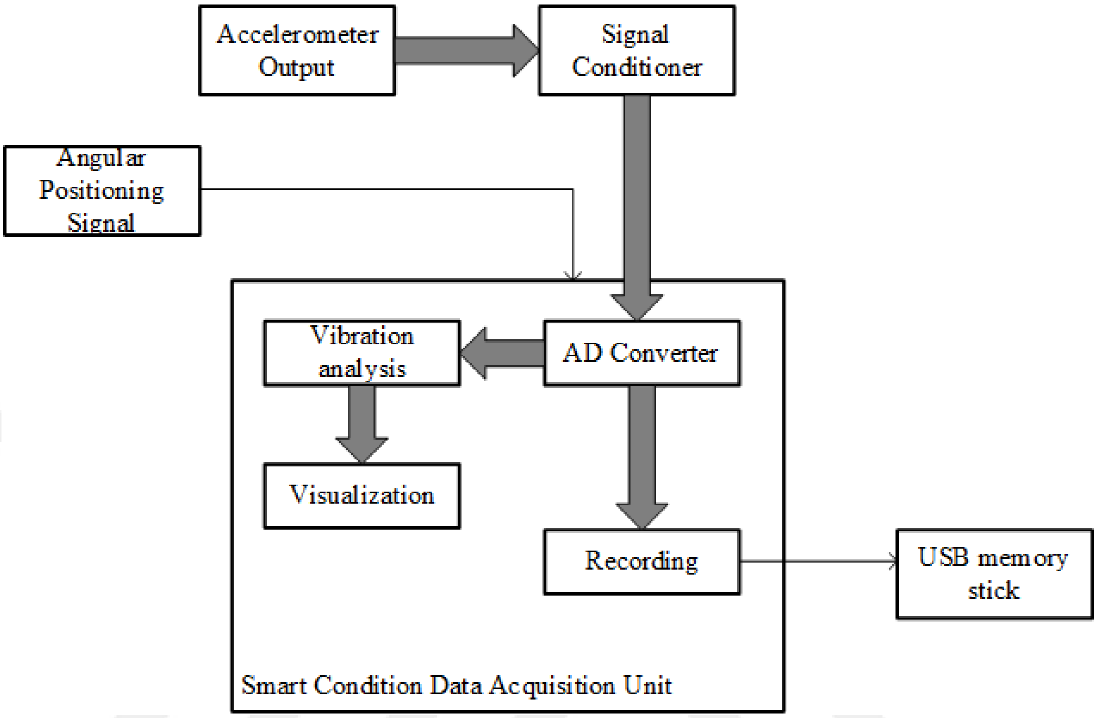


Figure 5.11 General scheme of smart condition monitoring

5.2.2 Software System Development

The software for the smart condition monitoring unit is completely written in C programming language. Drivers for the hardware components and the necessary algorithms are included using the header files. The development environment from Keil uVision with version 5 is used in this work. This is a free, but restricted software development environment for ARM Cortex MCU based microcontrollers. It debugs until allowing code size limit. In this research, we used professional edition of Keil.

The graphical user interface is designed for easy usage. The ST Company makes a contact with SEGGER company about various software packages. They support graphic software (emwin) for STM32F429 Discovery board. Emwin is designed to provide an efficient and independent graphical user interface (GUI) for any application that operates with a graphical LCD. For example; graphical user interface components such as button, text, check box, edit box, graph, icon, image, list box, menu, multi page, radio button, slider etc. can be operated on TFT LCD. In this research, buttons, text boxes, edit texts and graphs are used.

Discovery kit is programmed in order to find velocity of machine, real time representation of vibration signal, record and analyze the vibration signal and transferring data to USB memory stick. The microcontroller starts with the main program (main.c) when it is switched on. The microcontroller is initialized in the main program such as leds, TFT screen, button etc. The program starts 3 touch buttons on the screen, which are measurement velocity of wheel shaft, monitoring vibration in real time and data analysis of gearbox, as seen in Figure 5.12. Thus, the developed software has four main parts.

- Measurement velocity
- Real time data acquisition and monitoring
- Vibration analysis
- Data transferring

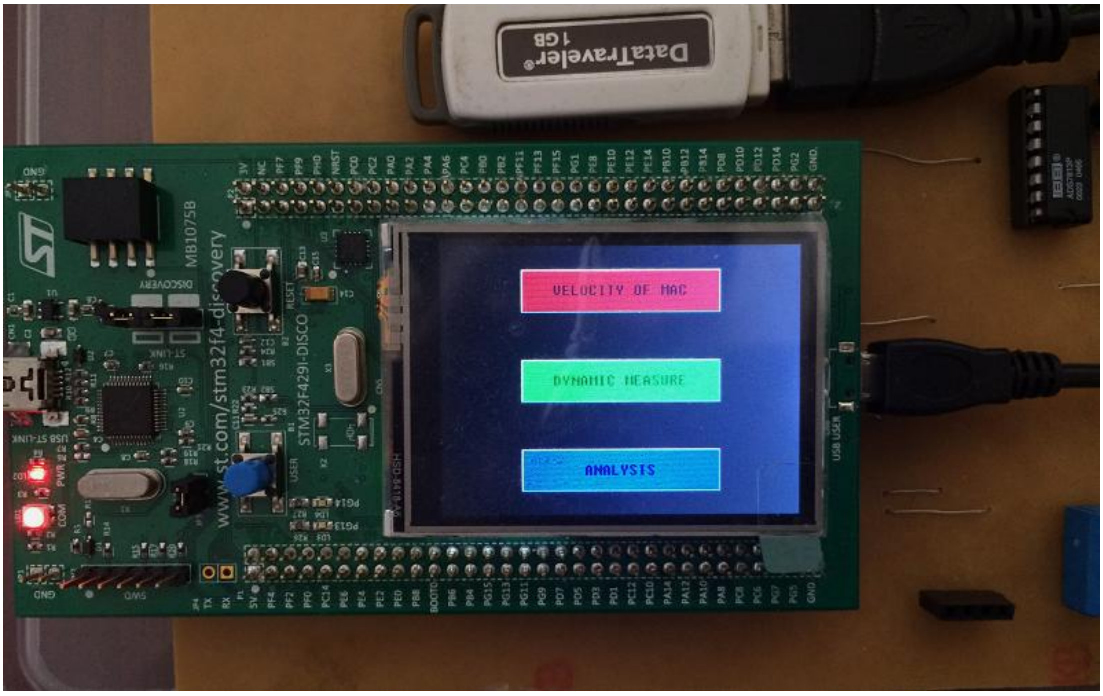


Figure 5.12 Start of the program

5.2.2.1 Velocity Measurement of Gear Shaft

In this part, velocity of wheel gear is measured with an inductive proximity sensor using timer. First, the program initializes timer as a counter which counts 2000 in one second and initializes external interrupt for detection of metal. When a metal object is detected, the interrupt comes up. Two interrupts mean one rotation of the shaft. Counter starts with first interrupt and stops with subsequent interrupt. The velocity of shaft is written in edit text, shown on TFT screen. Content of counter gives us duration between two interrupts. Figure 5.13 shows the flow chart of measurement velocity routine.

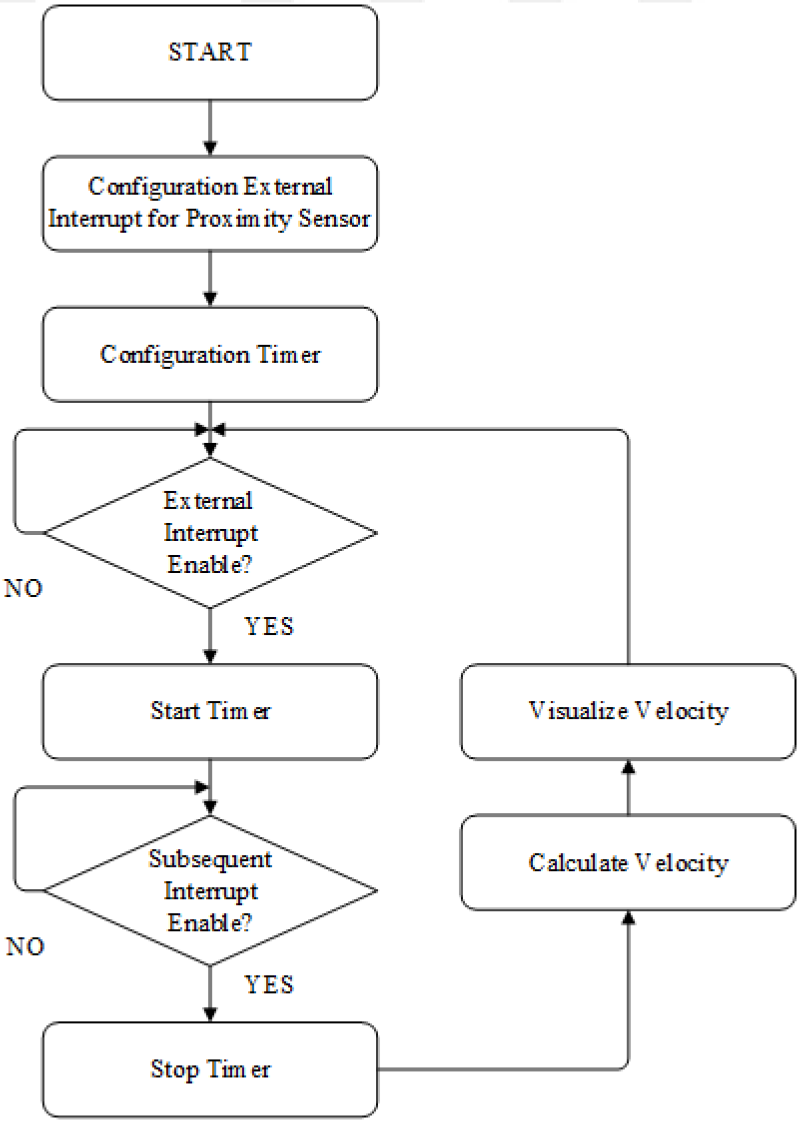


Figure 5.13 Flow chart of measurement velocity routine

The screenshot of TFT screen can be shown in Figure 5.14 when the developed monitoring system measures the velocity of wheel gear.

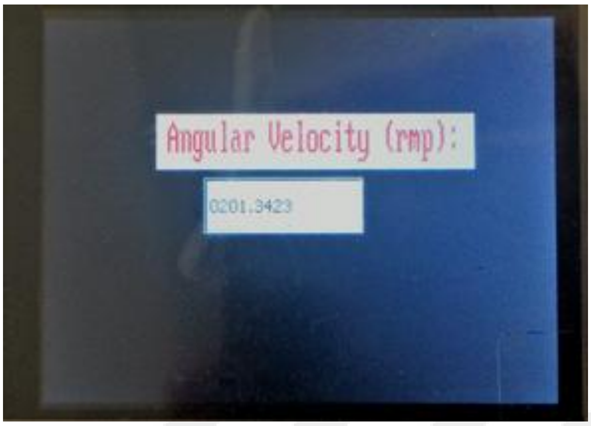


Figure 5.14 TFT screen when measurement velocity of wheel gear

5.2.2.2 Real Time Data Acquisition and Monitoring

Representation of vibration signal in real time is very important part of the condition monitoring. Real time and continuous vibration monitoring of industrial machines by means of electronic systems allows effective assessment of the machine status. It guarantees the safe running of the equipment. By studying the time domain waveform analysis, it is often possible to detect changes in the vibration signal caused by faults. The repetitive high amplitude impulse in vibration data is interpreted as failure. While the operator examines vibration data in time domain, he can decide condition of machine status and determine failures.

The PWM send by SCM device begins acquisition process in ADC. In this study, The 2% duty cycle PWM signal send from Discovery kit to ADC at every 0.5 millisecond (f_s=2 kHz) for acquiring vibration signal. After getting analog vibration signal, the conversion process starts. In this duration, analog vibration signal is converted into digital signal by external ADC. Subsequently, the digital data is ready to transmission from ADC to SCM device via SPI. Discovery Kit gets 16 bit digital vibration data at every external interrupt come from ADC. After that, the digital data turns into voltage value and illustrates on TFT screen directly. The graph is used for graphical visualization of vibration signal in real time. The flow chart of real time monitoring vibration can be seen in Figure 5.15. The screenshot of TFT screen can be shown in Figure 5.16 when the developed monitoring system measures vibration of the worm gearbox in real time.

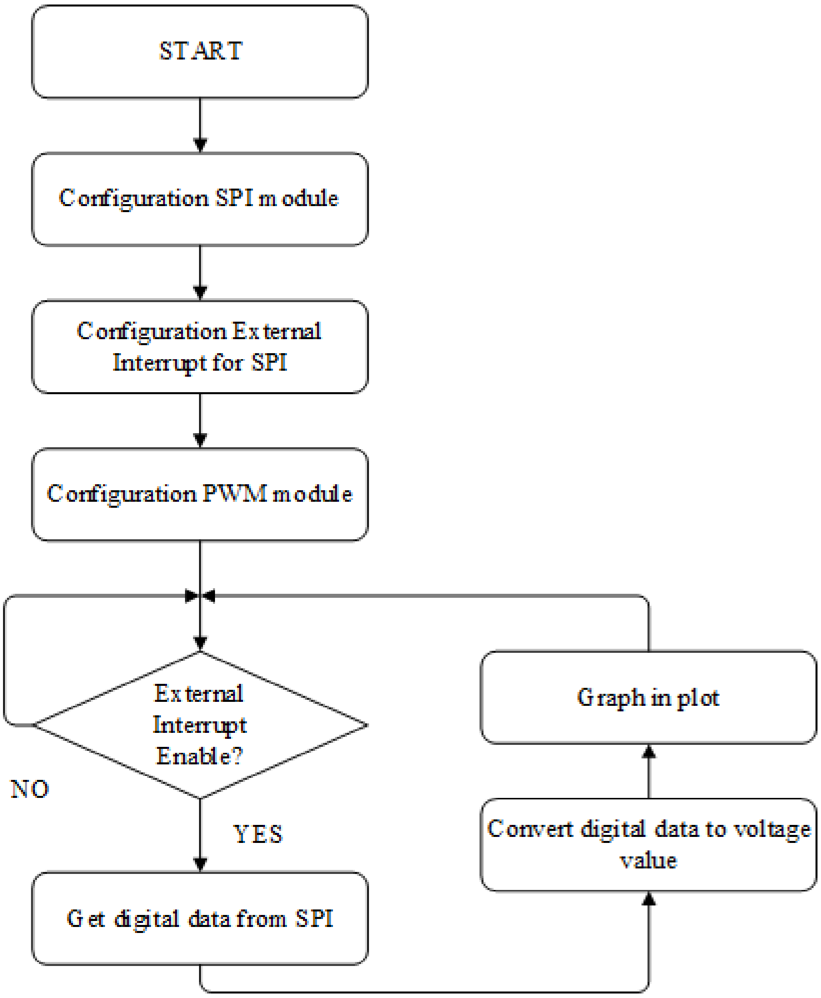


Figure 5.15 Flow chart of real time monitoring vibration routine

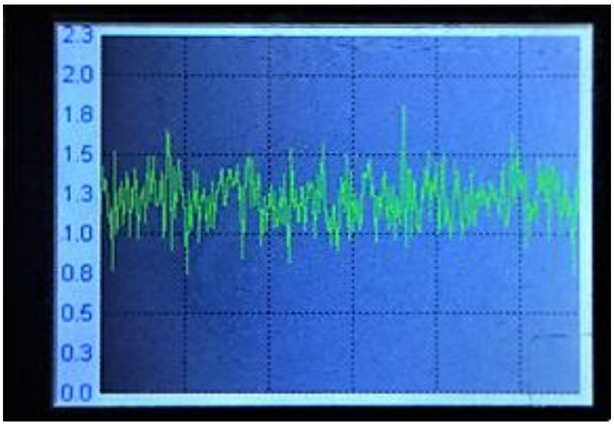


Figure 5.16 TFT screen output when measuring vibration in real time

5.2.2.3 Vibration Analysis

Suitable algorithms for microcontroller have been implemented in this thesis in order to reach to an effective vibration analysis. For this purpose, time domain indices, frequency domain representation and frequency component based statistical analysis are used. Data analysis is very important part of the software, because fault diagnosis for gearbox is carried out in this section. These algorithms are illustrated in Figure 5.17.

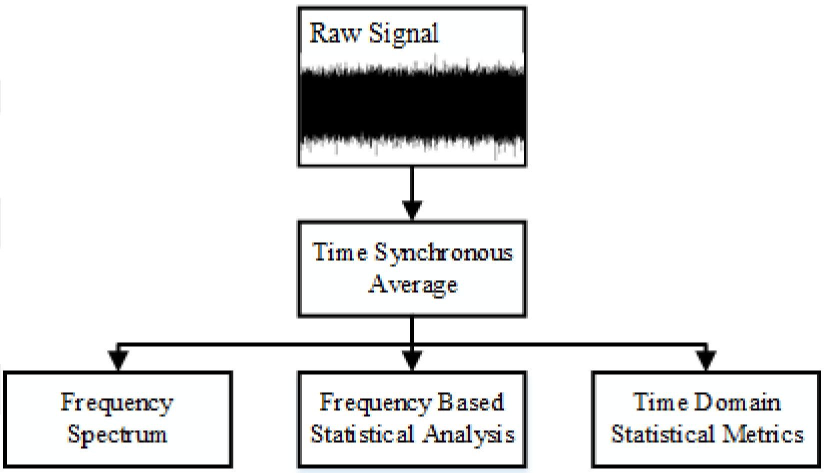


Figure 5.17 Algorithms for vibration analysis

First, the data analysis starts with measuring velocity of wheel gear in order to carry out time synchronous average method (TSA). TSA is used in order to eliminate effects of signal components that are not synchronous with the shaft rotation. TSA allows the removal of noise from a vibration signal. The signal coming from accelerometers is averaged in time, employing periodicity with wheel shaft rotating speed; thus significantly improving the signal to noise ratio. For implementation of TSA, the angular velocity of wheel gear has to be known. Synchronous averaging involves triggering data acquisition with respect to period of shaft pulses. The number of data, which will be acquired synchronously with the period of wheel shaft, is specified with the aid of velocity. Thus, acquired data is averaged in time with respect to one revolution of wheel gear.

Second, real time data acquisition starts after specifying TSA data. For acquiring vibration signal, 2% duty cycle PWM signal is sent from SCM device to ADC at every 0.5 millisecond (f_s=2 kHz). According to Nyquist sampling theorem, sampling frequency was taken as 2000 Hz, since the significant frequency components of vibration waveform are below 1000 Hz. The sampling frequency is chosen as 2 kHz, but it can be changed between 1 Hz to 40 kHz. The total number of acquired data is 32768. This total data is acquired in 16.38 seconds. Then, TSA is implemented for specified data size. The memory of total data is,

$$\text{Total data size} = 32768 * 2\ \text{byte} = 65536\text{byte} = 65\ \text{Kbyte} \tag{5.4}$$

After real time data acquisition and TSA, there are four buttons on TFT screen for conclusion of data analysis. These buttons are statistical analysis, frequency domain analysis, frequency component based statistical analysis and data transferring.

Time domain indices (statistical analysis) methods try to analyze the amplitude information of the vibration time signal to detect the failure of worm gearbox. It is one of the simplest fault detection approaches. It can give qualitative information about the machine condition. One of the facts about vibration of gearbox is increasing statistical indexes in case of failure on gear. The maximum value, minimum value, mean value, RMS value, standard deviation, power value and mean frequency value are used for this purpose.

Frequency domain representation includes fast Fourier transform. The frequency domain representation completely defines the vibration signal. It gives information about not only detection of faults but also the cause of defects. In this technique, acquired time domain vibration signal is transformed into the frequency domain by using FFT algorithm. In frequency domain of vibration data, the most important frequencies are the tooth meshing frequency, their harmonics and sidebands. It is very important to know that the distinctive frequencies related to rotating components in gear transmission systems will vary according to the rotational speed of gear. Therefore, before the implementation of FFT, rotating speed of worm wheel gear is measured. By using FFT representation, these frequencies and their qualitative information can be examined on TFT screen.

The CMSIS DSP library including specialized algorithms is used for computing the FFT of real data sequences. The FFT is defined over complex data but in many applications the input is real. Real FFT algorithms take advantage of the symmetry properties of the FFT and have a speed advantage over complex algorithms of the same length. The FFT of a real N-point sequence has symmetry in the frequency domain. The second half of the data equals the conjugate of the first half flipped in frequency. The functions support lengths of [32, 64, 128... 4096] samples. After discrete fast Fourier transform, graph is used for visualization of FFT. The real length N forward FFT of a sequence is computed using the steps shown below and in Figure 5.18.

- The real sequence is initially treated as if it were complex to perform a CFFT.
- Reshapes the data to obtain half of the frequency spectrum in complex format.

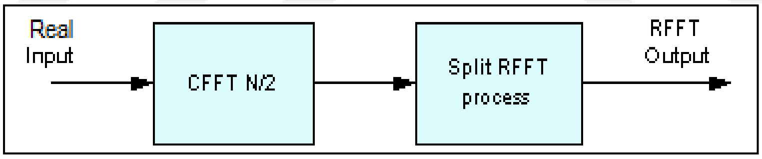


Figure 5.18 FFT for real inputs (CMSIS-DSP, n.d.)

Frequency component based statistical analysis is used for an effective analysis of vibration in frequency domain. For failure on worm gearbox, the worm shaft frequency and their harmonics can be shown in frequency domain. High amplitude of these frequencies is interpreted as asset of faults on gear. In this method, RMS value of these special frequencies and their ±10 Hz bandwidth is calculated.

After all, for further research, storage or implementation other analysis techniques, the vibration data can be transferred to a USB memory stick. First, the software checks connection between system and USB stick. Then, data is written in text document (txt). The flow chart of vibration analysis program is illustrated in Figure 5.19.

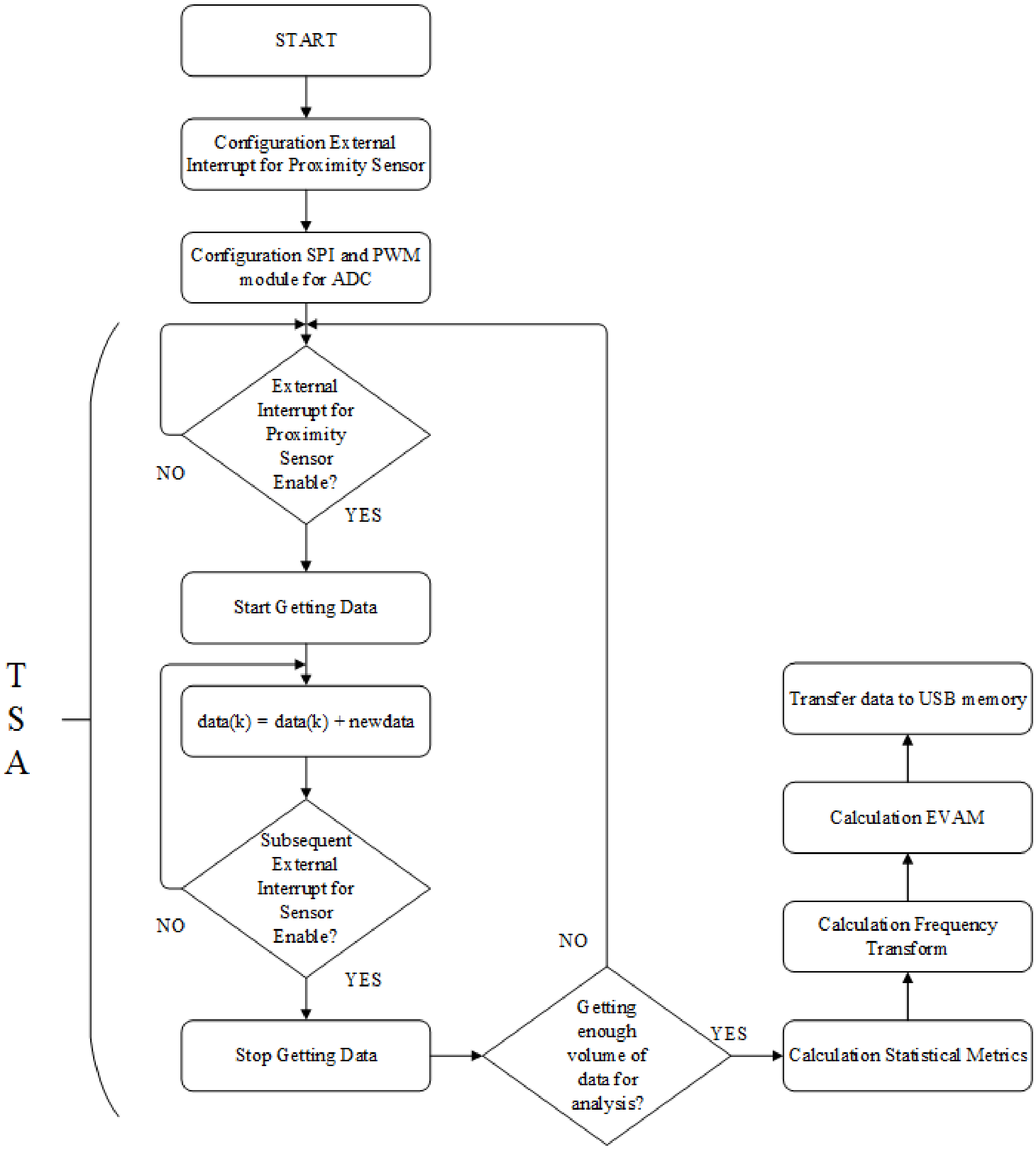


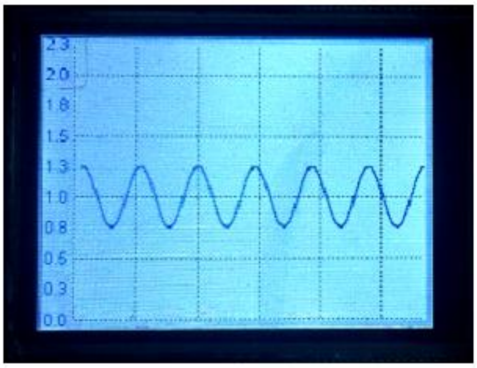
Figure 5.19 Flow chart of vibration analysis routine

5.3 Case Studies

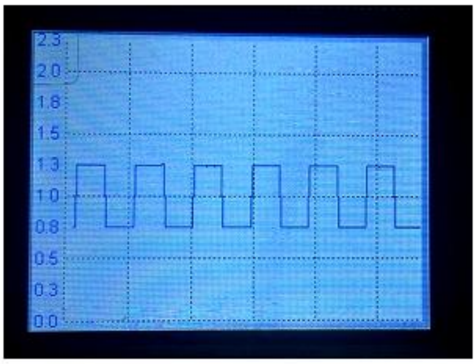
In this section, the case studies related to developed smart condition monitoring system are given. These studies are evidence of accurate software implementation. By examining these evidences, one can conclude that the vibration data analysis software is run correctly.

5.3.1 Case Study 1: Real Time Monitoring

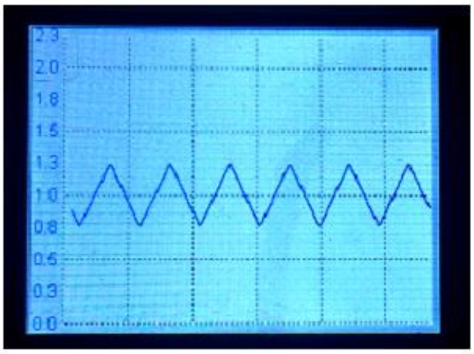
In this case study, the various signals are given to developed smart condition monitoring device by Rohde & Schwarz HAMEG brand HMF2525 series external signal generator equipment. In this case, visualization of known signal is carried out and tested. These signals are visualized on the TFT screen in real time, as shown in Figure 5.20.



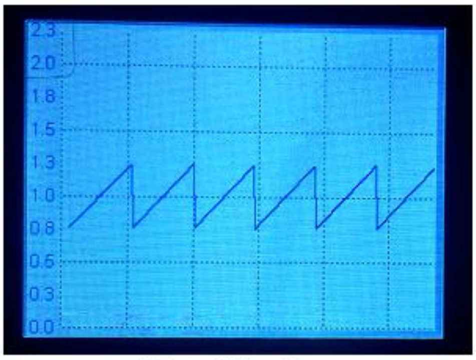
a)Sine



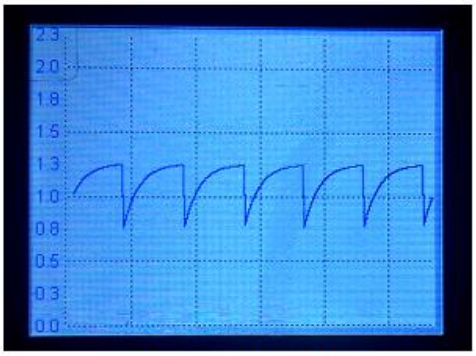
b) Square



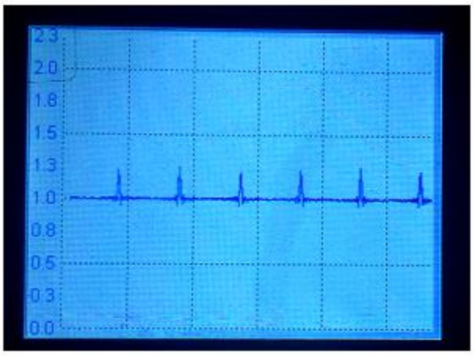
c) Triangle



d) Positive Ramp



e) Exponential Rising



f) Cardinal Sine

Figure 5.20 Various known signals visualized on TFT screen

5.3.2 Case Study 2: Frequency Domain Analysis

In this case study, sine waves which have different frequencies are given to smart condition monitoring device by external signal generator equipment. In this case, visualization of frequency domain of known signals is carried out and tested. Frequency spectrums of these signals are visualized on the TFT screen; as shown in Figure 5.21.

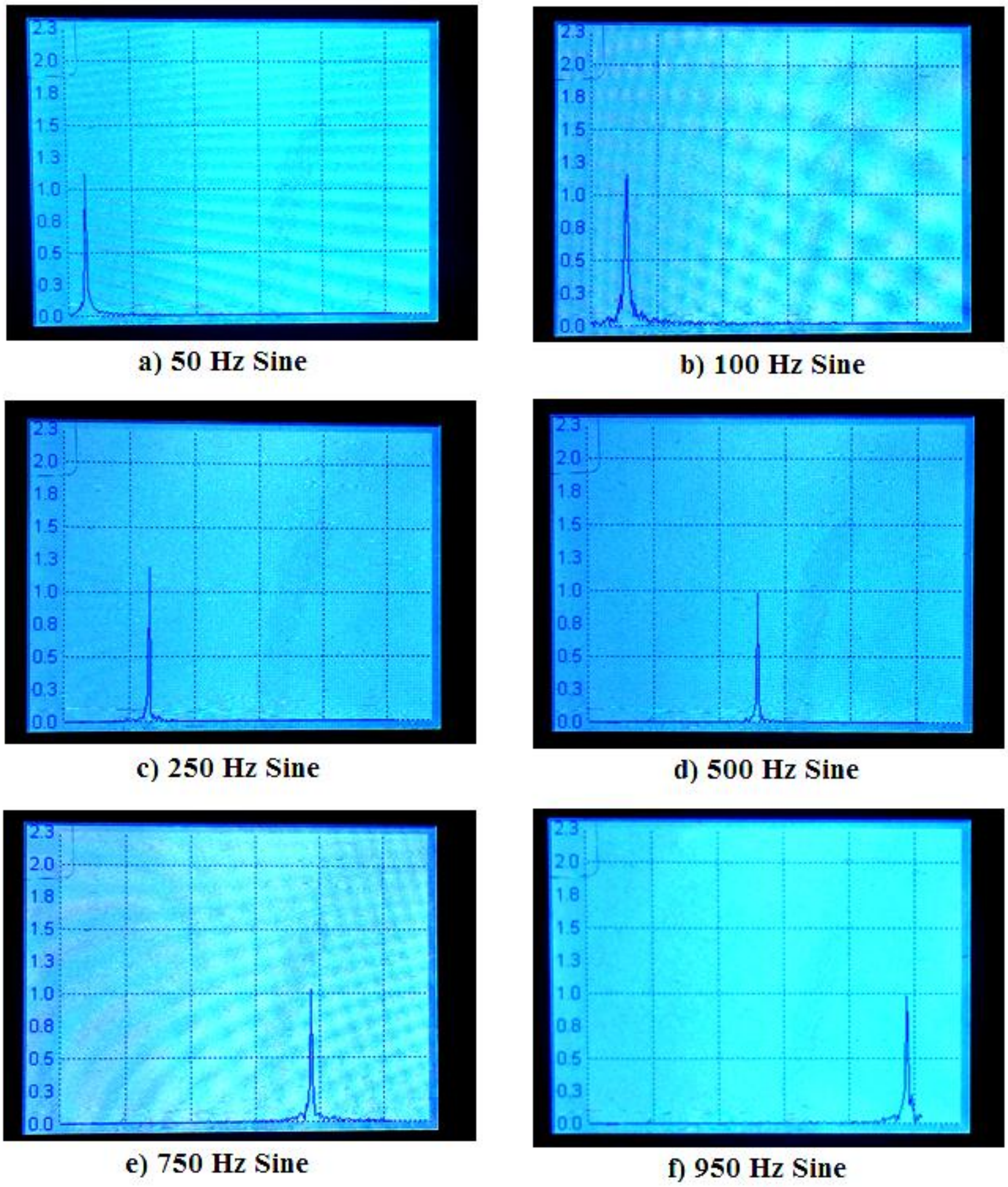


Figure 5.21 Frequency spectrums of known signals visualized on TFT screen

5.3.3 Case Study 3: Comparison of Two Different Data Acquisition System

In this case study, two data acquisition system are compared according to FFT results. Developed smart condition system and NI 6036E data acquisition card are used to measure the vibration of worm gearbox in succession. Sampling frequency is 2 KHz and the vibration data acquired for 20 second. The frequency spectrums are given in Figure 5.22.

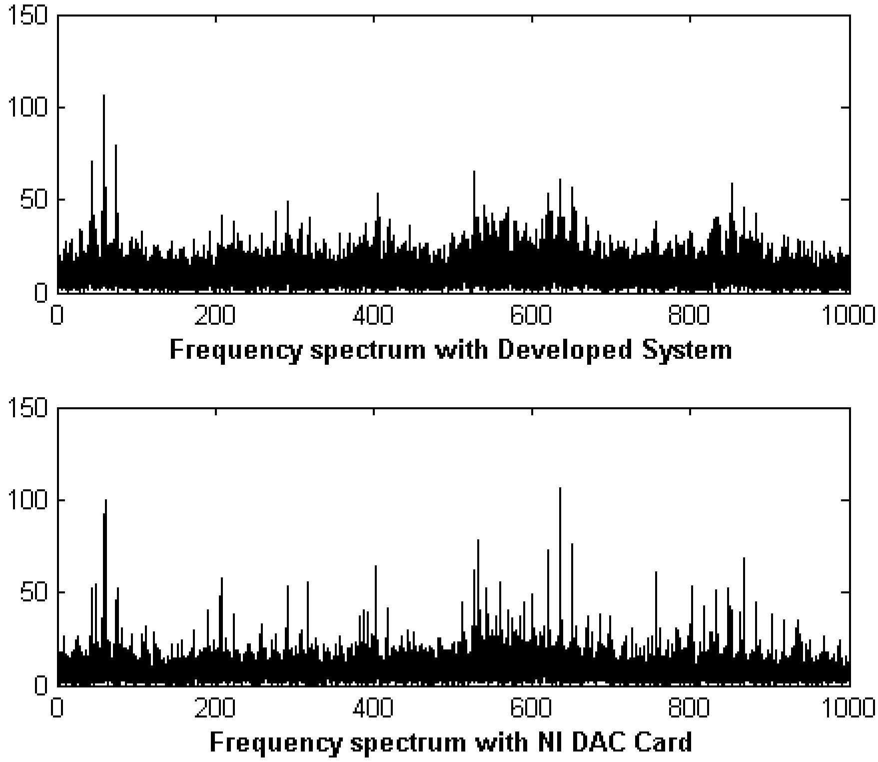


Figure 5.22 Frequency spectrums of developed system and DAC card

As can be seen in Figure 5.22, the frequency spectrums of two different acquisition systems are very similar. There are little differences between them, because acceleration signals were measured one by one consecutively.

CHAPTER SIX
EXPERIMENTAL TEST RIG

6.1 Introduction

In this thesis, an experimental test rig was built for fault detection of worm gearbox. This chapter present the development of the worm gearbox test rig and design of smart condition system and their PCB layout. Mechanical parts with their specifications, operational conditions of experiment and construction of test rig are given. Moreover, the natural frequencies of the experimental test rig are determined.

6.2 Construction of the Test Rig

The test rig components are mounted on a base which is designed in SolidWorks program and produced with CNC milling machine. The solid model of the designed test rig is shown in Figure 6.1.

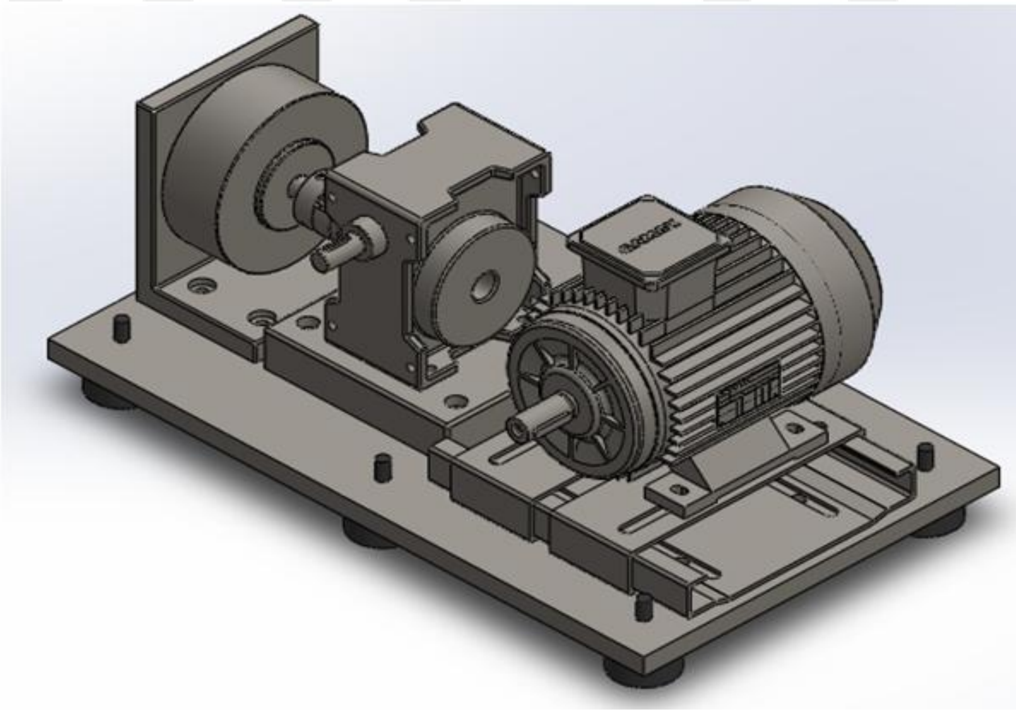


Figure 6.1 Solid model of designed test rig

6.3 Mechanical Parts

Mechanical components used in the test rig are an asynchronous AC motor, a worm gearbox and an electromagnetic brake. These components and their specifications are given in the following section. The mechanical parts of test rig can be shown in Figure 6.2. The AC motor is connected to the worm gearbox via two v-belts in order to avoid transferring motor vibrations to gearbox. The worm gearbox's output shaft and electromechanical brake are connected via a torsionally flexible coupling. The flexible coupling can accommodate misalignment up to 3 degree. In addition, they provide vibration damping and noise reduction.

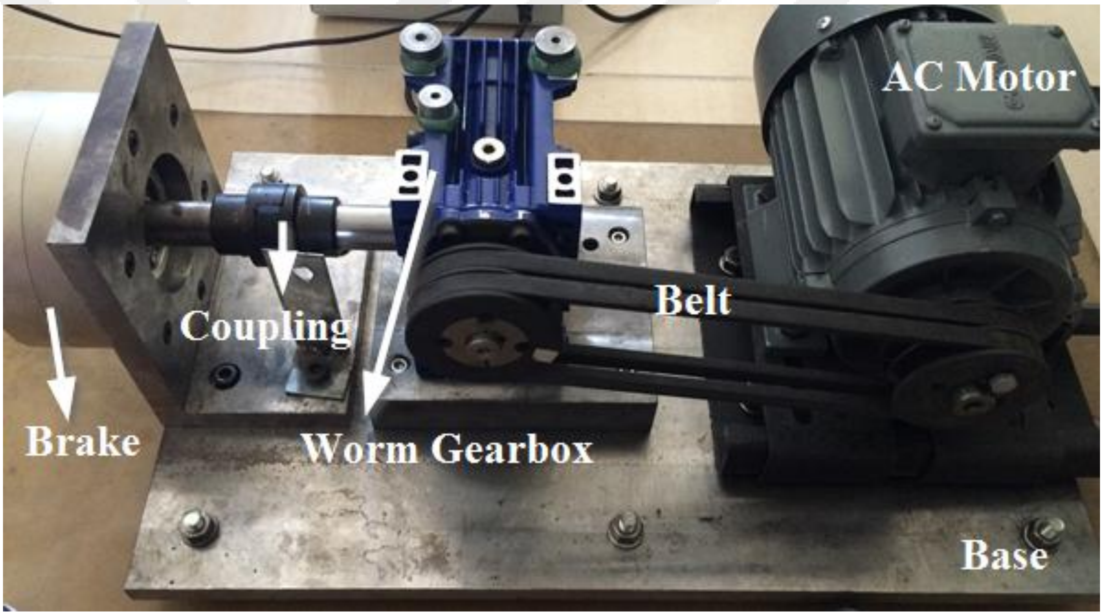


Figure 6.2 Mechanical parts of the test rig

6.3.1 AC Motor

The asynchronous AC motor is used as a power provider in the test rig, which generates rotational power in order to drive worm gearbox. The test rig also includes the Schneider Electric brand Altistart 58 three phase asynchronous AC motor speed controller. This controller can adjust continuously the AC motor speed and torque condition. It allows that the AC motor can operate in a speed range from 0 to 3000 rpm. The specifications of asynchronous AC motor are given in Table 6.1.

Table 6.1 Specifications of asynchronous AC motor

Phase:	3 phase asynchronous AC motor
Frequency (Hz):	50 Hz
Voltage (Volt):	400 V
Current (Ampere):	4.65 A
Nominal Power:	2.2 kW
Power Factor (cosφ):	0.82
Efficiency (%):	83.2%

6.3.2 Worm Gearbox

Worm gearbox is used as a speed reducer and torque multiplier in the experimental setup. This type of gearboxes includes worm gear and wheel gear, which contact each other with sliding action. Specifications of the worm gearbox can be seen in Table 6.2. The anti friction bearings are used in the worm gearbox in order to permit overhung loads. The use of anti friction bearings assures high efficiency and proper shaft alignment. Seal on both worm and wheel gear shafts prevent oil leakage and provide protection from dust and dirt for the bearings. In the worm gear, four bearings are used. Worm gear and its shaft are mounted on two of them and wheel gear and its shaft are mounted two opposed roller bearing.

Table 6.2 Specifications of the worm gearbox

Ratio (i):	1:15
Output Speed (rpm):	200,8 rpm
Output Torque (Nm):	84,7 Nm
Service Factors:	1,0

6.3.3 Electromagnetic Brake

Electromagnetic brake is used in experiment in order to apply mechanical resistance using electromagnetic force. Worm gearboxes used in industrial systems are subjected loading when running according to operation conditions. In order to simulate loading condition, an electromagnetic brake is utilized. EMF brand electromagnetic brake, shown in Figure 6.3, is used in this thesis.

Figure 6.3 Electromagnetic brake used in this study

This brake is supplied with DC voltage and operates in voltage range from 0 to 24 V. The torque of brake varies from 0 to 35 Nm changing with supply voltage. Variable torque brake and clutch systems can continuously switch to the desired torque by means of electronic voltage control. The current-torque and voltage-torque graphs of electromagnetic brake can be shown in Figure 6.4.

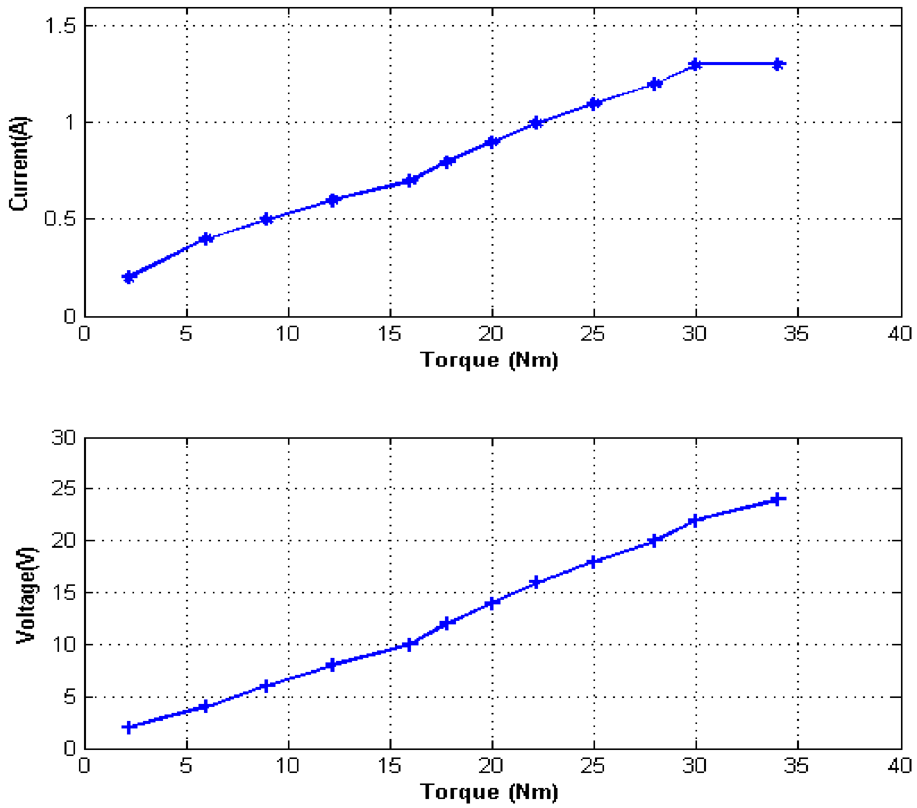


Figure 6.4 Current-torque and voltage-torque graphs of electromagnetic brake (EMF Fren, n.d.)

6.4 Design of Smart Condition Monitoring Device

The vibration signal generated by worm gearbox is measured by smart condition monitoring device. For this monitoring device, the circuit schematic diagram and printed circuit board (PCB) design are shown in Figure 6.5.

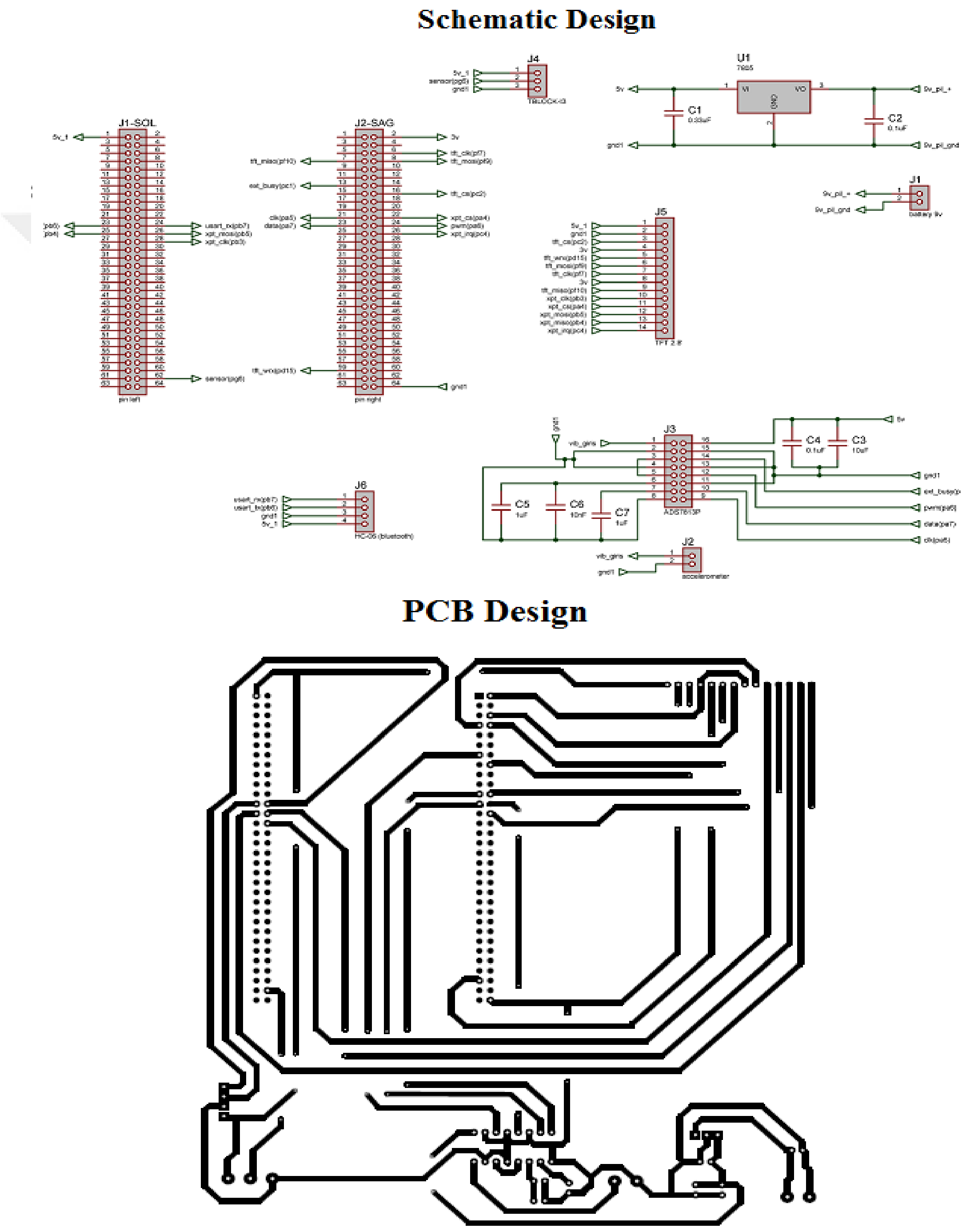


Figure 6.5 Circuit schematic diagram and printed circuit board (PCB) design

The overall experimental test rig and developed smart condition monitoring system are shown in Figure 6.6.

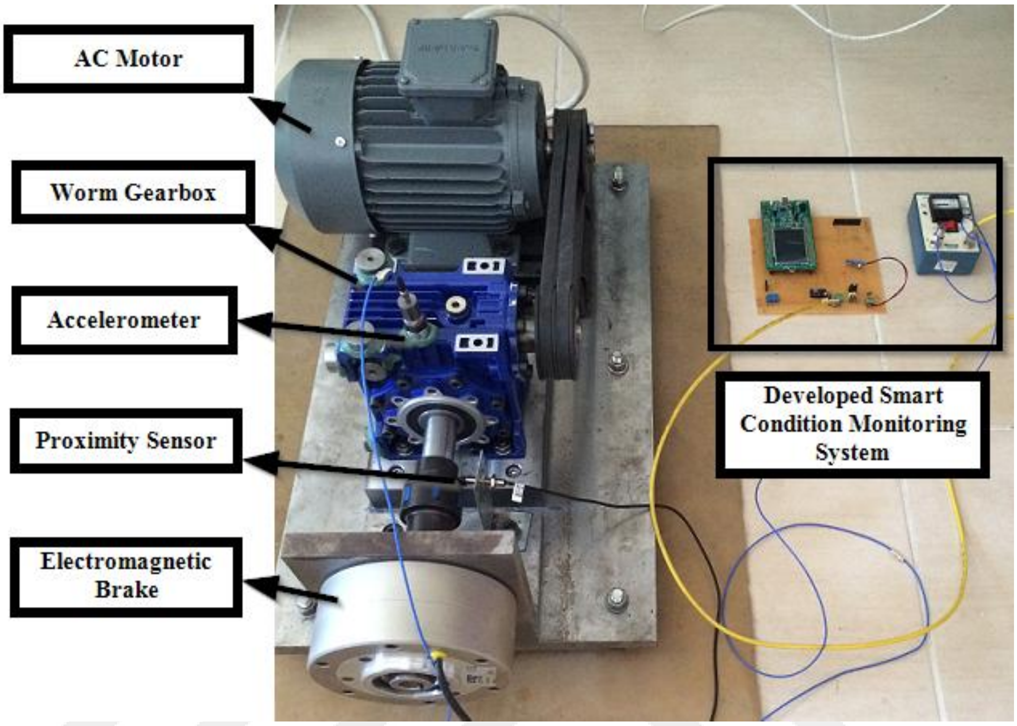


Figure 6.6 Overall experimental test rig

6.5 Placement of Accelerometer Sensor

One accelerometer is mounted on the top of the worm gearbox which is intersection area of worm and wheel gear through x axis, shown in Figure 6.7. This is common for many condition monitoring applications, in which the sensors are placed in close vicinity to vibration sources in order to acquire good vibration response characteristics. One accelerometer is also mounted on upper left area of worm gearbox through y axis, as shown in Figure 6.7. This axis is chosen, because the transmission of torque from worm gear tooth to wheel gear tooth is towards direction of tangential force of wheel gear. Although the vibration signal is picked up by two accelerometers from x and y axes, all vibration analysis is carried out only for x direction. On the other hand, the other accelerometer (y direction) is used in chapter eight.

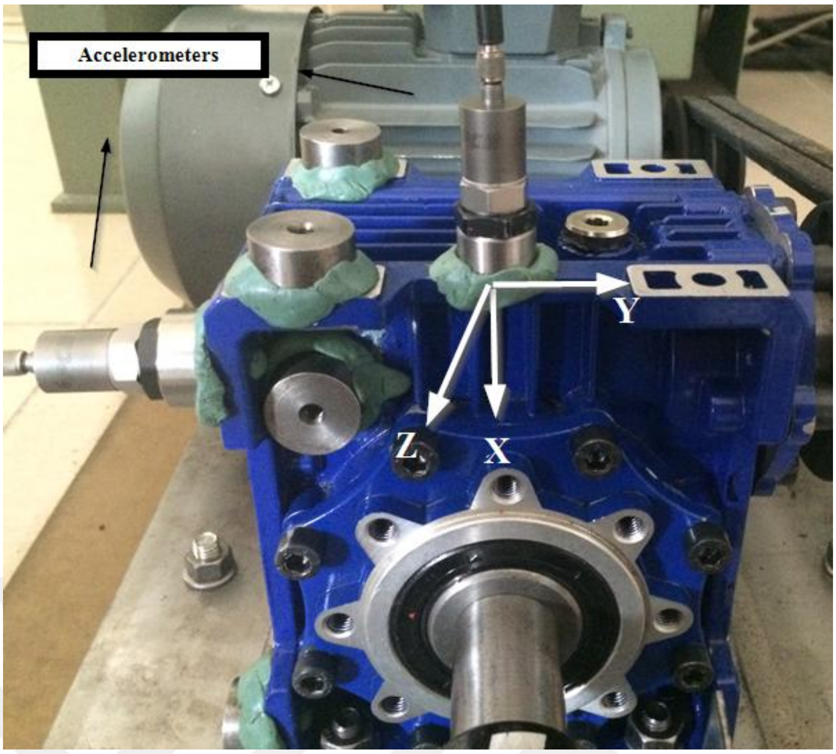


Figure 6.7 Placement of accelerometers

6.6 Experimental Operation Conditions

For the experiment, angular velocity of worm gear input shaft was set to 3000 rpm. The vibration data was captured for 60 seconds with 2 KHz sampling frequency. The vibration signal is averaged at every time of wheel gear rotation synchronously, and from now on the signal is named as TSA vibration signal. The operation conditions of test rig are given in Table 6.3.

Table 6.3 Operation conditions

Acquired data time duration (s):	60 s
Sampling Frequency (Hz)	2 KHz
Angular velocity of AC motor (rpm):	3000 rpm – 50 Hz
Angular velocity of worm gearbox (rpm):	200 rpm – 3.3 Hz
Brake voltage (volt):	23.5 Volt
Brake current (ampere):	1.3 Ampere
Brake torque (Nm):	32 Nm

6.7 Determination of Structural Fundamental Frequencies of Test Rig

Structural frequencies are vital global properties and an important describer on the dynamic behaviour of a structure. The experimental test rig vibrates while the power transmission system is running. These vibrations are related to the fundamental frequencies of the structure and can be seen in the frequency domain. One of the aims of this thesis is to detect distinctive frequencies of gear pitting failure by analyzing vibration signal of worm gearbox. The structural frequencies of the system may match or close to these distinctive fault frequencies in the frequency spectrum. In order to avoid such complexity, the structural frequencies of the experimental test rig are determined.

For this purpose, NI-6036 DAQ card and Labview program are used. Acceleration sensors properly placed on worm gearbox and recorded the vibration response of a structure due to a known excitation by an impact hammer. Accelerometer and impact hammer for measuring vibration are shown in Figure 6.8.

Figure 6.8 Accelerometer and impact hammer for measuring vibration

When an impact excitation was applied to test rig with impact hammer, acceleration signal was measured. Therefore, the structural frequencies of test rig are determined. The structural frequencies and power spectral density graph of the experimental test rig are shown in Figure 6.9.

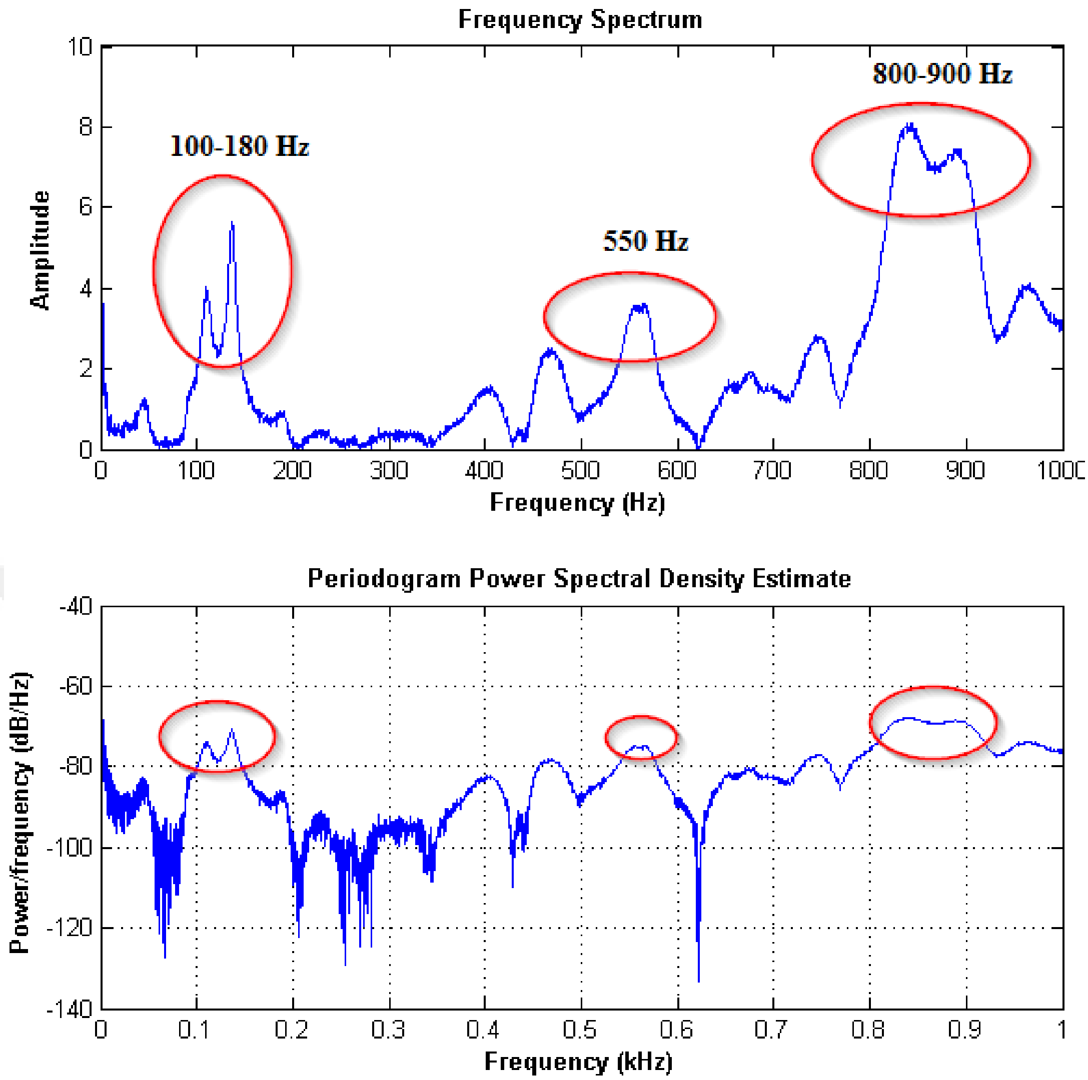


Figure 6.9 Structural frequencies and power spectral density of test rig

In figure 6.9, the red ellipses indicate structural frequencies of experimental test rig. According to structural frequency analysis; frequencies from 100 to 180 Hz, 550 Hz and from 800 to 900 Hz show high amplitudes and more power of vibration signal.

CHAPTER SEVEN
VIBRATION ANALYSIS OF WORM GEARBOX WITH SMART CONDITION MONITORING UNIT

7.1 Introduction

This chapter aims to detect transient actions caused by gear faults before the deterioration of gearbox via suitable vibration based techniques (i.e. time domain metrics, frequency domain analysis, and frequency component based statistical analysis).

7.1.1 Artificial Pitting Fault Simulation

In the experiments, specified gear load (35 Nm) was applied to worm gearbox by the electromagnetic brake. During an overloading condition, some teeth on a gear may be subjected to a higher load than the capacity of the gear. In such cases, a pitting fault may occur in time on the wheel tooth surface. In order to simulate the deterioration due to the excessive load condition, artificial local surface pits were introduced on three of the wheel gear teeth. These local tooth pits causes transient actions on gearbox when that faulty tooth is in contact. One of the main purposes of the thesis is detection of these transient events happening on worm gearbox. Pits are seeded on some of the wheel gear tooth in varying number. These pits act like a regular gear fault which happens spontaneously. The number of simulated pits was increased on the neighboring teeth surfaces in order to represent the development of the pitting fault.

The entire simulated surface pits were introduced to some of the wheel gear teeth using a milling machine as shown in Figure 7.1. Artificial pitting failures performed firstly on a single tooth, and then developing over the neighboring teeth surfaces. The diameter and depth of those pits are approximately 2 mm and 1 mm, respectively.

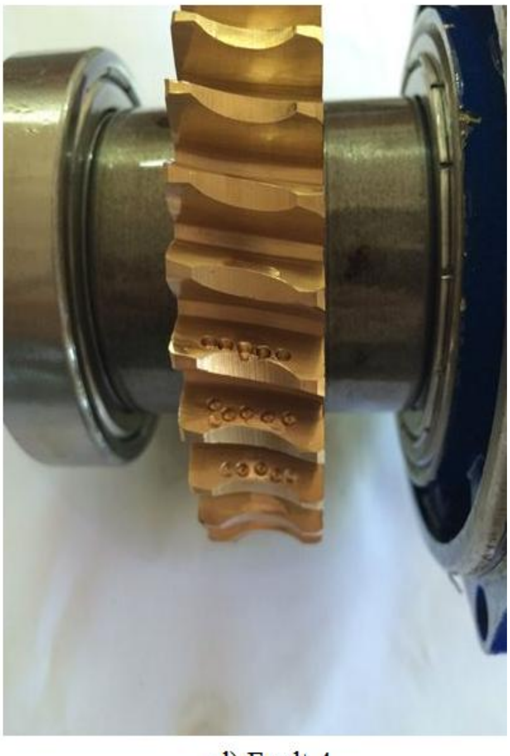
Figure 7.1 Simulated pits with a milling machine

Three circular pits were seeded onto a single specified tooth surface as shown in Figure 7.2(a), named as Fault 1. In order to simulate the deterioration due to the excessive load condition, two more artificial surface pits were performed on the same of the wheel gear tooth, as shown in Figure 7.2(b), and named as Fault 2. The number of simulated pits was increased on the two neighboring teeth surfaces with three artificial pits in order to represent development of the pitting fault, as illustrated in Figure 7.2(c), named as Fault 3. Two more artificial surface pits were performed on the same of the two neighboring wheel gear teeth, as shown in Figure 7.2(d), named as Fault 4.

a) Fault 1

b) Fault 2

c) Fault 3



d) Fault 4

Figure 7.2 Simulated pitting faults on wheel gear

7.2 Time Domain Analysis

In this section, time domain metrics such as RMS value, Kurtosis etc. of worm gearbox are examined for the cases of healthy and faulty condition of the equipment. The most common statistical metrics are used for time domain analysis. The vibration is measured as acceleration of gearbox and the acceleration is measured as voltage signal from acceleration sensor. The vibration signal recorded from the worm gearbox for healthy and faulty gears under the same operational conditions. The acceleration-time graphs are illustrated for all conditions of gearbox in Figure 7.3. The TSA vibration signal is used for the time domain analysis.

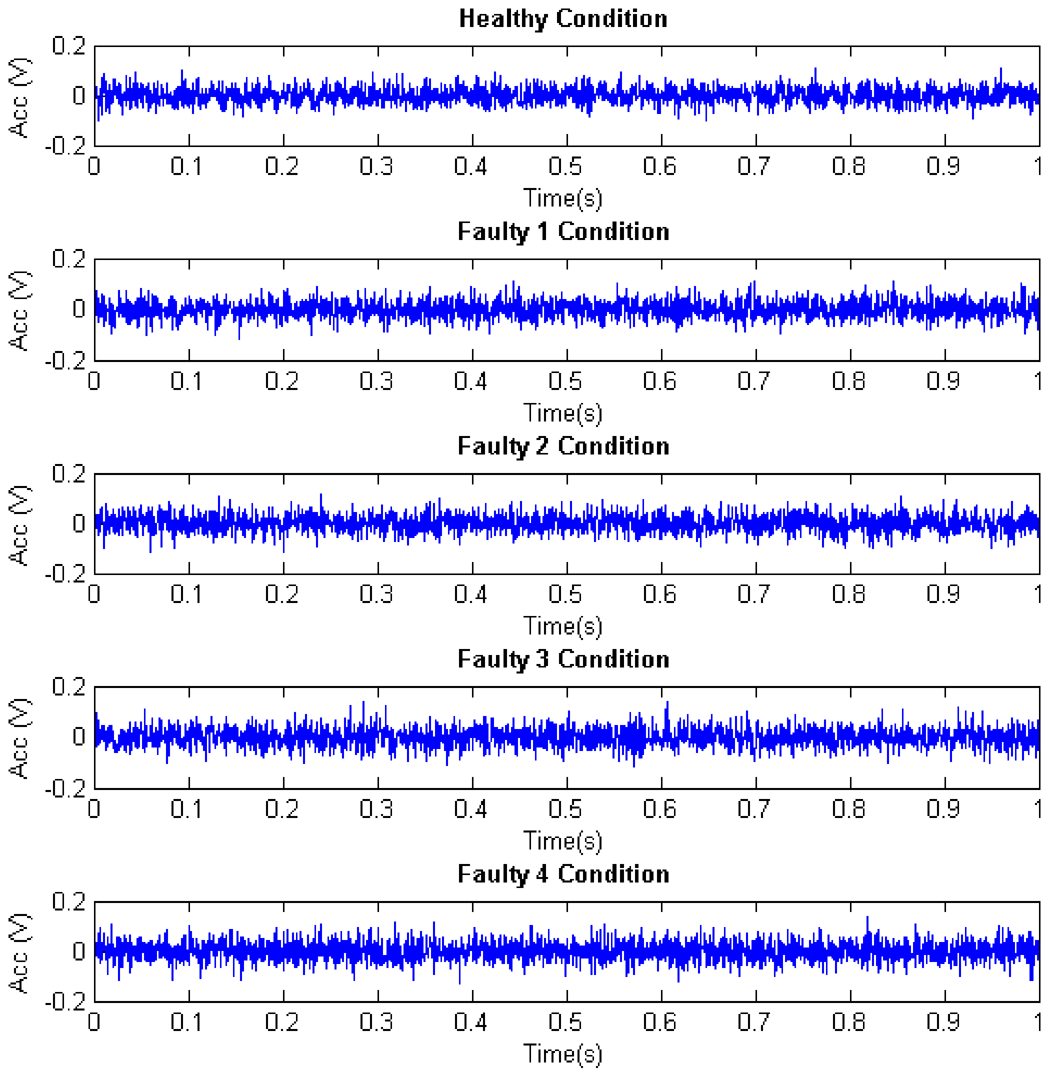


Figure 7.3 Acceleration-time graphs for all conditions of gearbox

For all conditions, results of statistical metrics are illustrated on graphs in Figure 7.4.

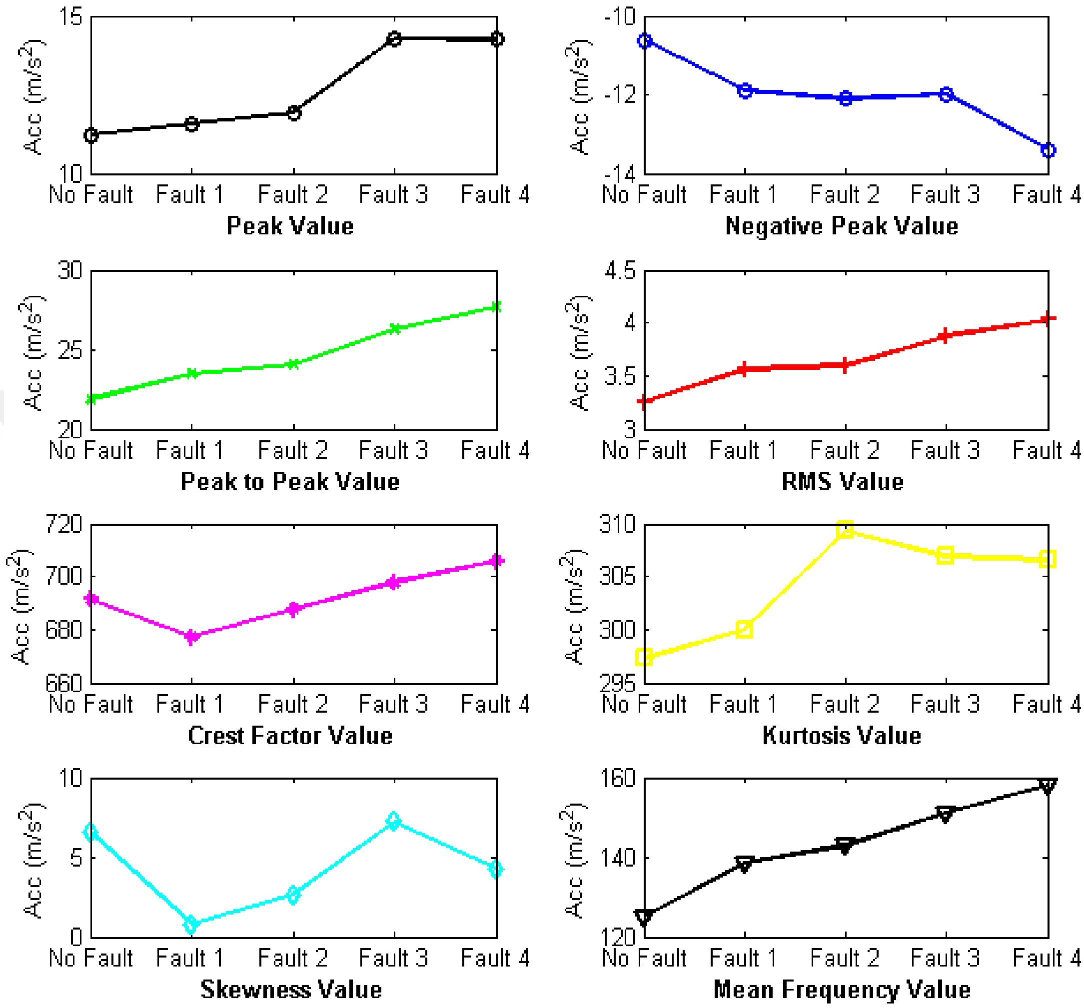


Figure 7.4 Results of statistical metrics

From Figure 7.4, it can be seen that RMS, peak to peak and mean frequency values exhibit an increasing trend with the fault progression, although Kurtosis, Crest Factor and Skewness values do not show the fault progression. Peak to peak value shows increasing the fault progress, because the high peaks of vibration signal occurs as the number of the simulated pits increases. The increasing faults affect the RMS value of vibration signal gradually, because the power of signal also rises. The mean of amplitude of frequency domain increases with the fault progression. That means; the amplitude of frequency domain rises as the severity of fault increases.

The statistical metrics are calculated from averaged vibration signal. In order to get better examination of behavior of statistical metrics, they are re-calculated for each wheel gear shaft rotating in 60 seconds, as illustrated in Figure 7.5. The wheel gear rotates with 3.3 Hz (3.3 turns in one second), approximately. That's why, 200 values approximately are calculated in 60 seconds for each statistical metric.

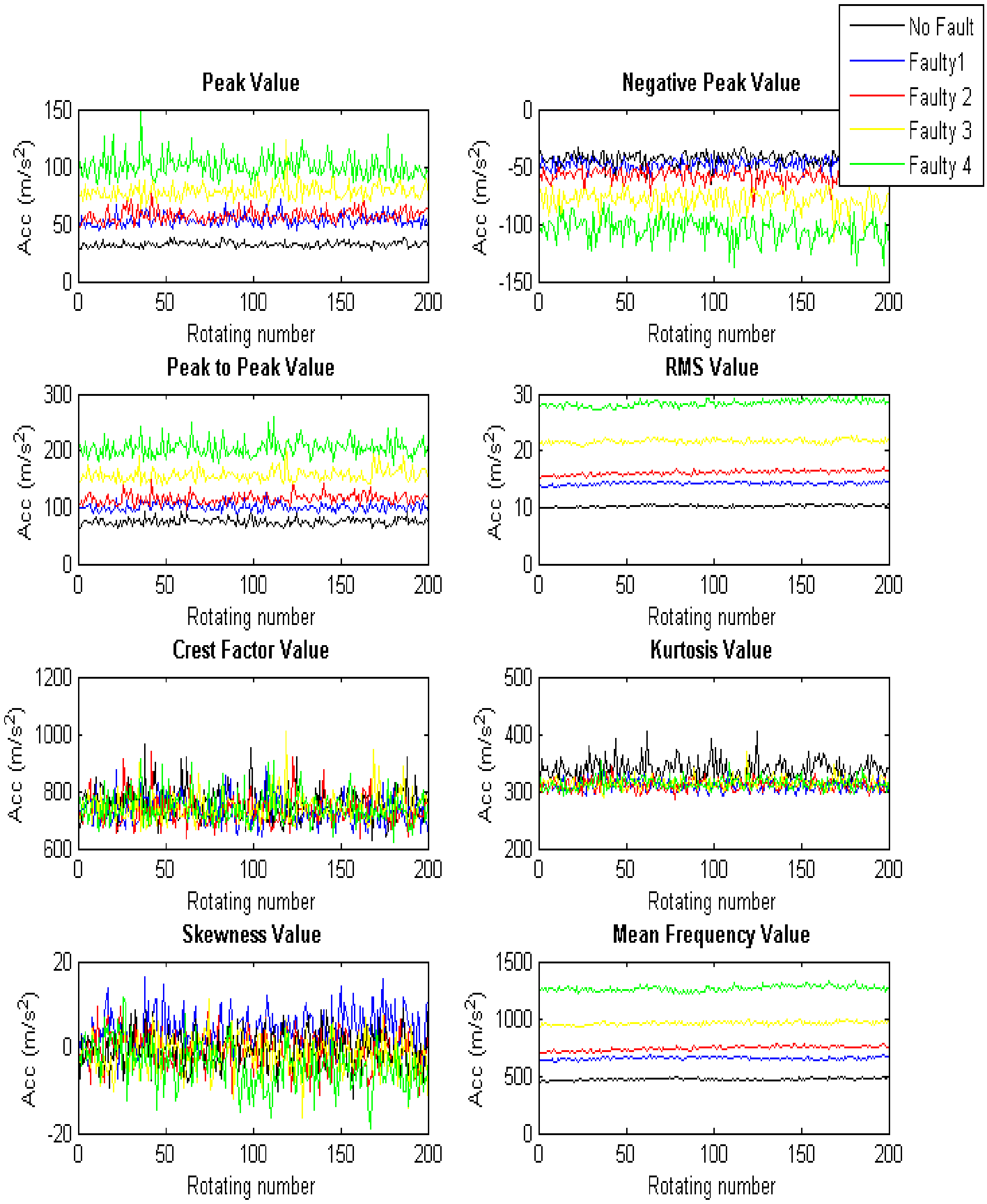


Figure 7.5 Statistical metric graphs for each wheel gear shaft rotating

In Figure 7.5, it can be clearly seen that Skewness, Kurtosis and Crest Factor values interferes each other for all conditions of worm gearbox in 60 seconds. The detection of faults cannot be possible with using these statistical metrics. On the other hand, RMS value and mean of amplitude of frequency domain are indicator of failure and also severity of faults. These statistical metrics have an increasing linear trend as the number of simulated pits increases.

7.3 Frequency Domain Analysis

In this section, time domain vibration data measured on worm gearbox is transform into frequency domain. The frequency domain analysis is carried out for all conditions of worm gearbox. According to Nyquist sampling theorem, sampling frequency was taken as 2000 Hz since the significant frequency components of vibration waveform are below 1000 Hz. Thus, the frequency domain analysis focused on low frequency range (<1 KHz). The vibration frequency domain analysis measured from a mechanical system in healthy operating conditions is commonly used as a reference model for monitoring and analysis.

The most important components in the frequency domain for gearbox are gear mesh frequency and its harmonics. The faults on gear tooth demonstrate itself as increasing amplitude of gear mesh frequency and existence of its harmonics in frequency spectrum (Choy, 1996). The gear mesh frequency is calculated as (where f_i=Input gear rotate frequency, f_o=Output gear rotate frequency, N_i=Number of teeth on input gear, N_o=Number of the teeth of output gear);

$$f_m = f_i * N_i \quad \text{or} \quad f_m = f_o * N_o \tag{7.1}$$

But, the topic of the gear mesh frequency for the worm gearboxes is controversial. While some researchers define gear mesh frequency for worm gearbox as multiplication of number of thread in worm gear and worm gear rotate frequency, some believe that there is no gear mesh frequency for worm gearbox. It has been discussed for many years.

For the all conditions, frequency spectrums of worm gearbox are illustrated on graphs in Figure 7.6.

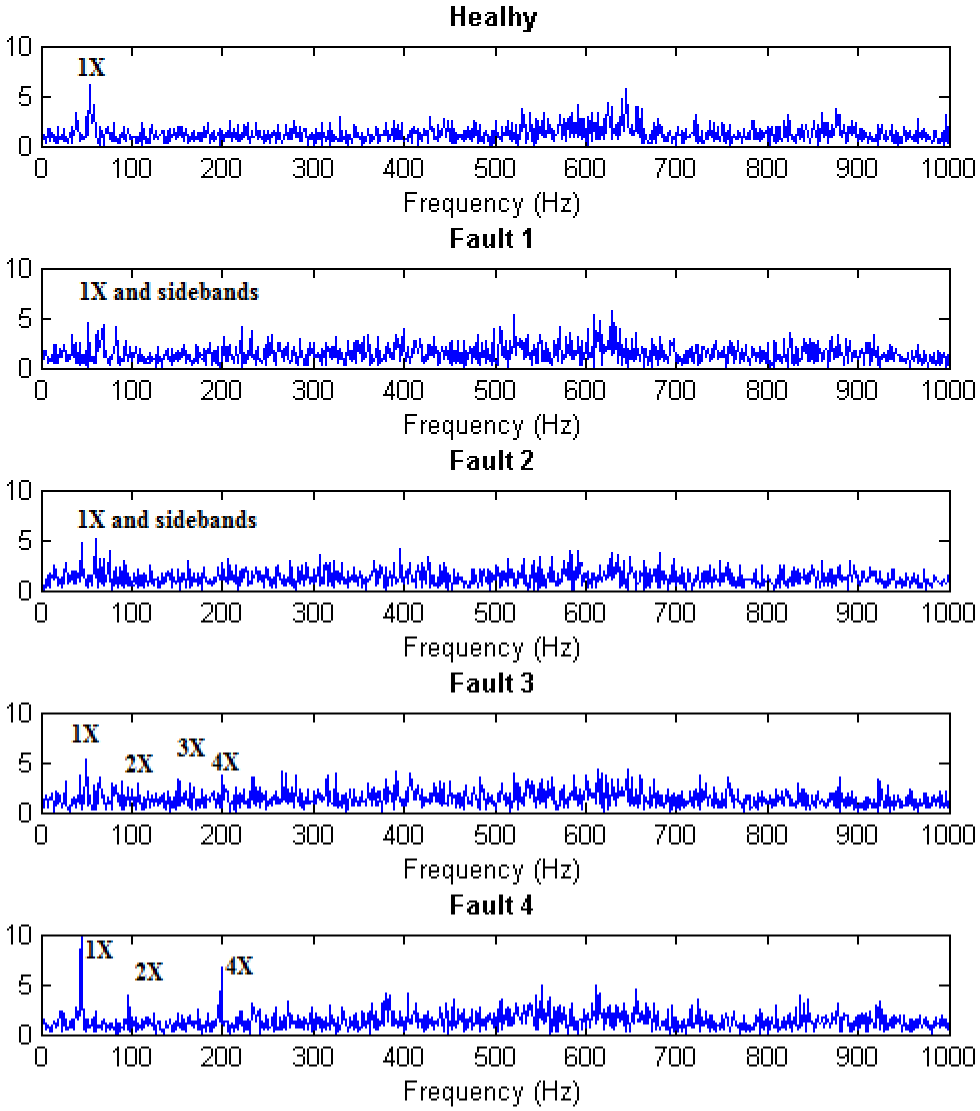


Figure 7.6 Frequency spectrums for all conditions

The worm gear teeth and wheel gear teeth contact each other smoothly. The worm gear teeth slides in the wheel gear teeth during the transmission of torque. Thus, the energy transfer between worm and wheel gear is smooth. Therefore, the worm gearboxes don’t behave as the other gearboxes in frequency domain. On the other hand, the previous studies conducted on worm gearboxes shows that the worm shaft frequency and their harmonics are seen in frequency domain in case of gear failures.

For instance, Elasha et al. and Teng et al. report similar results about frequency spectrum of worm gearboxes. The worm shaft frequency and their harmonics in frequency spectrum were interpreted as gear pitting by these researchers.

According to our results, the worm shaft rotating frequency can be seen with high amplitude in frequency spectrum of healthy worm gearbox. In addition, the frequency components between 550 and 600 Hz have high amplitude and complexity because of structural frequencies of test rig. For Fault 1 and Fault 2, the worm shaft frequency and their sidebands can be seen. Besides, the worm shaft frequencies and their harmonics are seen in frequency spectrum of Fault 3 and Fault 4. These results are interpreted as existence of pitting failure.

However, the frequency spectrum analysis for worm gearboxes is still controversial analysis because there aren't adequate studies about this topic.

7.4 Frequency Component Based Statistical Analysis

In this section, the frequency domain analysis and statistical metrics are combined. Normally, gear mesh frequency (GMF) and its harmonics are used for this analysis, but GMF is not valid for worm gearbox. Therefore, the worm shaft frequency is used instead of GMF, because worm shaft frequency and their harmonics are appeared in the frequency spectrum in case of worm gearbox failures. In this method, RMS value of worm shaft frequency and their harmonics are calculated in specified bandwidth.

The result of method is given in Figure 7.7. The bandwidth is chosen 10 Hz and the frequency band is 0-500 Hz. (45-55, 95-105 … 495-505). The results are normalized according to results of no fault condition. Firstly, pitting faults affects the results of this method positively. There is an increase after no fault case. Although there is no gradually increase between Fault 1 to Fault 4, all faulty cases are higher than no fault condition. As it can be seen from Figure 7.7, results of FCSA increase in case of pitting fault.

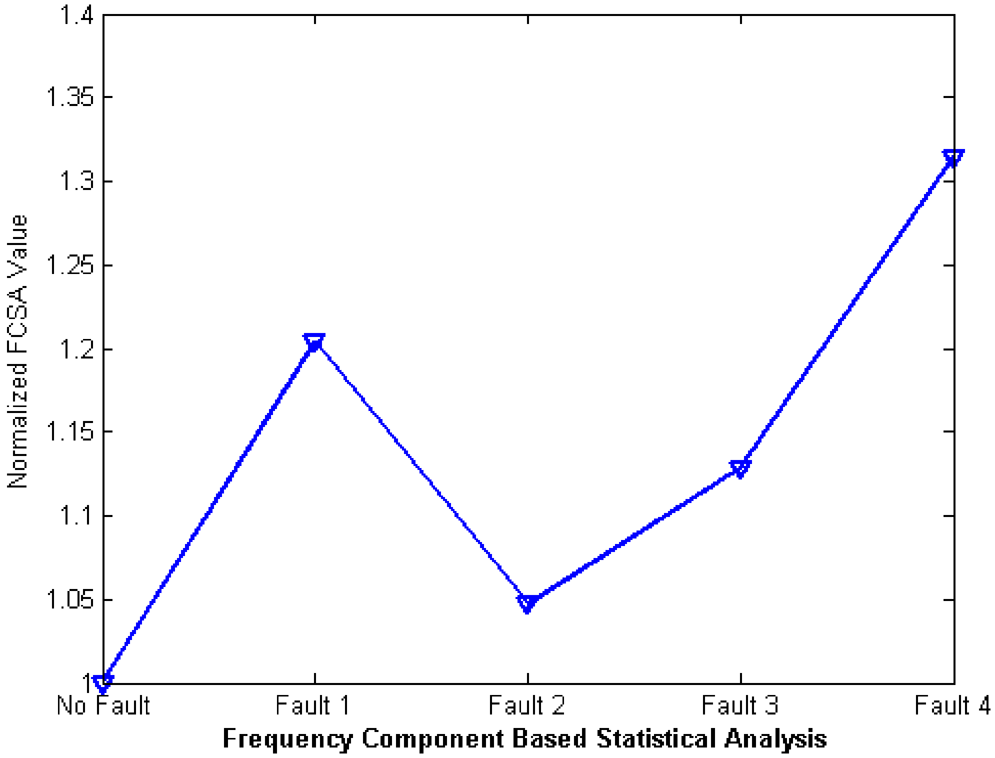


Figure 7.7 Results of frequency component based statistical analysis method

CHAPTER EIGHT
FAULT DETECTION AND PATTERN RECOGNITION OF WORM GEARBOX

8.1 Introduction

This chapter aims to apply fault detection and pattern recognition techniques on vibration of worm gearbox. The vibration based fault detection is a tool which focuses on the study of damage identification in mechanical systems. The process of fault detection involves the specification of potential damage scenarios for the system, measurement and monitoring of appropriate features of system and analysis of these features in order to determinate the current state of condition of the system. In recent studies, researchers have begun to utilize statistical pattern recognition and classification algorithms. For instance, artificial neural network (ANN), support vector machine (SVM), linear discriminant analysis, Kernel estimation and etc. are the some examples of pattern recognition algorithms using in fault diagnosis of mechanical equipments.

Pattern recognition is a branch of machine learning that focuses on the recognition of patterns and regularities in data (Bishop, Christopher, 2006). This method provides a reasonable answer, classification and localization for unknown inputs. It decides most likely result for unknown patterns using previous data. In addition, the pattern recognition method uses unique features of system for reliable decision making. These features are derived from data and thus, reduce the amount of sources required to describe a large set of data. As compared to training features and new features of data, pattern recognition techniques make a decision which new data belongs to. This method is applied in various applications such as fingerprint, human face, speech recognition and so on. For instance, Özge Baltacı (2011) studied identity recognition via fingerprint analysis by neural networks and Ozan Taşova (2011) worked on face recognition with artificial neural networks.

In this thesis, pattern recognition and fault detection techniques are applied for identification existence of failure on worm gearbox and precise localization of damage.

8.2 Dynamic Squared Error Based Fault Detection

In this section, dynamic squared error is calculated between each faulty condition and healthy condition. The acceleration signal alters because of existence of pitting faults on gear teeth. By examining the time domain acceleration signal, determination of location of these faults on gear is possible. The dynamic squared error is suitable and easy method in order to detect abnormalities between normal and faulty condition. The dynamic squared error (DSE) is computed for each faulty condition based on normal condition. The DSE is evaluated by taking the squared difference between the faulty and healthy acceleration values of gearbox. The equation of DSE is given below, where x_i and $\bar{x}$ are measured faulty and healthy values, respectively.

$$\mathrm{DSE}(i) = (x_i - \bar{x}_i)^2 \tag{8.1}$$

The specified wheel gear teeth are subjected to artificial pitting faults. For Faulty 1 and Faulty 2 conditions, one wheel gear tooth is faulted. For Faulty 3 and Faulty 4 conditions, total of three wheel gear teeth are faulted. These three gear teeth are consecutive. In figure 8.1(a), the reference point, accelerometer point and direction of rotation are illustrated. Reference point is a location of proximity sensor and measurement of vibration starts at every this point. Accelerometer point is a location of accelerometer sensor and acceleration signal is measured from this point. The aim is to find the angle of faulty teeth according to reference point. The angle was calculated according to reference point when faulty teeth at acceleration point. Hereby, the angle of pitting faults on gear tooth is specified. The faults affects the acceleration signal at every this angle. When the faulty gear teeth pass on the accelerometer point, the angle between reference point and faulty teeth is illustrated in Figure 8.1(b).

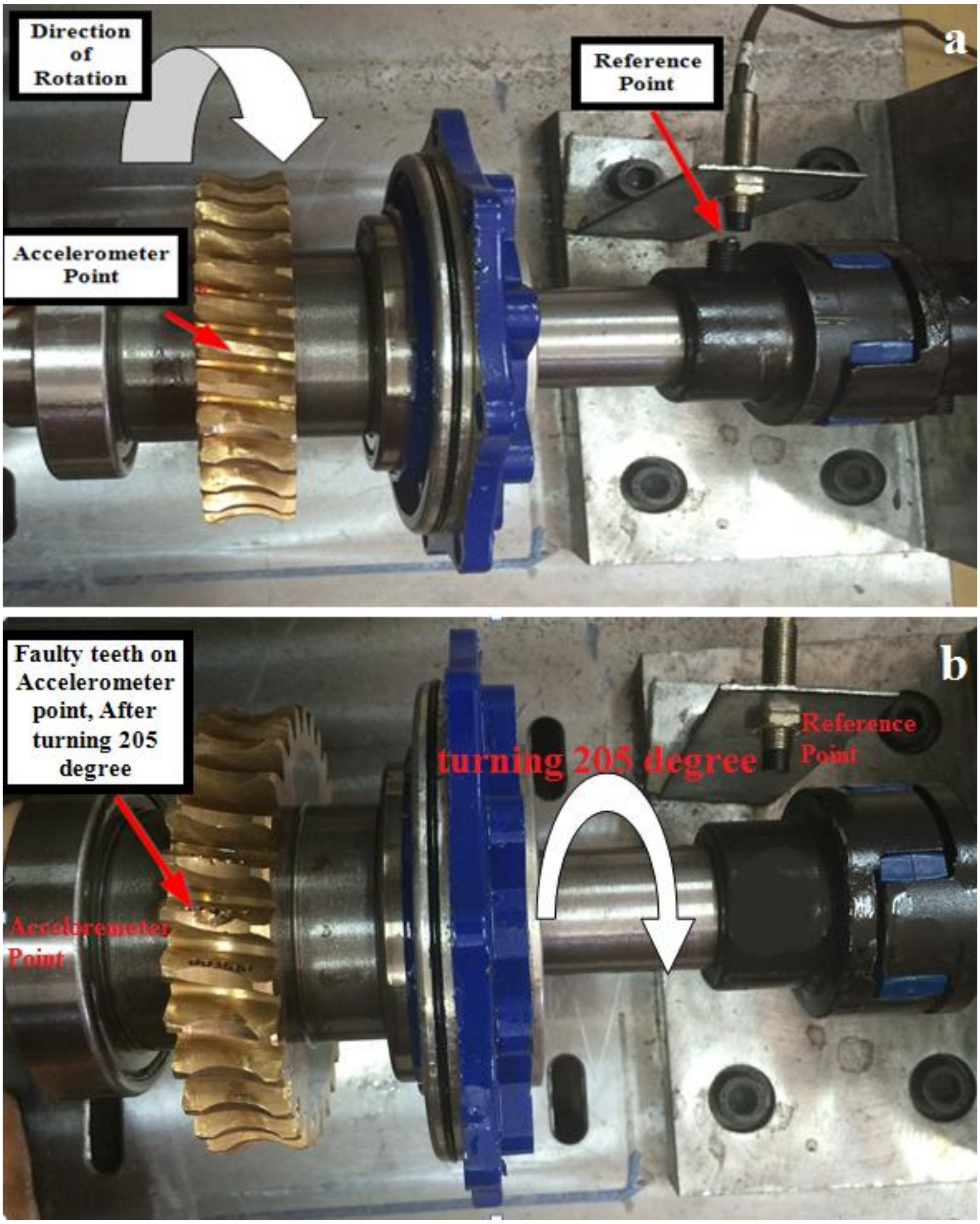


Figure 8.1 Angle of faulty teeth

The effects of these pitting faults are illustrated thanks to computing acceleration dynamic squared error between each faulty condition and healthy condition in Figure 8.2.

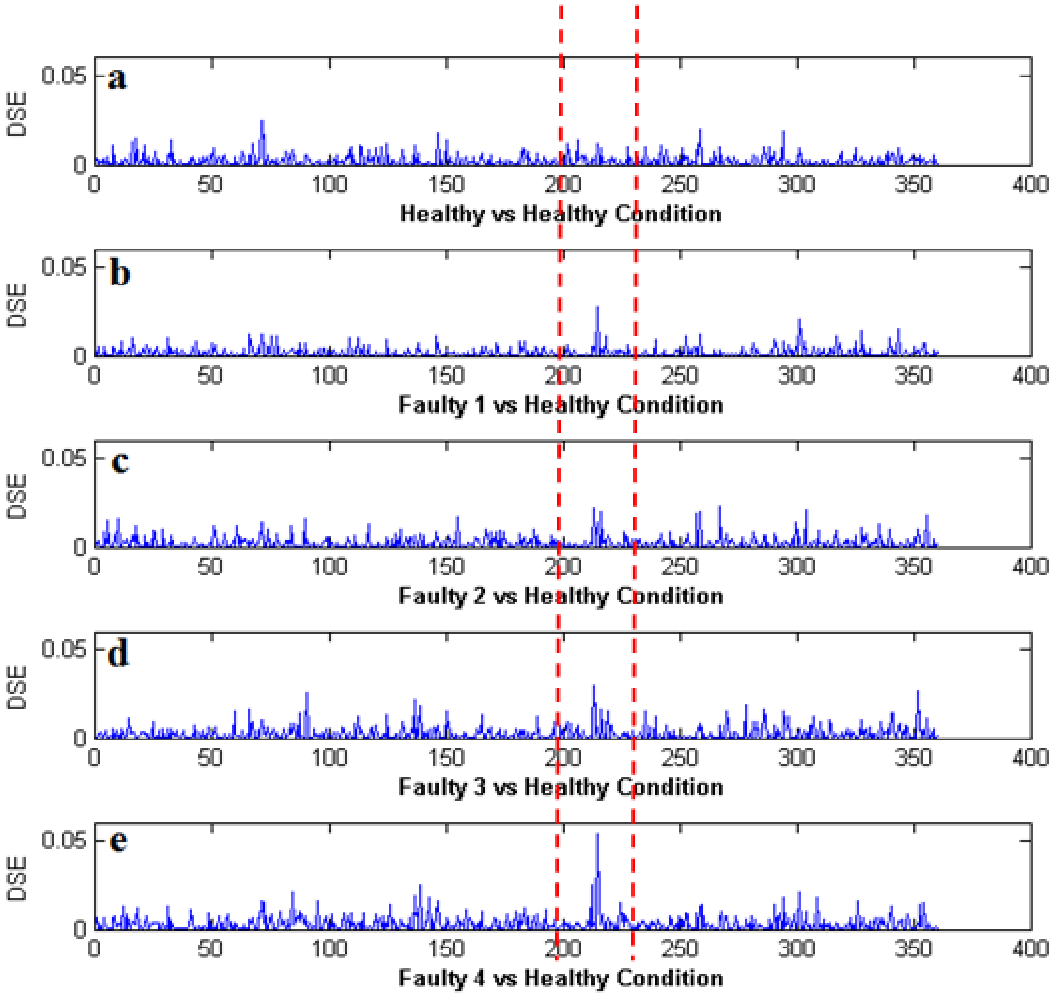


Figure 8.2 Dynamic squared errors for all conditions

Although the gearbox continues to operate in normal condition, the DSE chart will show little fluctuation as shown in Figure 8.2(a). The reason of fluctuation is little changes in experimental conditions such as mounting of acceleration, temperature of gearbox, temperature of brake etc. Thus, two vibration signals which are acquired at different times can't be same, although they are measured from the same gearbox for same operation conditions. When the local pitting fault is beginning to develop in single tooth, the DSE shows high amplitude at 208 Hz approximately, as seen in Figure 8.2(b). The high amplitude at 208 Hz approximately can be seen in graphs given in Figure 8.2(b) – (e). The peaks appear in the same region consistently, which indicates that the location of the pitting faults in the gear is around 205 Hz. The higher amplitude of peaks is shown in Figure 8.2(e) for Faulty 4 case.

8.3 Image Processing Based Fault Detection

This section presents a gear tooth fault assessment using image processing on time domain vibration data. In this study, the image processing method is used for finding effects of pitting faults on two dimensional acceleration signals of gearbox. Although image processing method is applied in many applications such as remote sensing, medical field, machine vision etc., this method is not a common technique used for fault detection of mechanical equipment. In this proposed approach, two directions of acceleration signal are plotted with acceleration in x direction versus the corresponding acceleration in y direction for every condition, as shown in Figure 8.3.

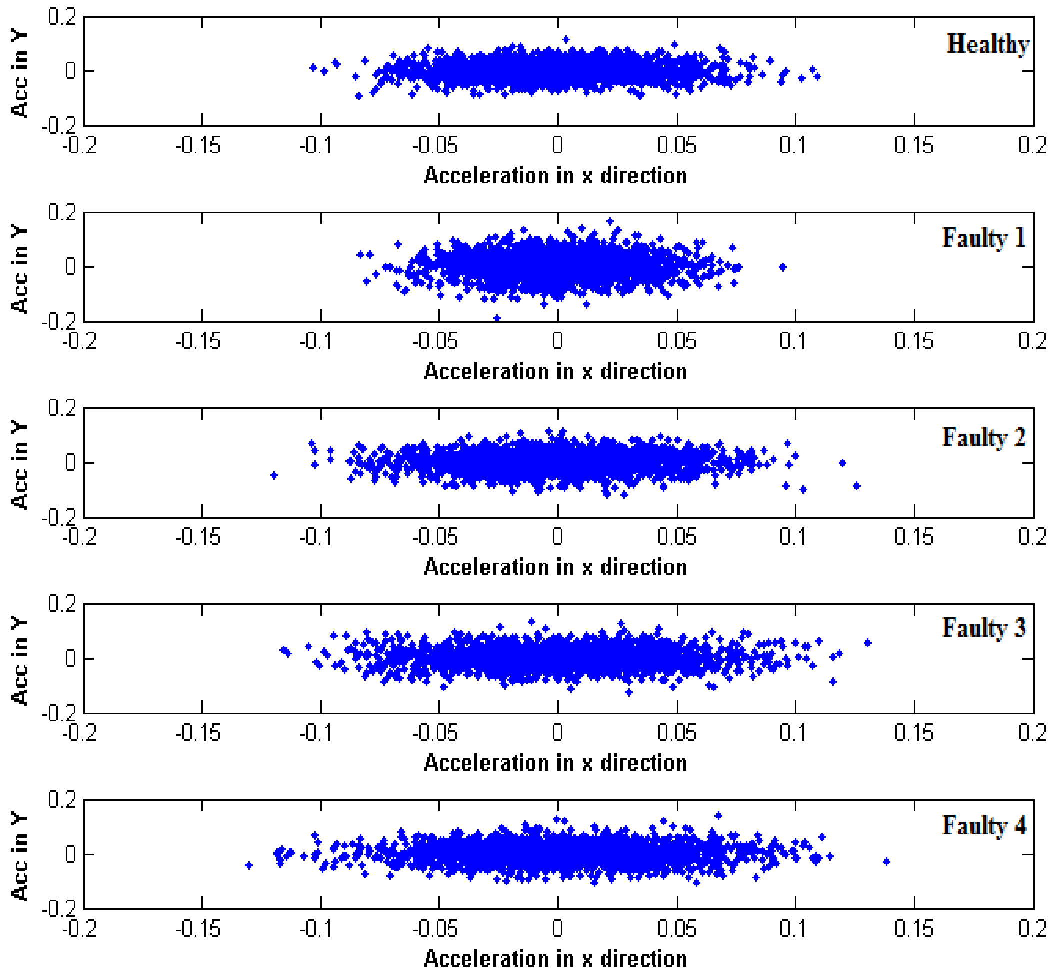


Figure 8.3 Acceleration signals direction of x versus y for all conditions

All graphs of accelerations signals are saved as one image. The covered area value of each condition is computed by using image processing technique. The RGB image is converted to grayscale intensity image, as shown in Figure 8.4. After that, the connected components are found in image and they are separated from each other. The number of the pixel is found in the area of each condition, as shown in Figure 8.4.

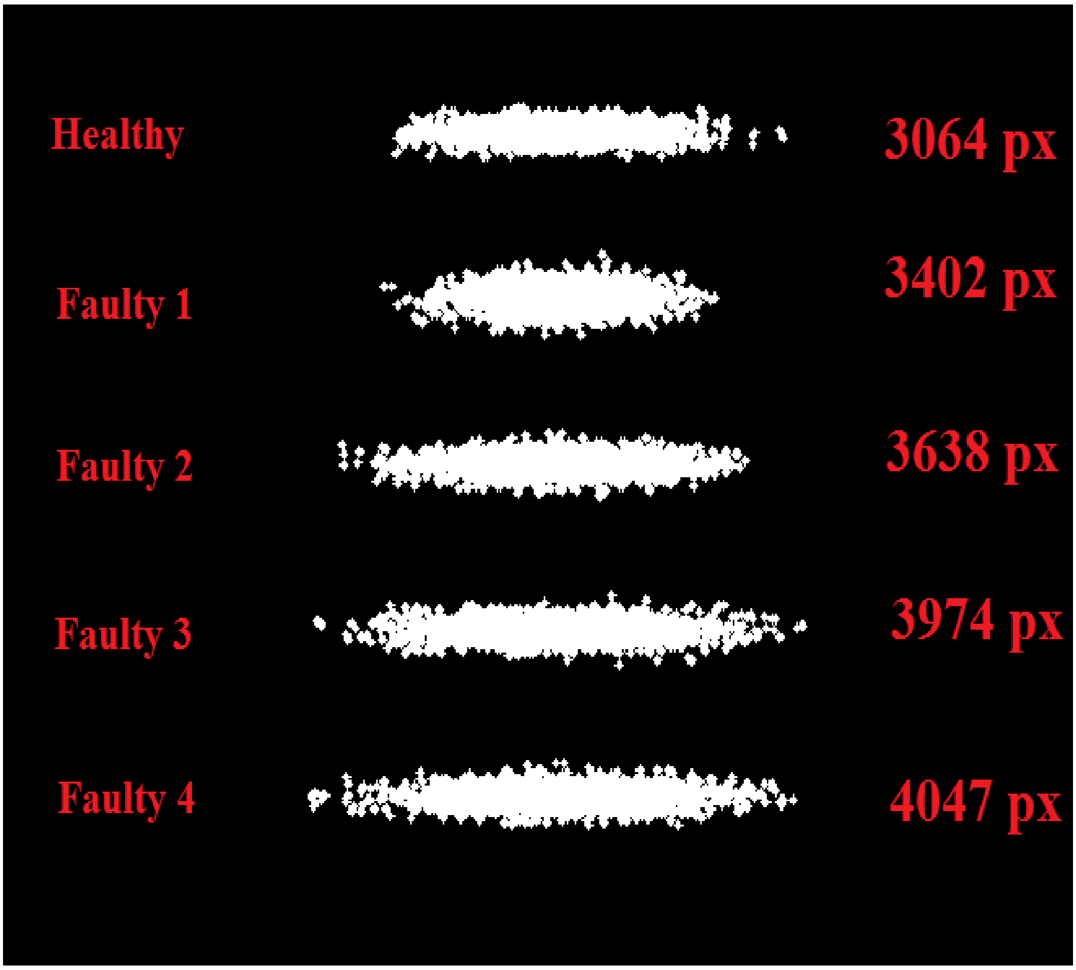


Figure 8.4 Number of the pixel is found in area of each condition

It can be seen from Figure 8.4 that the pixel values of covered area, written with red for each condition, shows increasing trend as the number of pitting fault develops. The areas also spread out along the x direction progressively from healthy condition to Fault 4 condition. These results are interpreted as effects of pitting faults on accelerations of machine.

8.4 Support Vector Machine Based Pattern Recognition and Classification

Support vector machine method (SVM) solves classification problems using the features of data. By using some given data points, the SVM decide which class a new data point will be in. In this section, SVM is used for decision of gearbox faulty condition. By using training acceleration data, SVM determines whether the condition of worm gearbox is healthy or faulty. Moreover, the SVM is applied between healthy and each faulty condition. Thus, the comparison of performance of classification of healthy and each faulty condition is illustrated.

SVM can be considered to create a line or hyper-plane between two sets of data for classification. The goal is to find an optimal hyper-plane, which separates two sets of data each other by maximizing the margin between the separating hyper-plane and the closest data points of training set (Chen, Tang & Chen, 2013). In Figure 8.5, the two sets of data for two classes are shown as circles and squares. The SVM algorithm attempts to place a hyper-plane between two classes. Although there can be many hyper-planes for classification of two groups, the best choice will be the hyper-plane that leaves the maximum margin from both classes. Thus, the distance of nearest data for each class is maximal. The nearest data points are known as support vectors and used to define the margins.

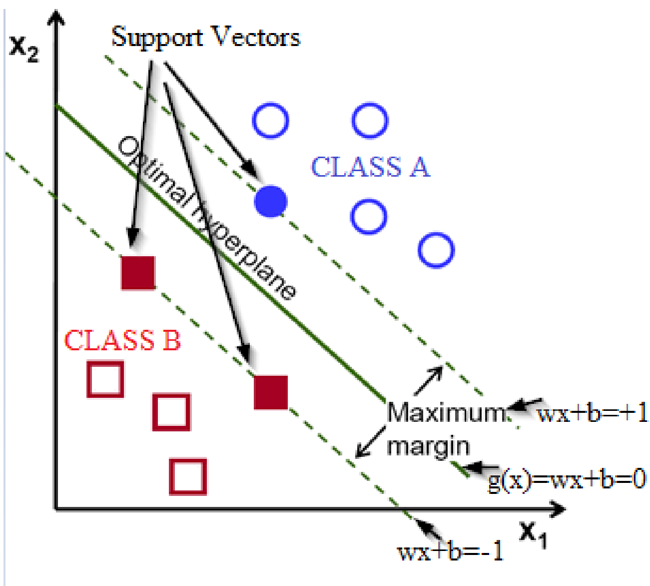


Figure 8.5 Optimal hyper-plane of SVM

The hyper-plane can be expressed as Equation (8.2), where the vector w defines weights, x is the input and b is the scalar bias.

$$g(x) = (w * x) + b = 0 \qquad w \in R^N, b \in R \tag{8.2}$$

The new data points are classified by using following equation,

$$\begin{aligned} &\text{if } g(x) \geq +1 \qquad \text{x belongs to Class A} \\ &\text{if } g(x) \leq -1 \qquad \text{x belongs to Class B} \end{aligned} \tag{8.3}$$

From the geometry, the distance between a point and a hyper-plane can be computed. Thus, the total margin is given following equation.

$$\text{Total Margin} = \frac{1}{\|w\|} + \frac{1}{\|w\|} = \frac{2}{\|w\|} \tag{8.4}$$

The aim is that minimizing w term will maximize the total margin. Minimizing weight vector provide the biggest margin that split this two classes.

The SVM can be divided into two categories, which are linear SVM and nonlinear SVM. Linearly separated SVM create a linear hyper-plane and nonlinear SVM create a nonlinear hyper-plane by applying the nonlinear Kernel function. Gaussian Radial Basis Function (RBF) is commonly preferred for non-linear SVM.

SVM algorithm classifies only two classes. Therefore, one for healthy and one for faulty condition, the features of two acceleration signals were used for training SVM. Two features of acceleration signals, which are RMS value and Mean Frequency value, were chosen. These features were preferred, because they are informative for fault detection of worm gearbox. They showed increasing trend as the severity of faults increased.

For accurate and trustworthy classification, SVM algorithm needs adequate number of samples. Therefore, the size of acceleration data is chosen as 20000, which means that vibration of worm gearbox was measured for 10 seconds. Due to determine RMS and Mean frequency value for each revolution of gear shaft, acceleration signals are divided into 32 equal parts. Afterwards, the features (RMS value and mean frequency value) are calculated for each part. Totally, 128 features are used for training of SVM algorithm. This process is also applied for testing of SVM algorithm. The scheme of algorithm applied in this section is shown in Figure 8.6. This procedure is applied for every faulty condition.

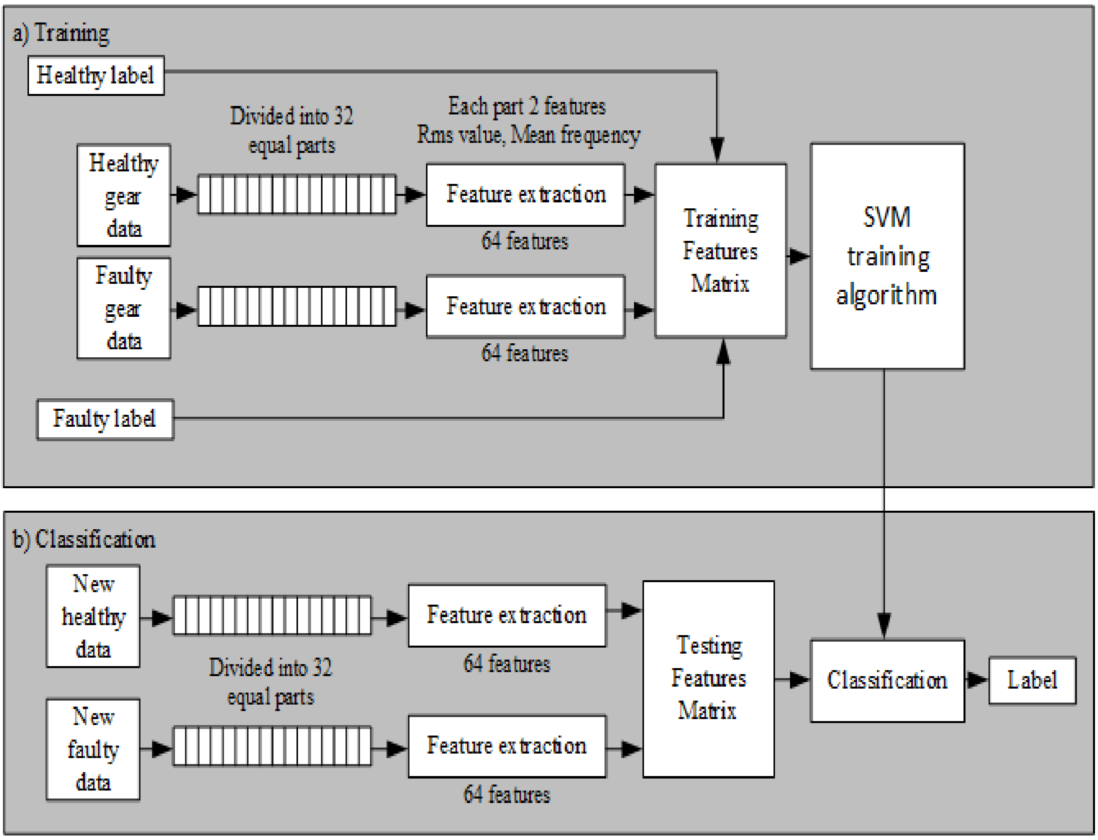


Figure 8.6 Scheme of SVM algorithm applied in this section

An example of training SVM for healthy and faulty worm gearbox is given in Figure 8.7.

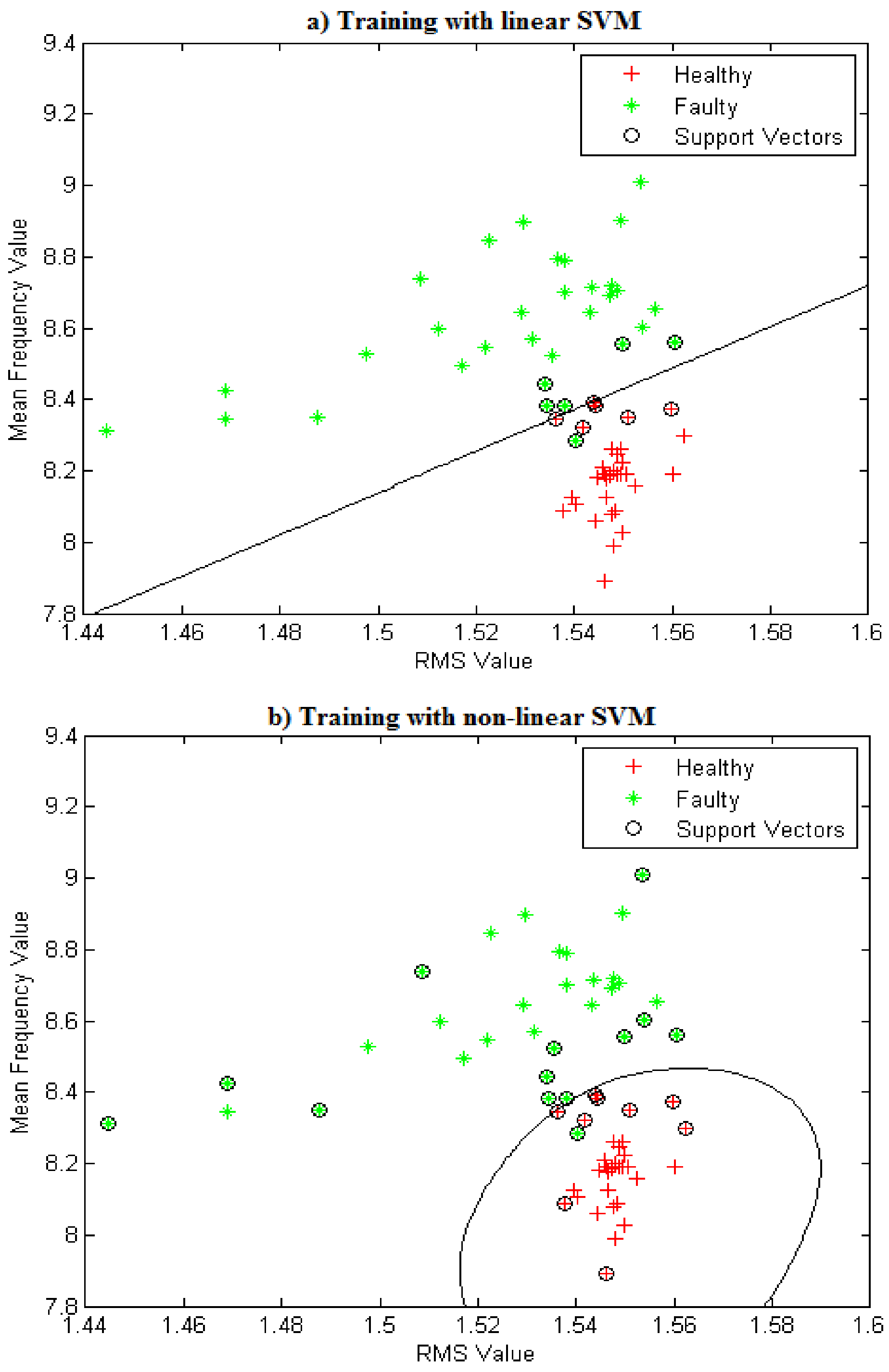


Figure 8.7 Training of SVM for this study

For testing, new vibration sets of data, which are measured another time for each condition, are used. The procedure of features extraction was repeated with all samples in all conditions. An example of classification of new data for this study is illustrated in Figure 8.8.

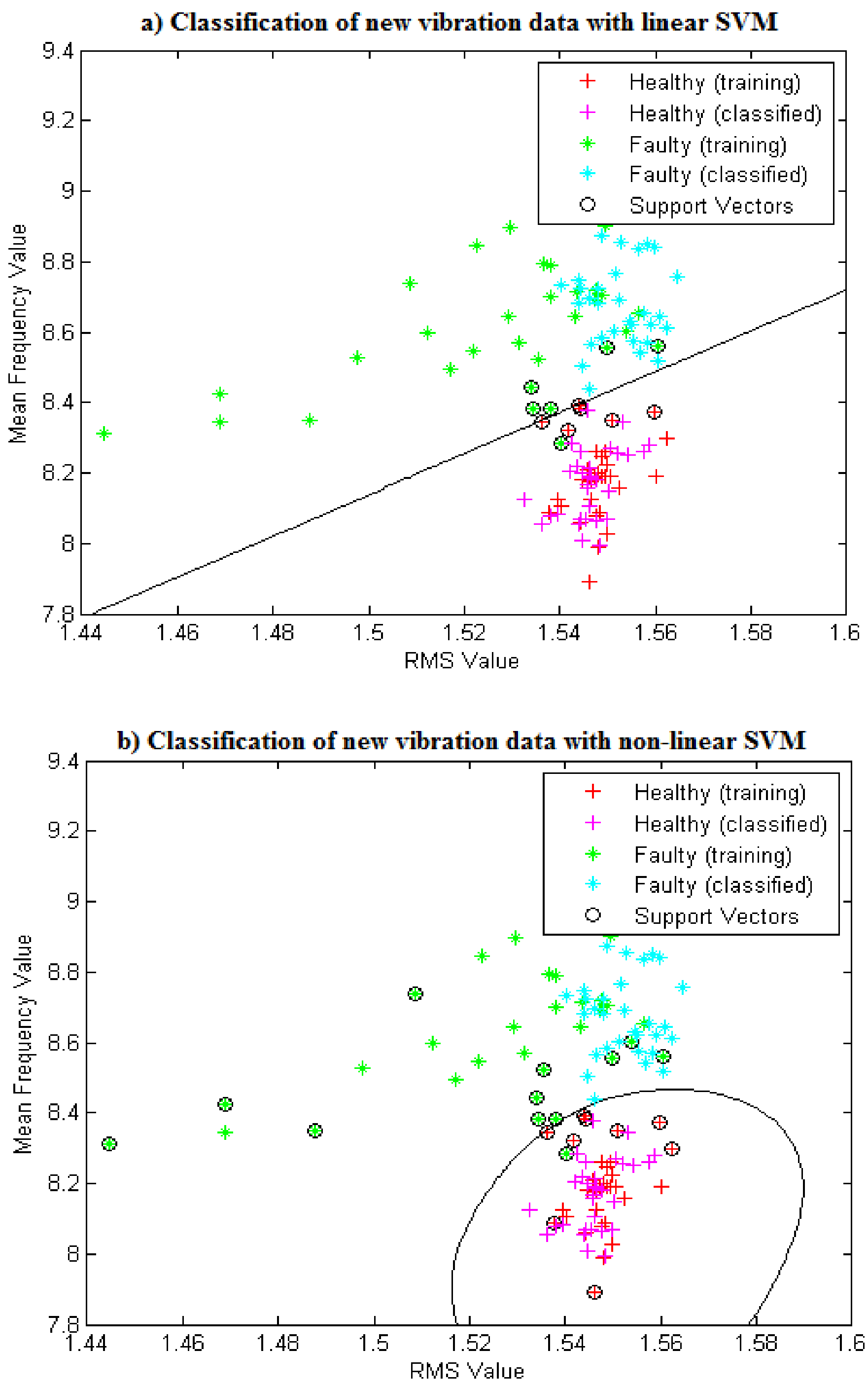


Figure 8.8 Classification of new data for this study

The comparison of performance results of SVM for healthy and each faulty condition are given according to linear and nonlinear SVM in Table 8.1. Results of SVM for this study are also illustrated in Figure 8.9.

Table 8.1 Comparison of performance results of SVM for this study

Conditions	**Kernel**	**SVM test accuracy (%)**
Healthy - Fault 1 condition	Linear	100
	RBF (non-linear)	100
Healthy - Fault 2 condition	Linear	96.87
	RBF (non-linear)	98.43
Healthy - Fault 3 condition	Linear	100
	RBF (non-linear)	100
Healthy - Fault 4 condition	Linear	100
	RBF (non-linear)	100

Results show that SVM achieved successfully classification of healthy and faulty gears for all fault conditions. For fault classification, SVM method has high diagnostic accuracy (more than 95%). It can be concluded from the results that the fault identification with SVM algorithm shows great performance. By comparison of kernels of SVM, linear and non-linear kernels have not significant difference on performance of SVM for this study. The experimental results indicate that support vector machine is very effective method for gearbox fault detection.

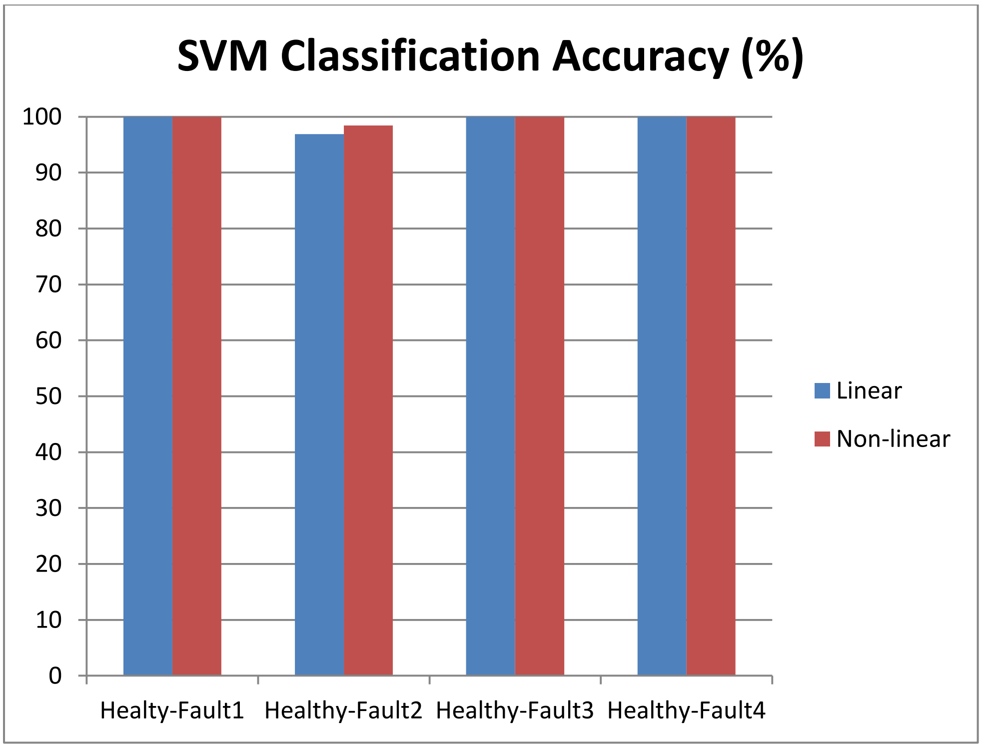


Figure 8.9 Results of SVM for this study

CHAPTER NINE
CONCLUSIONS

This thesis has focused on the real time smart condition monitoring of worm gearbox transmission system. Theoretical and experimental studies have been carried out on vibration signal of gearbox and suitable vibration analysis techniques have been implemented in order to understand the condition of worm gearbox. Embedded system based architecture for vibration analysis is described. Smart monitoring systems, hardware architecture, signal conditioning, data acquisition and signal processing algorithms have been explained. To test the developed smart monitoring system, the experiments have been conducted under increasing severity of simulated pitting faults.

The contributions of this thesis are summarized as follows:

- Most commonly researches in the literature have been specified. Worm gearboxes, their types, tooth forces acting on them and most common worm gear failures have been cited. Condition monitoring techniques and their benefits have been mentioned.
- Fault diagnosis of gearboxes and vibration analysis techniques have been investigated. Commonly used vibration analysis techniques including time analysis and frequency analysis, joint time frequency analysis and frequency component based statistical analysis (FCSA) have been explained. FCSA has been interpreted as advantageous method which is generally used for fault diagnosis of gearbox.
- Vibration based smart condition monitoring system, alias vibration feature extractor or condition monitor, has been created and developed. Hardware system and software system development have been explained. Methodology of developed smart monitoring system has been illustrated. The developed monitoring system has been tested by known signals in order to illustrate evidence of accurate software implementation.

- An experimental test rig has been designed and formed. Fundamental frequencies of test rig have been determined.
- Measurement velocity of worm gearbox, vibration data acquisition, real time vibration monitoring and implementation of vibration analysis techniques have been carried out and visualized on graphical screen for worm gearbox via developed smart condition monitoring device.
- Simulated pits on teeth surface of wheel gear for pitting failure have been implemented. For faulty gearbox, vibration data acquisition and analysis have been carried out. The vibration data were transferred into memory stick. According to comparison results of healthy and faulty gearbox,
    1. Time domain analysis shows that the increasing severity of faults affect the RMS and mean frequency value of vibration signal gradually. These statistical metrics show an increasing trend as the number of simulated pitting faults increases. It can therefore be concluded that RMS and mean frequency value provide the most useful indicators for the monitoring of pitting faults.
    2. In frequency domain analysis, the worm shaft frequency and their harmonics have been shown in case of high severity of pitting failure. This result has been interpreted as existence of pitting failure. Elasha et al. and Teng et al. report similar results about frequency spectrum of faulty worm gearboxes.
    3. Results of FCSA, which is more recent method for vibration analysis, shows increase after no fault condition. Although there is no gradually increase for faulty conditions, results of FCSA for all faulty conditions are higher than that for no fault condition. Pitting faults affect the results of this method positively.
- To indentify existence of failure and find localization of pitting damage, fault detection techniques and support vector machine (SVM) algorithm have been applied. According to results of these methods,
    1. Dynamic squared error based fault detection method provides localization of pitting faults on wheel gear surface. The squared differences between each

faulty and healthy acceleration values of worm gearbox showed that the pits exist at 210 degree approximately from the reference points.

2. Image processing based fault detection method has been used for finding effects of pitting faults on acceleration signals of a worm gearbox. Although this method is a new technique, it is informative for fault detection of mechanical equipment. The results of this method illustrates increasing trend as the number of pitting faults develops. The areas formed by plotting accelerations on two directions show increasing trend with fault progression and spread out along the x direction progressively. This method provides facility for monitoring behavior of acceleration signals which are changed with failure.
3. SVM has been used for decision of gearbox condition. By using training acceleration data, SVM determined whether the condition of worm gearbox was healthy or faulty. The results of SVM show that the method achieved successfully classification of healthy and each faulty gear for all conditions.

Future research includes:

- Future work should be conducted on improvement of smart condition monitoring device. For better vibration analysis, the new embedded system can be used. The visualization of results and graphical user interface can be improved.
- Not only acceleration sensor but also other sensing equipments such as acoustic sensor, thermocouple etc. can be used together. That may provide more precise results for condition of mechanical equipments.
- The literature for fault detection of worm gearbox is very scarce. Recent analysis methods for fault detection and diagnosis can be applied on worm gearbox.
- In this thesis, only constant operation condition is considered. In real applications, the operation conditions such as speed, torque, loading etc. are changeable. For further research, the dynamic operation conditions should be considered.

Consequently, it is believed that this thesis becomes beneficial for development of smart condition monitoring device and fault detection of worm gearboxes.

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