ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

INSTITUTE OF TECHNOLOGY

SCHOOL OF MECHANICAL AND INDUSTRIAL ENGINEERING

# Condition Monitoring of Rail Vehicle Wheel Profile

By

**Melese Gurmu**

**Zewdu Abdi (Dr.-Ing) Advisor**

**April, 2015**

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# ABSTRACT

Condition based maintenance or condition monitoring and fault detection systems are now becoming increasingly important in rail vehicles maintenance and operation, ensuring safety and reliability improvement. Up to now light rail vehicles were not the main target for this trend, because of low operation speed and lower safety factors. Nevertheless public transport operators begin to pay a closer attention to the condition monitoring of tramways, in order to reduce maintenance cost and increase safety and ride comfort for passengers, which is a very important task for public transport competitiveness in this century. To meet the above mentioned goal, this paper models rail-wheel condition monitoring program based on rail vehicle wheel profile analysis by using mathematical analysis and matlab simulation to extract different features. By extracting different features and using matlab simulation, it obtained graphical indication for monitoring of the wheel condition by setting expected goal. So it can be applied in any types of rail vehicles because it reduces maintenance cost and increase safety factors. Good or bad wheel profile can easily be identified by using such matlab algorithm for specified rail vehicles. Therefore, this paper focuses on identification of proper wheel profile for any types of rail vehicles. Moreover, other monitoring system such as vibration, sound and etc can also be applied by using such algorithm.

# Chapter 1

# Introduction

## 1.1 Background

Vehicles and track, meet at a wheel/rail interface that sees large forces, and stresses much higher than the tensile strength of wheel and rail steels. The forces in this interface act positively to steer the vehicle. However, they also lead to rolling contact stresses that work negatively to cause wear and cracks, spalls, and shells produced by rolling contact fatigue. Vehicle steering forces depend on many factors including vehicle and bogie type, track curvature, the degree of wheel/rail lubrication, and the detailed transverse profile shapes of the wheels and rails. Inappropriate profile shapes can lead to vehicle instability and even derailment. Wheel/rail stresses also depend critically on the wheel and rail profiles and the way they interact [2]. The railway transport braking processes are likely to form surface defects on the tread if the wheel locks up and slides along the rail. This action can be produced by a defective, frozen or incorrectly tuned brake, as well as by a low rail-wheel adhesion caused by environmental conditions (rain, snow, leaves, etc.). The abrasive effect of skidding causes a high wear on the rolling surface (a wheel-flat), with lengths ranging typically from 20 to over 100 mm. The rise in temperature caused by abrasion followed by a fast cooling may lead to the formation of brittle martensite beneath the wheel-flat. This can be associated to the beginning of further flaws like cracks and spalls with the loss of relatively large pieces of tread material. When the wheel rolls over a flat, high impact forces are developed and may cause a rapid deterioration of both, rolling and fixed railway structures. Moreover, the incidence of hot bearings, broken wheels and rail fractures are coincidental with the number of wheel-flats and out-of-round wheels [3].The dynamic behavior of railway vehicles on the track is greatly influenced by wheel-rail interaction. In depth understanding of wheel-rail contact theory enables railway researchers study problems such as wear, rolling contact fatigue, corrugation, friction and track irregularities. Also information about wheel-rail contact forces can be investigated to allow for informed decisions on designing intelligent condition monitoring systems. Wheel-rail contact models can also be used to investigate stability of the vehicle on the track and to study the dynamics of the railway vehicle as it moves on the surface. The dynamic parameters of the wheel-rail contact model that greatly influence the motion of the vehicle on the track are the lateral displacement and the yaw angle [4]. Modeling and simulation of wheel-rail interaction using a scale roller rig is necessary for better understanding of dynamic behavior of the railway vehicle in a controlled laboratory environment less prone to noise and disturbances. Applications of roller rigs include vehicle stability tests, track irregularities, ride comfort, wheel-rail interaction, wear, rolling contact fatigue. Raising performance needs and increased importance on scheduled maintenance and life cycle costs for railway vehicles and tracks have attracted interest to the necessity of predicting wheel and rail wear by simulation. Developing a wear prediction model enables railway researchers to better understand wear mechanisms and its effect on the dynamic behavior of the system so that re-profiling of the wheels-rails can be easily carried out without planned maintenance schedules. It also helps in improvements in wheel design and materials in order to reduce wear. For enhanced understanding of the phenomena, roller rigs are can be used to simulate wheel wear and its effects of the railway vehicle dynamics [5]. Figure 1.1 shows a schematic of a new railway wheel and a new rail. A typical railway wheel has a wheel tread, where the wheel is usually in contact with the rail, and a flange to improve the lateral guiding. Wheel profiles are conical (shown as “a” in Figure 1.1) to facilitate steering performance. Rails are mounted with an inwards inclination (shown as “b” in Figure 1.1) to match the conical wheel profile and for better load transfer to the sleepers and ballasts. Depending on the wheel and rail profiles, the curvature of the track, and the wheel position, the exact contact position can be determined. In most cases, the contact positions between the wheel and the rail are wheel tread–rail head contact and wheel flange–rail gauge contact. These two basic contact positions are shown in Figure 1.1 as “c” and “d”. Along straight tracks, the wheel treads and rail head are likely to be in contact, while wheel flange–rail gauge contact occurs along curved tracks. Adhesion research considers only the wheel tread–rail head contact [5].

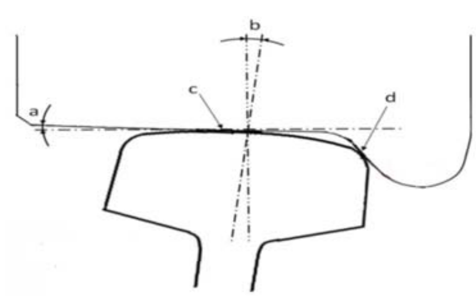



**Figure 1-1 Schematic of wheel–rail contact positions [5]**

**a) Conical wheel profile (b) rail inclination (c) wheel tread–railhead contact and (d) wheel flange–rail gauge contact**

Well-performed maintenance implies seeing as few corrective maintenance actions as possible while performing as little preventive maintenance as possible. This might seem as a utopia (everything is perfect), but during the past decades strategies and concepts have evolved for support. One of these is condition based maintenance. In condition based maintenance, critical item characteristics are monitored (through, for example, vibration or temperature monitoring) in order to gain early indications of an incipient failure. Today, most maintenance actions are carried out by either preventive- or corrective maintenance. The preventive maintenance, with its fixed intervals, is often guided by subcontractors or operation experience. With this technique, one tries to prevent components, sub-systems or systems to degrade to the degree of breakdown. This is done by repair, service or component exchange in preset intervals. Preventive maintenance is sometimes called planned-, historical- or calendar based maintenance. With corrective maintenance one instead lets the component, sub-system or system, run until breakdown or obvious fault occurs before maintenance action is considered. Corrective maintenance is sometimes called breakdown maintenance or run-to-failure maintenance. Since a few decades industry has started to use predictive- and proactive maintenance. In the predictive maintenance, one decides on the maintenance intervals by assessing the condition of the asset. This is done through analysis of vibrations, oil quality, temperature, voltages and currents, acoustics etc. Preventive maintenance is also called Condition Based Maintenance (CBM). Proactive maintenance is also called Reliability based maintenance and Precision maintenance. In proactive maintenance one tries to find the root cause of a failure and then tries to prevent it from happening again by making changes in construction, operations or production.

**A railway company may not place or continue a rail vehicle in service if:**

(a) A wheel rim, flange, plate or hub area has a crack or break. Heat checks or chips in wheel rim are not considered to be cracks or breaks;

(b) A wheel has a chip or gouges more than 1-1/2 inches (38.1 mm) in length and 1/2 inch (12.7 mm) in width;

(c) A wheel has a shelled spot that is more than 1-1/4 inches (31.8 mm) in width and 1-1/4 inches (31.8 mm) in length;

(d) A wheel has a slid flat that is more than 2 inches (50.8 mm) in length;

(e) A wheel shows evidence of being loose;

(f) A wheel flange is worn to a thickness of 7/8 inches (22.2 mm) or less at a point 3/8 inches (9.5 mm) above the tread of the wheel;

(g) The height of a wheel flange from the tread to the top of the flange is more than 1-1/2 inches (38.1 mm);

(h) The thickness of a wheel rim is 7/8 inches (22.2 mm) or less;

(i) A straight plate wheel has:

- A blue or reddish brown discoloration on the front and back face of the plate that extends more than 4 inches (101.6 mm) into the plate;
- A combination of heat discoloration on the rim and plate with a rim thickness of 1-1/4 inches (31.8 mm) or less;
- Any visible tread defects with a rim thickness of 1-1/4 inches(31.8 mm) or less; or
- 1 inch or (25.4 mm) or less of rim thickness; or

(j) A wheel is the wrong size. [1]

## 1.2 Condition Monitoring

A modern railway system relies on sophisticated monitoring systems for maintenance and renewal activities. Some of the existing conditions monitoring techniques perform fault detection using advanced filtering, system identification and signal analysis methods. These theoretical approaches do not require complex mathematical models of the system and can overcome potential difficulties associated with nonlinearities and parameter variations in the system. Practical applications of condition monitoring tools use sensors which are mounted either on the track or rolling stock. For instance, monitoring wheel set dynamics could be done through the use of track-mounted sensors, while vehicle-based sensors are preferred for monitoring the train infrastructure. This paper attempts to collate and critically appraise the modern techniques used for condition monitoring of railway vehicle dynamics by analyzing the advantages and shortcomings of these methods. Mostly, the track bed-based sensors are used to monitor the condition of wheel set, whereas, the rolling stock-based sensors are concerned with the monitoring of the rolling stock infrastructure. Modern rolling stock is fitted with high-capacity communication buses and multiple sensors which require advance processing units for data collection and management. For instance, an on-board data processing unit should have decision-making capabilities, hence, should be able to decide how much data to store depending on the severity of the fault and priority of notification [2, 3].

## 1.3 Statement of Problem

The most commonly used policy in practices is to replace upon failure or to replace periodically. Problems associated with replacement upon failure are that it would result in higher operating cost, incur failure cost and also raise safety concerns. For the periodic policy, it is hard to decide the right life limit at which components will be replaced. The same components on different rail vehicles may have different lengths of physical lives because of different usage patterns. If the replacement limit is conservative a risk exists that the components may be replaced under the schedule maintenance regime well before its useful life has elapsed; this would result in excessive and unnecessary maintenance higher life cycle costs. In the cases where the replacement limit is too optimistic, many components will fail before being replaced, and costs will be similar to replace upon failure. In this research, condition based maintenance (CBM) policy is proposed for rail wheel components in order to obtain the greatest benefits from system maintenance. CBM is the strategy by which maintenance is undertaken only when the component or system reaches a particular state or condition, usually one which is believed to be a precursor to in-service failure. CBM allows a railroad to replace a component after it has had a fairly long life, but before it deteriorates so much as to cause sharply increased operating cost or a significant risk in-service failure. CBM therefore is like to result in the lowest life cycle cost among the three policies. Condition Based Maintenance (CBM) is a predictive maintenance technique focusing on performing a maintenance action based on the actual condition of a system. It is based on monitoring the underlying deterioration process of the equipment. As this deterioration reaches a predefined threshold level, a maintenance action is initiated. By predicting the Remaining Useful Life (RUL) of a unit using remote monitoring techniques, operational and technical maintenance costs can be reduced.

## 1.4 Objective

The overall research goal is to evaluate rail vehicle wheel profile monitoring as tools for cost effective implementation of condition-based maintenance for railway vehicles, in particular the rail wheels. The goal is to increase the life length of the wheels by knowing the condition of the wheel profile. In addition, to show the effectiveness and advantages of rail vehicle wheel profile based condition monitoring for condition based maintenance by help of time-domain analysis, frequency-domain and time-frequency domain feature extraction techniques and to work with artificial neural network and indicate the application of artificial neural network for rail wheel condition monitoring.

## 1.5 Scope and Limitations

There are different types of condition monitoring parameters such as temperature, sound, even lubrication oil based condition monitoring system. This thesis paper is limited to only rail-wheel profile based condition monitoring system for varieties of reason such as lack of data, shortage of time and also to limit the amount of paper (in terms of content). The scope of this article is also dealt with the profile of rail vehicle wheel to show difference between normal rail-wheel and worn out rail-wheel by observing graphical result of the programmed matlab algorithm.

# Chapter 2

# Literature Review

## 2.1 Introduction

What is maintenance and why is it performed? Past and current maintenance practices in both the private and government sectors would imply that maintenance is the actions associated with equipment repair after it is broken. The dictionary defines maintenance as follows: "the work of keeping something in proper condition; upkeep." This would imply that maintenance should be actions taken to prevent a device or component from failing or to repair normal equipment degradation experienced with the operation of the device to keep it in proper working order. Unfortunately, data obtained in many studies over the past decade indicates that most private and government facilities do not expend the necessary resources to maintain equipment in proper working order. Rather, they wait for equipment failure to occur and then take whatever actions are necessary to repair or replace the equipment. Nothing lasts forever and all equipment has associated with it some predefined life expectancy or operational life. For example, equipment may be designed to operate at full design load for 5,000 hours and may be designed to go through 15,000 starts and stop cycles.

The need for maintenance is predicated on actual or impending failure – ideally, maintenance is performed to keep equipment and systems running efficiently for at least design life of the component(s). As such, the practical operation of a component is time-based function. If one were to graph the failure rate a component population versus time, it is likely the graph would take the "bathtub" shape shown in Figure 2.1. In the figure the Y axis represents the failure rate and the X axis is time. From its shape, the curve can be divided into three distinct: infant mortality, useful life, and wear-out periods.

The initial infant mortality period of bathtub curve is characterized by high failure rate followed by a period of decreasing failure. Many of the failures associated with this region are linked to poor design, poor installation, or misapplication. The infant mortality period is followed by a nearly constant failure rate period known as useful life. There are many theories on why components fail in this region, most acknowledge that poor O (operation) & (maintenance) M often plays significant role. It is also generally agreed that exceptional maintenance practices encompassing preventive and predictive elements can extend this period. The wear-out period is characterized by a rapid increasing failure rate with time. In most cases this period encompasses the normal distribution of design life failures.

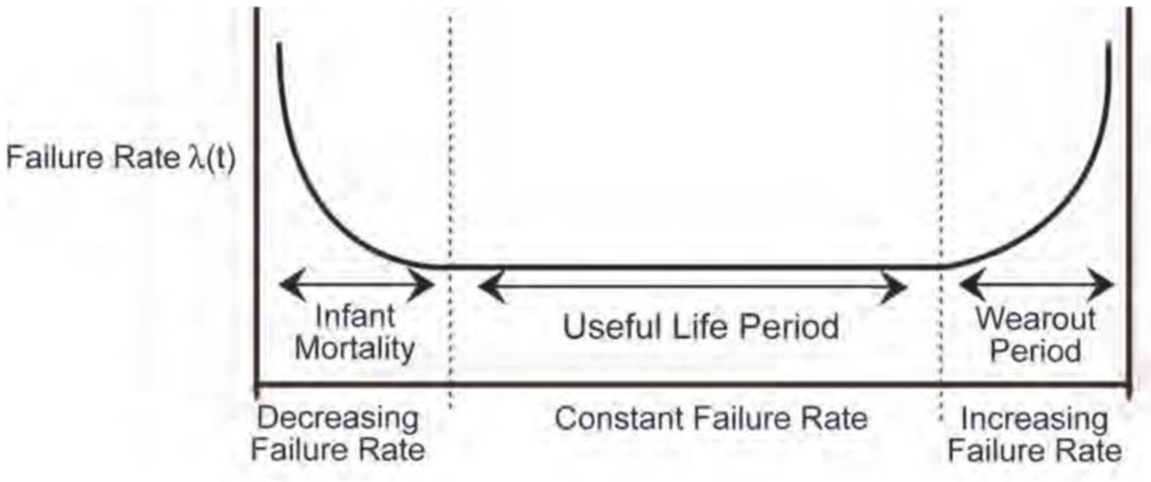



**Figure 2-1 Component failure rate over time for component population [5]**

The design life of most equipment requires periodic maintenance. Belts need adjustment, alignment needs to be maintained, and proper lubrication on rotating equipment is required, and so on. In some cases, certain components need replacement, (e.g., a wheel bearing on a motor vehicle) to ensure the main piece of equipment (in this case a car) last for its design life. Anytime we fail to perform maintenance activities intended by the equipment's designer, we shorten the operating life of the equipment. But what options do we have? Over the last 30 years, different approaches to how maintenance can be performed to ensure equipment reaches or exceeds its design life have been developed in the United States. In addition to waiting for a piece of equipment to fail (reactive maintenance), we can utilize preventive maintenance, predictive maintenance, or reliability centered maintenance.

**Figure 2-2 Profile system [7]**

## 2.2 Definitions of Maintenance

Maintenance can be defined as those activities required to up-keep a facility in as built condition, so that it continues to have its original productive capacity [7]. Depending on designer limitation of life span, manufacturer recommendations, age and service conditions of equipment/vehicle, it is possible to adopt the particular maintenance types along with their implementation interval. According to the Oxford Dictionary, "maintenance is defined as, 'the act of maintaining or the state of being maintained; the work of keeping something in proper condition; upkeep". In the context of industrial sector, maintenance can be defined as actions to control the deterioration process leading to the failure of a system, which is often called "preventive maintenance", and the restoring of the system to its operational state through corrective actions after the occurrence of failure, often called "corrective maintenance". From the above definitions, it can be seen that maintenance is necessary to keep any product or system, with a finite life span, operating at an acceptable level, so as to support the needs of the user or organization.

## 2.3 Reasons for Maintenance

There are several, quite obvious reasons for maintenance, for example:

- **Safety** – Probability for accidents needs to be low.
- **Comfort**– Comfort is important, both for passengers and freight as well as for the environment in terms of noise and vibration.
- **Availability** – With lots of failures and speed restrictions due to safety etc. the availability of the track will be low.
- **Economy** – A track with low quality is cost driving, since the deterioration of both track and trains will be higher. At the same time maintenance is expensive and optimization and Life Cycle Cost (LCC) planning is needed.

## 2.4 Types of Maintenance

Maintenance may be categorized in to the following major types [7]:

**2.4.1 As Required Maintenance**: "as required maintenance is simply doing maintenance works as the need develops (arise**).** This type of maintenance is applied for non-critical equipment.

**2.4.2 Corrective Maintenance:** corrective maintenance covers all maintenance activities that are carried out in order to correct (repair) a fault in equipment/ vehicle. It may include emergency or break down maintenance.

**2.4.3 Conditioned Based Maintenance:** Condition Based Maintenance (CBM) or predictive maintenance is a technology that strives to identify incipient faults before they become critical which enables more accurate planning of the preventive maintenance. It may also be defined as Maintenance actions based on actual condition obtained from in-situ, non-invasive tests, operating and condition measurement or CBM is a set of maintenance actions based on real-time or near-real time assessment of equipment condition which is obtained from embedded sensors and/or external tests & measurements taken by portable equipments".

CBM or predictive maintenance is the means of improving productivity, product quality and overall effectiveness of manufacturing and production plants. CBM or Predictive maintenance is not vibration monitoring or thermal imaging or lubricating oil analysis or any of the other nondestructive testing techniques, as predictive maintenance tools. Rather, it is a philosophy or attitude that simply stated uses the actual operating condition of plant equipment and systems to optimize total plant operation. A comprehensive predictive maintenance management program utilizes a combination of the most cost-effective tools, i.e. thermal imaging, vibration monitoring, tribology, and other nondestructive testing methods, to obtain the actual operating condition of critical plant systems and based on this factual data all maintenance activities on an as-needed basis are scheduled. Including CBM or predictive maintenance in a comprehensive maintenance management program will provide the ability to optimize the availability of process machinery and greatly reduce the cost of maintenance. It will also provide the means to improve product quality, productivity and profitability.

The maintenance organization in a company probably has one of the most important functions, looking after assets and keeping track of equipment in order to secure productivity. A company with no or a poor maintenance organization will lose a lot of money due to lost production capacity, cost of keeping spare parts, quality deficiencies, damages for absent or late deliveries etc. A relationship between failure rates versus change in maintenance philosophy is showing decline trend as illustrated in figure 2.3, also representing the strengths and weakness of the different maintenance types.

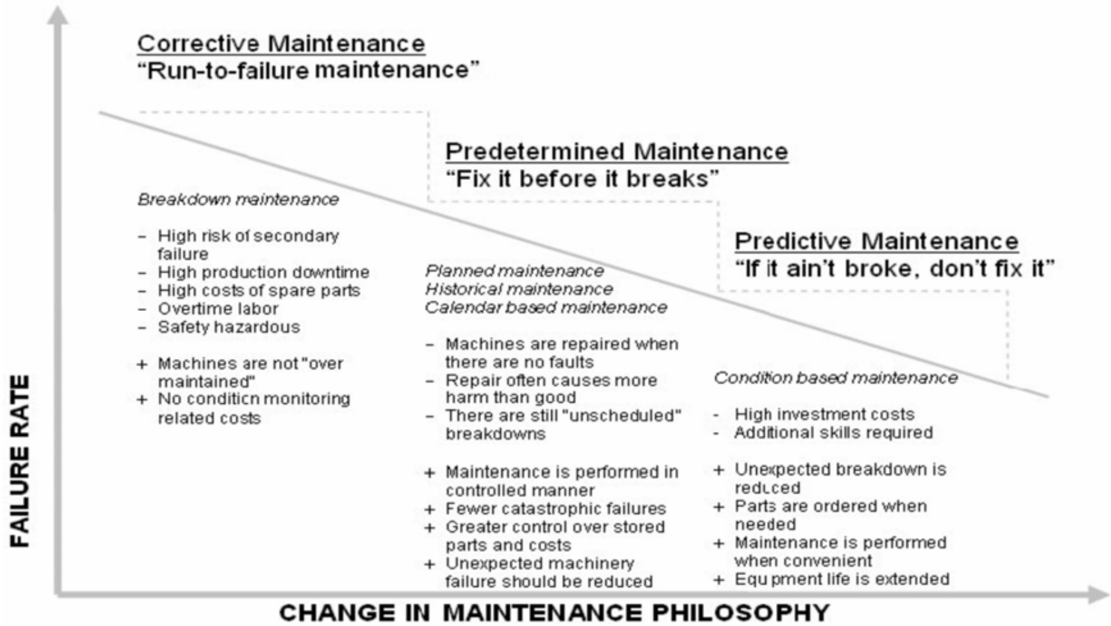



**Figure 2-3 Failure rate versus change in maintenance philosophy [56]**

The addition of a comprehensive predictive maintenance program can and will provide factual data on the actual operating condition of critical assets, including their efficiency, as well as the actual mechanical condition of each machine-train and the operating efficiency of each process system. Instead of relying on industrial or in-plant average-life statistics, i.e. mean-time-to failure, to schedule maintenance activities, predictive maintenance uses direct monitoring of the mechanical condition, system efficiency and other indicators to determine the actual mean-time-to-failure or loss of efficiency for each machine-train and system in the plant. This data provides maintenance management the factual data needed for effective planning and scheduling maintenance activities [56].

Condition based maintenance is a maintenance activity conducted to prevent failures before it happens using sensing, measuring, or condition monitoring devices to detect wear stages.

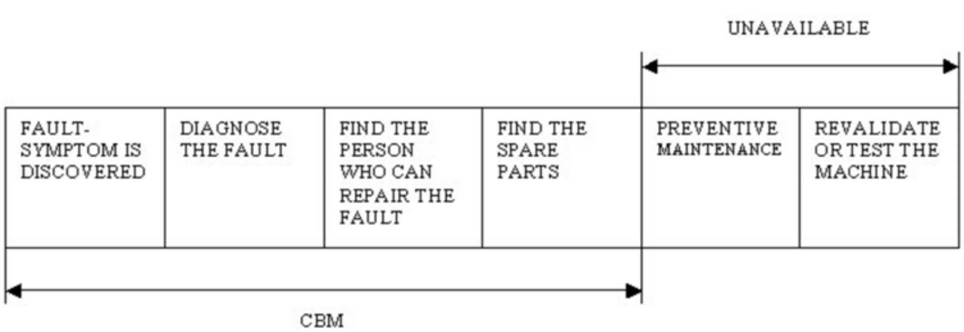



**Figure 2-4 The main process in CBM [55]**

CBM systems need several modules in order to give the information one needs to make the right maintenance judgments. Systems and organizations can vary in levels of automation.
One company can use handheld devices out in the field and then make analysis of the data either at site or in more controlled environments, while others use more complicated on-line system. Either way, it is how the company uses the data and analysis that tells if they are having a CBM strategy or if they are just making "quality checks" of their assets. When being on a CBM program one takes the results of the analysis and plans the maintenance actions thereafter.

The given the general demands of an on-line condition monitoring system [41]:

- Real-time application
- High reliability
- At early stage, alert when fault is impending, so that maintenance can be planned when asset is not being used
- Identification of the fault and tell where the fault is located
- Classify faults in different categories, when a fatal fault occurs automated shut down should be a possibility
- The alerts should be easy to understand
- The system should be connected to a superior computer

**For CBM to be successful there are some issues to be considered:**

- The accuracy of the inspection;
- The inspection interval, that has an associated cost;
- The definition of the most representative key performance indicators
- The condition limit.

### 2.4.4 Preventive Maintenance

PM is done to prevent the occurrence of failures and to detect failures before they develop to break down or disturbances in operation (product/service).

Preventive maintenance has become a term with broad definition. The generic definition of PM is any planned maintenance activity that is designed to improve equipment life and avoid any unplanned maintenance activity. In its simplest form it can be compared to the service schedule for vehicle. There are certain tasks scheduled at varying frequencies, all designed to keep the vehicle from experiencing any unexpected breakdowns.

Preventive maintenance activities that help to avoid failure of equipment are listed in [8] as follows:

- Equipment inspections to uncover deficiencies before failure and in sufficient time to plan deliberate repairs;
- Non-destructive testing techniques (predictive maintenance) to detect equipment deterioration and monitor equipment to note abnormal operation;
- Routine maintenance such as lubrication to reduce friction that causes heat, wear, misalignment, or seizure;
- Routine, cleaning and adjusting done in conjunction with inspection or lubrication, or performed by frontline operators;
- Replacement of minor components to reduce chances of more important components failing;

It is recommended that maintenance being cause and effect situations, it is logical that efforts be directed towards correction of the causes, rather than continuing to treat the effects [6]. Therefore, it is feasible and economical to adopt a mechanism by which maintenance is conducted to prevent the cause of failures and detect the failures before it occurred. It is recommendable to adopt preventive maintenance when:

- Corrective maintenance cannot be justified
- Condition based maintenance cannot be applied and
- As required maintenance effects cannot be tolerated

In preparing this thesis, concepts are drawn and ideas are incorporated from various works of different authors whose contributions have been significant in the development of maintenance function, and maintenance management. The works of the authors' quoted in [6], [7], [9] and can be summarized as follows:

- Maintenance department shall be organized based on some universal truths and modified to adopt it to different sizes and sections according to the following parameters:
- Plant size and type
- Company policy
- Industry wide and sectional precedent
- Particular technical, geographical and personnel situations involved
- State of training and reliability work and

- Available facilities
- Maintenance work shall be as much as possible preventive
- Maintenance planning and control system is crucial for implementation and cost effectiveness of maintenance
- Computerized maintenance management system is necessary
- Maintenance system can be centralized or decentralized

## 2.5 Analysis of Wheel-rail Interactions

To analyze the wheel-rail interactions in presence of wheel/rail defects, two different techniques, namely, Frequency domain and Time domain techniques are widely used. Frequency domain technique has been used to study the impact load due to wheel defects, track irregularities and the formation of corrugations [58, 59]. This technique takes less time to analyze and is effective for the prediction of the frequency response related to excitation. However, it is limited to investigation of the linear models only. When nonlinearity is present either in vehicle-track system model or in contact model, it is necessary to adopt the solution process in time domain. Time domain analysis can be further classified into modal analysis method and finite element method. Modal analysis method has been used to study the wheel-rail impact load due to wheel flats and rail joints, noise generation and rail corrugations [60-61]. This method has the advantage of fast computing when the local variations of the track are small. However, many modes are required to exactly model the track in order to have accurate prediction of the track behavior.

### 2.5.1 Detection of Wheel Defects

Imperfections on the wheel tread and rail surface can have detrimental influence on both vehicle and track components such as vehicle bogies, wheel sets, bearings, rails and rail pads. The high impact forces from a defective wheel cause stress in the rail, and in extreme cases can break the track or cause the wheel to jump off the track, resulting in derailment. The repetition of impacts on rail, together with the high forces involved, cause rapid deterioration of both rolling and fixed railway equipment. If ignored or underestimated, the fault will wear out materials up to the breakdown. Thus, various methods have been proposed for detecting flat wheels. One method is to employ inspectors to listen to the trains as they move through a particular location. In some cases, flat wheels are identified through routine inspections when the cars are being serviced. These methods employ a range of technologies from optical systems that gauge the wheels in real time to sensors that look for vibrations and stress levels.

Continuous wavelet transform has been applied to vibration signal analysis of railway wheels in order to detect the wheel tread defects by Belotti et al. [63] and Yue et al. [64]. Belotti et al. [63] has shown a wheel-flat diagnostic tool by using wavelet transform method, as shown in Fig. 2.5. In this study, an experimental layout was designed to develop and to validate a reliable, effective, and low-cost wheel-flat diagnostic tool. The method implies the detection of the wheel flats through the measurement of peak acceleration by the use of several accelerometers placed in fixed positions on the rail. The results obtained from experimental study validate the theoretical model and demonstrates the advantages of wavelet-based detection of signatures. However, the wired connections between the accelerometer and the analysis house make the overall system bulky. Furthermore, the entire train has to pass through the specific test section that can be far from the train operating area.

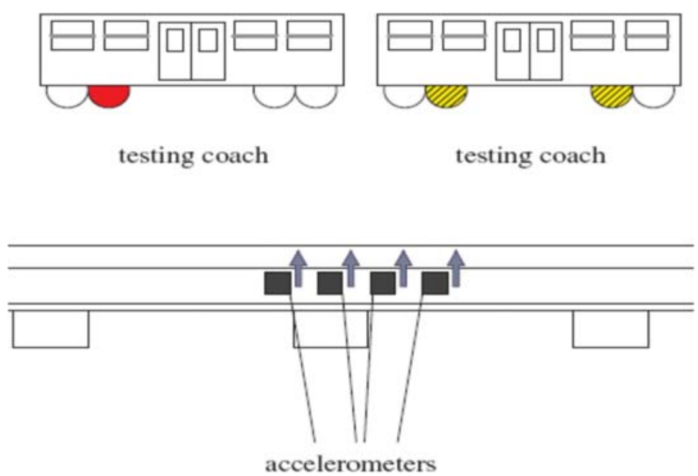



**Figure 2-5 Testing train scheme with damaged wheels [65]**

Represented by deep marked and instrumented rail where the arrows near the accelerometers indicate their measuring axis.

Another method of detecting wheel flats employs scanning with laser beam [65], as shown in Fig. 2.5. The entire module consists of a detector to send and receive radiation signals after the scanning of the wheel. The module also has a smart electronics box (SEB) that contains digital signal processors and connection to the wayside personal computer (PC) for further analysis. Wheel flats can be clearly detected from the unique signature and the gradients between scans at different heights on the wheel.

Ultrasound technique has often been used as a non-destructive technique in order to inspect the defects of rail wheel [58, 66]. The methods consist of sending an ultrasound pulse over the rolling surface to detect echoes produced by the defects. The inspections can be carried out manually or by expensive and complex installations. In both cases, however, long inspection time is required. Moreover, ultrasound techniques use high frequencies that cannot penetrate certain type of defects because of excessive attenuation.

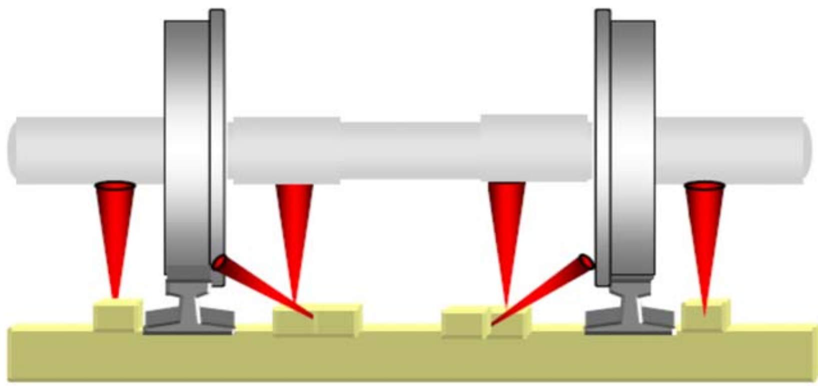


**Figure 2-6 Assemblies to view inner bearing, outer bearing, and wheels [58]**

The most common approach to detect wheel defects is based on the analysis of impact loads or accelerations of wheels or rails developed due to the presence of wheel and rail defects in time-domain schemes [58, 67]. These methods employ several accelerometers placed on rails in order to detect the wheel/rail defects by inspecting the acceleration levels. Detection of the wheel/rail defects depends on the analysis of the frequency spectrum of the measured rail accelerations. Bracccialli et al. [67] presented a description of this type of method based on the cepstrum analysis of rail accelerations. These accelerometers can be micro-electronics and micro-electromechanical systems (MEMS) based accelerometers or conventional piezoelectric accelerometers. The vast majority of accelerometers are based on piezoelectric crystals, but they are too big and too clumsy, whereas, MEMS based accelerometers are tiny and are made using a highly enabling technology with a huge commercial potential. They provide lower power and robust sensing. The most common application for MEMS based accelerometers in railway engineering is health monitoring of the track [58, 67]. However, all these MEMS based sensors are developed to monitor the track only.

## 2.6 Feature Generation

Features for wheel flat detection are generated either based on the original signal in time domain, its frequency spectrum or its envelope spectrum. For the analysis in time domain, features are statistical values such as standard deviation, absolute maximum, crest factor or peak to peak value. Using the spectra more complex features are generated. Figure 2.7 shows the Fourier spectrum and the envelope spectrum (using the Hilbert transform) of a wheel with a wheel flat [68].

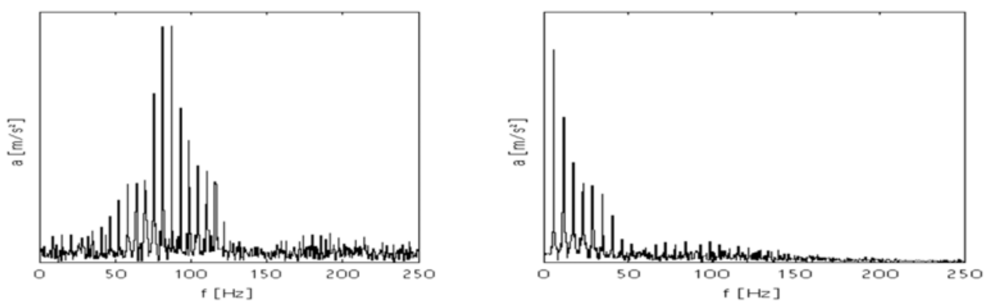



**Figure 2-7 Fourier spectrum (left), envelope spectrum (right) [68]**

Generally wheel flats cause peaks in the spectra which can be found at the excitation frequency (fw1) and its harmonics (fwn, n = 2, 3...). In the Fourier spectrum only higher order harmonics can be seen whereas in the envelope spectrum already lower orders are clearly visible. Features based on the Fourier spectrum are named (Ks), features based on the envelope spectrum are named (Ke). Usually the principles behind the features can be applied to both spectra.

Feature (Ks1/Ke1) and (Ks2/Ke2) use the spacing between the peaks in the spectrum (Δfn-n+1, n = 1, 2 ...). When a wheelflat occurs, the distance between the (n = 1, 2 ...) maxima should be equally distributed (Ks1/Ke1) therefore is the variance of these n distances. This feature only gives general information about harmonics in the spectrum and could lead to similar results for other faults such as a damaged bearing. For a damaged wheel, fw1 should be equal to Δfn-n+1. Feature (Ks2/Ke2) therefore compares the distances between the peaks with an excitation frequency calculated out of the wheel diameter and the wheel speed, this way allowing more detailed conclusions about the failure type.

A different approach is used for feature (Ks3/Ke3), where the position of the peaks in the spectrum is compared with the harmonics of the excitation frequency. For a damaged wheel, the frequency of the n maxima should be integer multiples of the excitation frequency. The cumulated differences form feature (Ks3/Ke3). Similarly to (Ks1/Ke1), the features

(Ks4/Ke4) and (Ks5/Ke5) analyses the structure of the signal without any direct reference to the fault type to be diagnosed. For feature (Ks4/Ke4) the spectrum is normalized, afterwards the peaks exceeding a threshold are counted. Feature (Ks5/Ke5) is the kurtosis of the spectra [68].

## 2.7 Condition Monitoring of Rail-Wheel

Most of the condition-monitoring systems for railway vehicles are focused on the wheel and bogies since these are the parts that have the largest impact on the performance and are also the mayor cost drivers in maintenance.

Many of the products for condition monitoring of railway vehicles are wayside monitoring systems and not directly mounted on the vehicles. In many cases, it still would not be economical to have sensors on every vehicle to monitor the entire vehicle condition because the cost of monitoring would become more costly than handling the faults if they occur. The vast numbers of vehicles that are in use on the railway makes it very costly to equip them all and also it is a challenge to both organize and maintain detector technology on every vehicle. Possibilities exist in the railway sector however due to the fact that the vehicles are track bound and that the vehicles are most often used on specific routes even though they may be used over very long distances. But this makes it possible to monitor the vehicles with equipment standing adjacent to the track. The amount of monitoring systems and detectors can then be limited but still monitor and measure a large number of vehicles.

To achieve the goal of bringing the railway industry from time/mileage based maintenance to more condition-based maintenance, there have to be ways to monitor the condition and thereby be able to predict the remaining life length of the component. The wheel/rail interface is the most important parameter in the vehicle’s condition. This is where most of the cost for maintenance on both rail way vehicles and infrastructure occurs. There are also systems for measuring the condition and status of the infrastructure from systems mounted on trains or service vehicles, and the measured condition correlated to geographical information, from for example GPS-systems. This would give a good overview of the total infrastructure condition. This provides an opportunity to have continuous control of the infrastructure status to follow up the degradation, but also to locate potential incipient failures and problem areas in the infrastructure. It is also important to monitor the condition to avoid potential accidents. For example a derailment is very costly and can cause loss of life. Condition monitoring is a tool for the maintenance management and function as input to the decision support. The condition monitoring information is combined with information about the operation to plan maintenance activities in an effective way to achieve increased equipment life, uptime and decrease costs to reach a better business result.

### 2.7.1 Wheel Condition Monitoring

To evaluate the wheel condition it is the status of the wheel surface and the wheel profile that are of interest. But the crack propagation inside the wheel is also of great importance for the condition and life time of the wheel.

Information regarding health and physical status of wheels or components is a key to successful maintenance planning. Therefore, many maintenance actions are directed towards collecting information on wheel conditions [32]. A definition of the term condition monitoring (CM) is the continuous or periodic measurement and interpretation of data to indicate the condition of an item to determine the need for maintenance [38]. This is normally carried out with the item in operation, in operable state or removed but not subject to major strip down.

The monitoring can be executed with different levels of automation, from relying entirely on human senses to assess the condition to fully automated and integrated monitoring systems, measuring and analyzing e.g. vibrations, temperatures, pressures etc[16].

Traditional inspection techniques used in the railroad industry such as drive-by inspection, are not as accurate and reliable as more rigorous and quantitative inspection methods [49]. On-board measuring can measure the chosen parameter along the whole route where the test trains runs, while wayside measuring can measure the parameters for the full train set as it runs through the measuring points [36]. Wayside detection systems provide a means of monitoring the condition of vehicles, ensuring that they are in a serviceable condition [44].

#### 2.7.1.1 Wheel-rail Forces

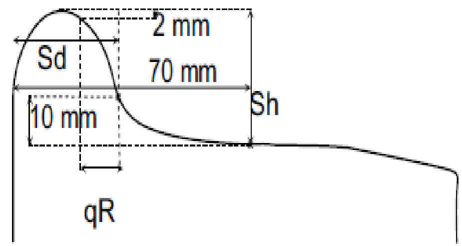
Force measurement detectors make it possible for vehicles with defective wheels, which are likely to cause damage to the permanent railway structures, to be identified and removed from service immediately [44]. Vertical impact loads between wheel and rail resulting from surface anomalies such as wheel flats has been used to create mathematical models of wheel-rail impact behavior [11]. Systems that solely measure the axle load of wheel flats are mostly placed on a tangent track with no gradient or a negligible gradient and where trains do not accelerate or brake [34].

Lateral forces are the result of poor steering bogie and train speeds outside the track design, and of longitudinal buff and draft forces transmitted through train action and coupler angularity [15]. In order to prevent derailment accidents and abnormal wear, it is important to determine the actual state of the contact forces between wheel and rail [36]. According to Matsumoto et al. [36] lateral and vertical contact forces are especially important. The knowledge gained from measurement of wheel-rail forces is allowing for reduction in the stress state of the railway [13].

#### 2.7.1.2 Wheel Profile

Wheel profile is critical to the railway vehicle's dynamic behavior, stability and ride comfort; also important are the rate of wear and rolling resistance of the wheel and rail [14, 27]. The shape of the profile has a relationship to derailment safety and material strength of heavily worn wheels. Condition monitoring of wheels enables scheduled maintenance of each vehicle. The MiniProf™ measurement system is used by many railroads to monitor wheel and rail profiles [24]. This is one of the most reliable and accurate monitoring systems available. In fact, the results of other wheel profile monitoring systems are often compared to Mini Prof to check their accuracy.

Mini Prof™ Wheel, see Fig.2.8 has a sensing element consisting of a magnetic wheel which is 12 mm in diameter, attached to the end of two joint extensions. To measure the wheel profile, the Mini Prof is magnetically attached to the wheel, as seen in Fig.2.8 the back and top of the wheel are used as the horizontal and the vertical references, respectively [24]. The system measures the profile with two degrees of freedom, and a computer calculates the profile in Cartesian coordinates. The resolution is in thousandths of a millimeter.




(a) Picture of MiniProf measurement equipment. (b) Explanation of the parts of the profile

**Figure 2-8 Profile measurement and explanation [24]**

Automatic wheel profile monitoring technology uses high speed cameras and lasers to capture the wheel tread profile of each rolling stock wheel as it passes [18, 53]. The equipment monitors wheel profiles against a maintenance standard for detection of worn wheels.

## 2.7.2 Wheel-rail Rolling Contact and Deterioration

How wheel profiles affect the performance of rail vehicles mainly fall into two main categories. In the first category the safety of the system is related to the wheel profiles. The second category is related to the dynamic performance of the vehicle, for instance vehicle dynamic stability, vehicle-track force levels and ride comfort [26]. Wheel and rail profiles are designed to meet certain desired properties of conicity, gravitational suspension stiffness and resultant contact stresses [51]. The wheel and rail then enter service and change shape over time. The interaction between wheel and rail resulting in material deterioration is a complicated process, involving vehicle track dynamics, contact mechanics, friction wear and lubrication [21].

The course of events called wear is similarly complicated, involving several modes of material deterioration and contact surface alteration [23]. Two important deterioration mechanisms are wear and rolling contact fatigue (RCF). Frictional heating occurs when train cars reduce speed by using their pads against the running surface of the wheels (i.e., braking). When the wheel surface layer is frictionally heated, and this is followed by the rapid cooling of the body of the wheel itself, there is an increased risk of forming martensite [29]. As martensite is much harder and more brittle than the surrounding material, it can break and initiate cracks. In addition, freight car wheels in service may develop tread irregularities in the form of slid-flats, shells or spalls [47]. Any of these irregularities can cause high wheel impact forces [47, 49], with slid-flats, also called wheel flats, being the most common.

### 2.7.2.1 Wheel Profile Wear

Wear is the loss or displacement of material from a contacting surface [25]. Material loss may be in the form of debris. Material displacement may occur by transfer of material from one surface to another by adhesion or by local plastic deformation. In wheel-rail contact, both rolling and sliding occur in the contact zone.

The nature of the shape change in the wheel is a function of the wear and material flow caused by various contact conditions between the two bodies [51]. These contact conditions depend on track curvature, vehicle alignment, axle load, vehicle speed, vehicle type, traction and braking.

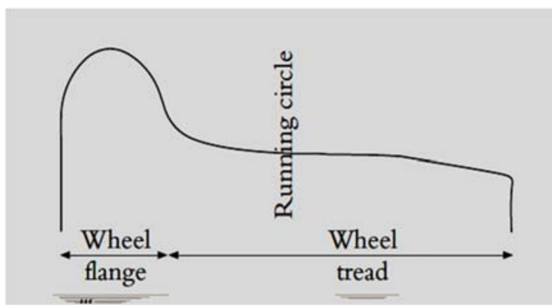



**Figure 2-9 Profile parts explained [51]**

Most techniques to reduce the wheel profile change are based on limiting the wear, or material removal [26]. Wear is not generally a critical failure mode in rolling contact [28].

### 2.7.2.2 Wheel Flats

Wheel flats are formed when a wheel set is locked and skids along the rail [12, 41]. The reason for this may be that the brakes are poorly adjusted, frozen or defective. The friction between wheel and rail causes the surface of the wheel to become flat instead of round [49].

### 2.7.2.3 Rolling Contact Fatigue

Rolling contact fatigue is the principal mode of failure of rolling surfaces and governs the safe life of components under a prescribed load [28]. Wheel damage occurs as fatigue cracks; initiated at or below the surface, result in material fall-out like shelling or spalling [23].

Shelling is a term normally used for all types of subsurface induced cracks (31). Wheel shelling is defined as the loss of relative large (greater than 5 mm) pieces of metal from the wheel tread as the result of contact fatigue [39]. Typically, shelling cracks grow at an acute angle to the surface. Impact load can affect shelling in both crack initiation and crack propagation modes [48].

**Figure 2-10 Wheel shelling defect [39]**

Spalling is the term used for the RCF phenomenon occurring when surface cracks of thermal origin meet, resulting in part of the wheel coming away from the tread [41]. It is associated with cracking induced by high transformation stress caused by surface martensite formation [39]. Cracks from spalling form both perpendicular and parallel to the wheel tread surface.

## 2.8 The APT-WORM (Wheel flat and Out of Roundness Monitoring) System

Apart from regular wheel wear such as decreasing wheel diameters and reduced flange thicknesses and heights, wheel flats (WF) and oval wheels (or OOR, Out-Of-Roundness) are the most common wheel set problems for urban light rail vehicles [10].

Vibration spectra are commonly used for non-destructive testing since they contain comprehensive information about the object under test. The vibration spectra of railway vehicles are not only altered by flats or wheel-out-of-roundness, but also other defects such as broken wheel gummies, wheel shelling, wheel cracks and bearing defects cause variations in the vibration spectra. The main advantages of vibration analysis techniques are the short measurement time of just a few seconds, and the very limited number of sensors to be installed, only one on each rail. As a consequence, the track space required for the installation of the equipment is very limited and thus the associated installation cost is significantly reduced.

**Figure 2.11(a)** shows a wheel gummy as used on PCC tram vehicles, which can break off. **Figure 2.11(b)** illustrates the very limited space requirements of the APT-WORM installation in the street surface.

Figure (a) & (b)

**Figure 2-11 Illustration of installation [10]**

## 2.9 Axle load wheel condition and wheel profile check

A check-up of each passing train by this new axle application will be beneficial for infrastructure manager as well as rolling stock manager. The infrastructure manager will get exact information about the total impact on his infrastructure and the rolling stock manager will get detailed information about the wheel quality of his trains.
The system is also able to measure exact noise emission per wheel due to wheel rail contact.

Axle load monitoring

**Figure 2-12 Laser and Strain gauge sensor [69]**

Two measuring sensors can be supplied, both having their specific qualities. A combination of both sensors is also possible. Just for axle load purposes the low cost strain gauge solution is a good option.

**Axle load monitoring provides the following reports:**

- Date, time, location, direction, train number, speed including acceleration or deceleration, axle count, train length in meters
- Static weight: total train weight, wagon weight and each wheel load
- Train composition, recognition of known locomotive types and wagon types
- Check on compliance of railway line parameters

The system will automatically raise an alarm in case of exceeding preset values for axle load, wagon weight, etc.

Axle load monitoring is self-calibrating and has low maintenance costs.

**Wheel condition monitoring**

This application uses the same sensors as axle load monitoring, depending on customer needs.

**The following wheel defects can be detected**:

- Load shifting within an axle, bogie, vehicle
- Dynamic behavior of vehicles
- Incorrectly adjusted bogies
- Tendency of buffer climbing
- Flats, shelling, built-ups, etc.
- Eccentricity, out-of-roundness
- Polygonalisation
- Wheel roughness

Wheel roughness measurement can detect differences between wheels with cast iron brake blocks and wheels with synthetic brake blocks. This axle application can also measure highly accurately the noise emission caused by wheel to rail contact. This measurement is not disturbed by nearby road traffic etc. The noise level of each single wheel will be presented. The wheel flat detection does not only detect wheel flats but also measures the exact size in mm. In case a wheel has more than one flat, the system also measures the length of the other wheel flats.

Wheel condition monitoring can reduce maintenance costs for rolling stock as well as track infrastructure. It is an important tool to implement condition-based maintenance in your company.

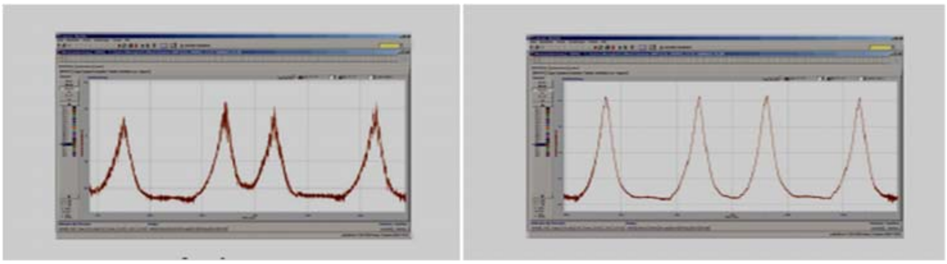


**Figure 2-13 Wheel with synthetic brake blocks and Wheel with cast iron brake [69]**

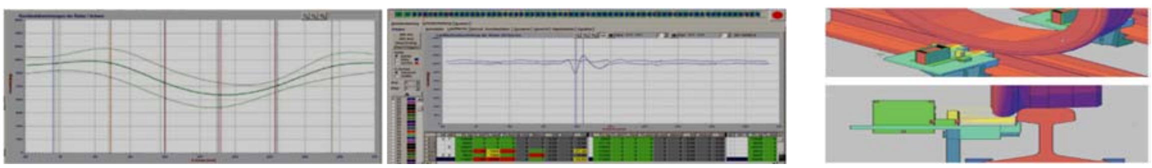


**Figure 2-14 Detected eccentricity and Detected wheel flat [69]**

**Wheel profile monitoring**

Specially developed laser detectors measure each wheel of a passing train and check the following items:

- Wheel set diameter
- Wheel set diameter difference
- Wheel flange height
- Wheel set gauge

Wheel profile monitoring can prevent derailments by detecting wheel profile deviations in an early stage.

## 2.10 Vibration Based Condition Monitoring

Rotating machinery is widely used in today's industry some of which are complex, often with extremely demanding performance criteria. Machine failures can be catastrophic thus resulting in costly downtime. Without effective diagnosis, one is unable to make a reliable prediction of lead-time to failure. Therefore, conducting effective condition monitoring and fault diagnosis is desirable and imperative in industry. However, diagnosing faults in rotating machinery is often a labor-intensive and time-consuming practice. This makes conducting effective and efficient fault diagnosis a challenge for technicians and plant maintainers. Effective feature extraction techniques are very critical for the success of fault diagnosis [1].

After a vibration signal is measured usually, by accelerometers, different signal processing techniques are employed to extract the fault sensitive features to serve as the monitoring indices. The reported signal processing methods are categorized as time domain, frequency domain, and time-frequency domain. These techniques are not totally independent, and in many cases, they are complementary to each other.

Fault diagnosis is conducted typically in the following phases: data acquisition, feature extraction, and fault detection and identification as shown in Figure 2.15.

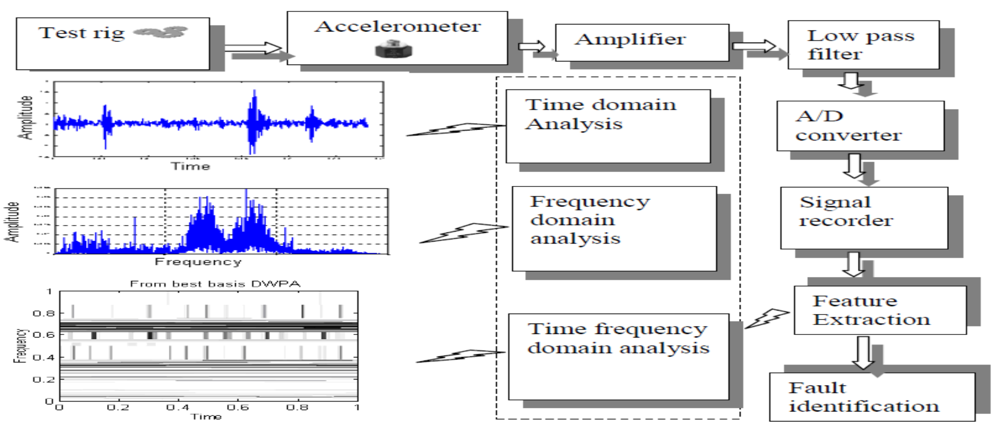



**Figure 2-15 Overview of fault diagnosis based on vibration signals**

The vibration actions are exposed by the acceleration or the amplitude of vibration, frequency, acting time and the direction of vibration (z is vertical direction, y is horizontal direction normal to the track axis and x is horizontal direction parallel to the track axis).


**Figure 2-16 Measuring devices for vibrations [57]**

By analyzing the recording diagrams, the maximal amplitude and frequency of inducted vibrations during train passing are determined. They are of a random character, depending of a wheel state, a train velocity, a vehicle mass, a track state and even the sort of a ground. Especially, objects near the turnouts and the level crossings are of interest for this kind of measuring, because the track is usually in the bad condition there, the sleepers have the significant vertical displacements and the expected vibration level unpleasant for the people is between 0.5 and 2Hz.

The vibration duration is not exceeding 30s for the long freight trains with the low speed.
The maximal amplitudes appeared for the vertical vibrations. The amplitudes of vibrations in horizontal plane, normal to the track are greater than parallel to it [57].

### 2.10.1 Time Domain Analysis

Time domain analysis has been widely employed. Successful results of Root Mean Square (RMS), Kurtosis, skewness, peak value, Crest Factor (CF), and synchronous averaging have been reported in the low frequency range of <5 kHz [2]. Band pass filtering has also been conducted in the time domain; it is based on the fact that the strike between the damage and the rotating component can excite high frequency resonances (10-100 kHz). The generated energy from this impact is not sufficient to excite the entire rotor's assembly, but is enough to excite vibration sensor resonance. Monitoring the vibration amplitude at the resonant band pass filtered frequency is the principle of the shock pulse method. It is implemented in shock pulse meters which are the most accepted diagnostic instrument in the industry. Time domain analysis has the advantage of simple calculations, straightforward signal pre-processing, and speed independency. However, insensitivity to early stage faults and deeply distributed defects are drawbacks of this approach.

**Table 2-1 Overview of time domain vibration feature extraction techniques**

| Time domain | | | |
|---|---|---|---|
| Raw signal | | Filter based method | Stochastic and advanced method |
| Statical parameters | Time synchronous averaged signal (TSA)based method | | |
| Root mean square (RMS),mean, variance, skewness, kurtosis, and crest factor | Time synchronous averaged signal(TSA), residual signal(RES),and difference signal(DIS) | Demodulation, prony model, and adaptive noise cancelling | Chaos, blind deconvulation, thresholding, and auto regressive model based method |

## 2.10.2 Frequency Domain and Time Frequency Domain Feature Extraction Techniques

Features regarding frequency information such as frequency domain features and time frequency domain features are being widely investigated at present. These features can generally indicate machinery faults better than time domain vibration features because characteristic frequency components such as resonance frequency components or defect frequency components can be relatively easily detected and matched to faults.

This section starts from the advent of modern fast Fourier Transform (FFT), then emphasizes various time frequency representations and includes time frequency scale analysis. As shown in Table 2.2, frequency and time frequency analysis techniques are being researched to effectively extract coefficients by increasing the order of frequency or time frequency transformation parameters. The techniques were also applied by calculating correlation or logarithmic value of transformation parameters. For example, the power spectrum as a second order spectrum was applied successfully after the spectrum had been used widely in both linear and logarithmic presentations.

Appropriate vibration techniques need to be selected according to applications to obtain optimal diagnostic performance. An overview of developed frequency techniques and time-frequency techniques is given in Table 2.2, which is followed by some detailed definitions and applications of these techniques.

**Table 2-2 Overview of frequency techniques and time frequency techniques**

| **First order** | **Second order** | **Third order** | **Forth order** |
|---|---|---|---|
| Spectrum (FFT) | Power spectra, power Spectrum,(logarithm of power spectrum) cyco-stationarity | Bi-coherence spectrum | |
| Correlation of spectrum, signal averaging, short time Fourier transform (STFT) | Spectrogram Wigner distribution | Bi-linearity | |
| Continuous wavelet transform(CWLT),Discrete wavelet transform (DWT) | Scalogram | Wigner bi spectra | Wigner tri spectra |
| Discrete wavelet packet analysis(DWPA),time-average wavelet spectrum(TAWS), time-frequency-scale domain(TFS) | | | |

## 2.10.3 Artificial Neural Networks (ANNs)

In many cases, particularly in speed and load variable systems, a simple inspection of the monitoring index does not provide reliable information regarding the condition of the machine. Therefore, there is still a demand for reliable, flexible, and automated procedures for the diagnosis of such systems. Artificial Neural Networks (ANNs) with their flexibility and learning capabilities are the best candidates for a decision making engine of a diagnostic scheme. The input to such a scheme is monitoring indices obtained from signal processing, and the output corresponds to the level of the machine’s health.

Different kinds of ANNs are proposed for machine condition monitoring with time and/or frequency domain features. The multi-layer feed-forward, radial basis function, wavelet neural networks, adaptive resonance theory network, and Adaptive Neuro-Fuzzy Inference System (ANFIS) are among the most referenced networks in machine condition monitoring. Also, other types of intelligent systems such as automated intelligent systems, pattern recognition models, cascade correlation algorithms, automated fuzzy inference, support vector machine, and genetic algorithms have also been employed, to extract the condition of the machine.

# Chapter 3

# Rail-Wheel Profile Condition Monitoring

## 3.1 Wheel Profile Monitoring Systems

These systems extracts data from the actual wheel profile which will be used to compare with measurement from a new wheel profile so as to make key analysis. Most of the available wheel profile measuring systems employs non-contact technique to monitor the wear on the wheel as the train passes. A laser line or high-intensity strobe light illuminates the wheels and the images are captured using high-speed digital cameras. The extraction of the wheel parameters is done using specialized computer software. The problem with such systems is the ability to identify cracks in the plate, rim, and flange and tread region. Some of the current systems that are commercially available for wheel profile measurement include DeltaRail'sTreadview,Image Map'sWheel Spec, Beena Vision's Wheel View and LynxRail'sATEx. The tread view developed by Delta Rail (UK) comprises of a series of lasers and cameras installed on the track. As the train passes by at low-speed (less than 10mph) the images of the wheel are captured then sent to a computer for image analysis. The wheel parameters (flange height and width, tread hollow and rim thickness, for example) are calculated and then stored so as to build each wheel wear history [26].

## 3.2 Data Explanation

This experimental data found from experimentally collected data source that used for master thesis in certain years ago [70], wheel has two conditions, normal (N) and worn-out or fault (F). Every condition acquired 5 groups. Sampling frequency is 10 KHz; sampling points are twenty eight (28). The recommended data collection system for such algorithm is by using continuously sensing equipments such as laser beam, accelerometers and strain gauge sensor.

As follows is idiographic name:

**Table 3-1 Failure of wheel data**

| Sample | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Name | F201 | F202 | F203 | F204 | F205 |

**Table 3-2 Normal wheel data**

| Sample | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Name | **N201** | **N202** | **N203** | **N204** | **N205** |

F--failure (worn-out) wheel, N-- normal wheel 1 to 5 samples

**Method**

First mathematical analysis of important parameters and algorithm of matlab by feeding the above data then visualizing and explanation of graphs and tables resulted from the matlab algorithm.

For example the wheel profile data (including all data points) for the normal and failure (worn-out) wheel is shown in Fig.3.1 and Fig.3.3 respectively.

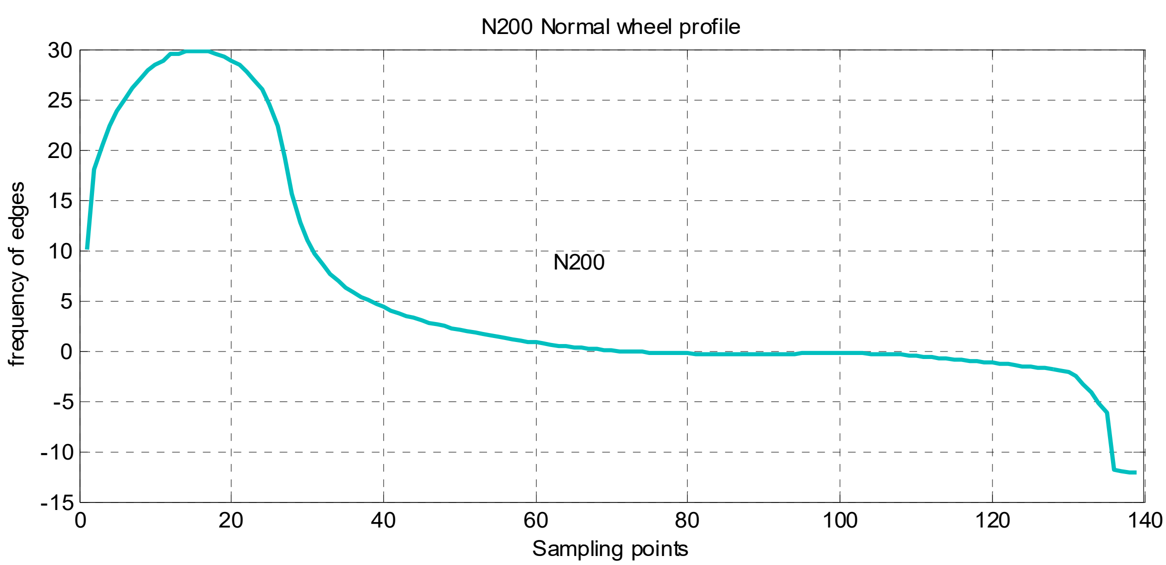
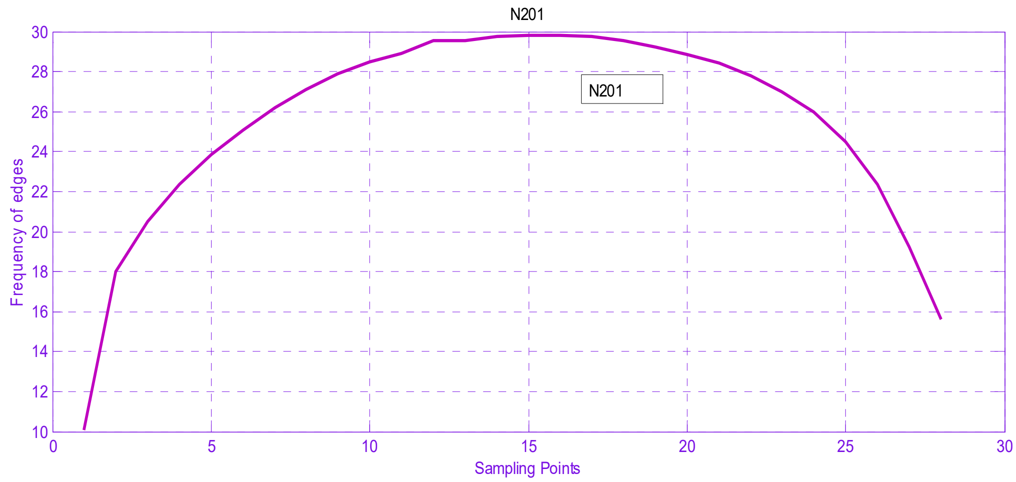
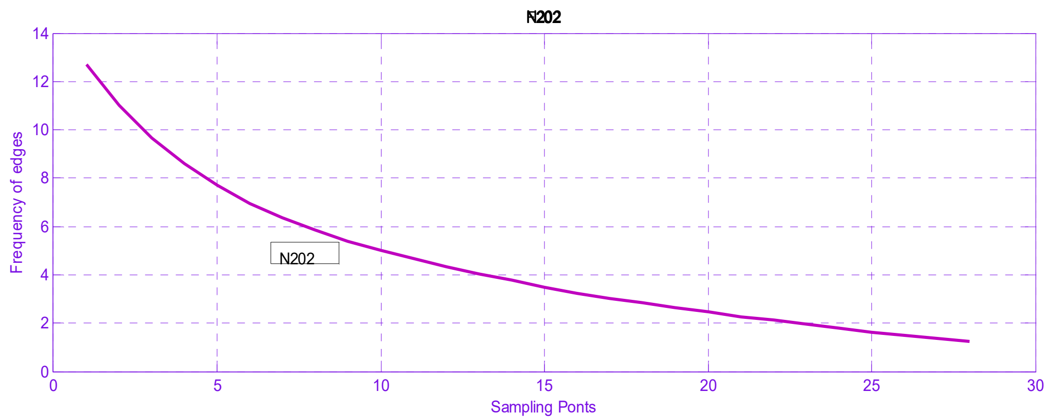
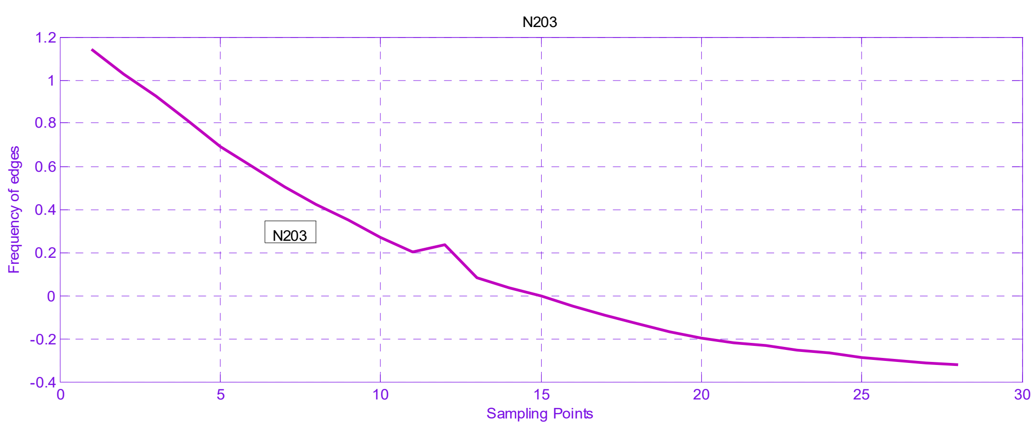
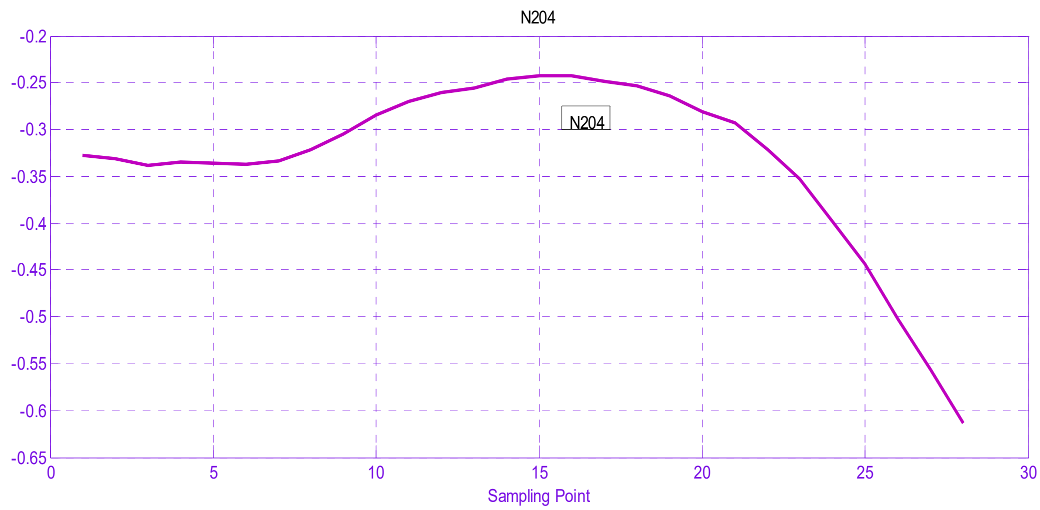



**Figure 3-1 Normal wheel profile**


N201
N201
Frequency of edges
Sampling Points


N202
N202
Frequency of edges
Sampling Ponts


N203
N203
Frequency of edges
Sampling Points



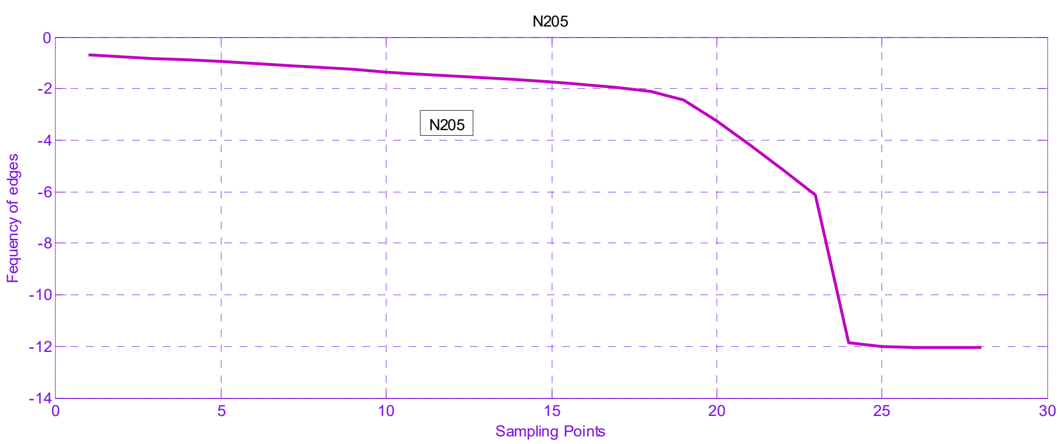




**Figure 3-2 Normal wheel profile signals**

Note that in these plots shown above the sampling points (N200) are divided into five points to make clearer where all the worn out points will occur on the wheel profile at all frequency points. It's shown before dividing the sampling points and looks like smooth curve (N200) so to make it more visible sampling points divided to appropriate amount. From the above graphs N201, N202, N203, N204 and N205 are for data points of 1 to 28, 29 to 56, 57 to 84, 85 to 112 and 113 to 140 respectively for normal condition of wheel profile which means each graph include 28 sample points. As shown in the table 4-5 below, it also helps to identify maximum and minimum values of amplitude of sampling points.

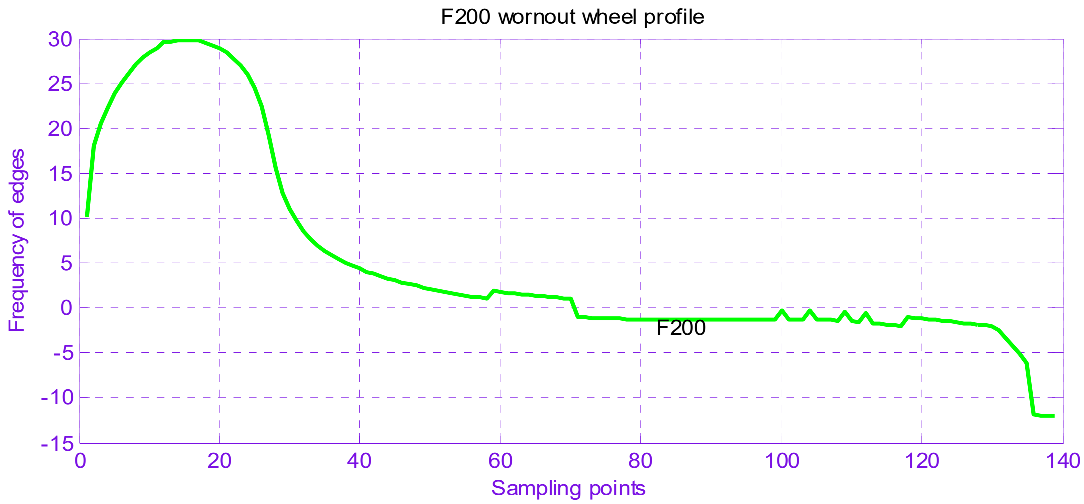
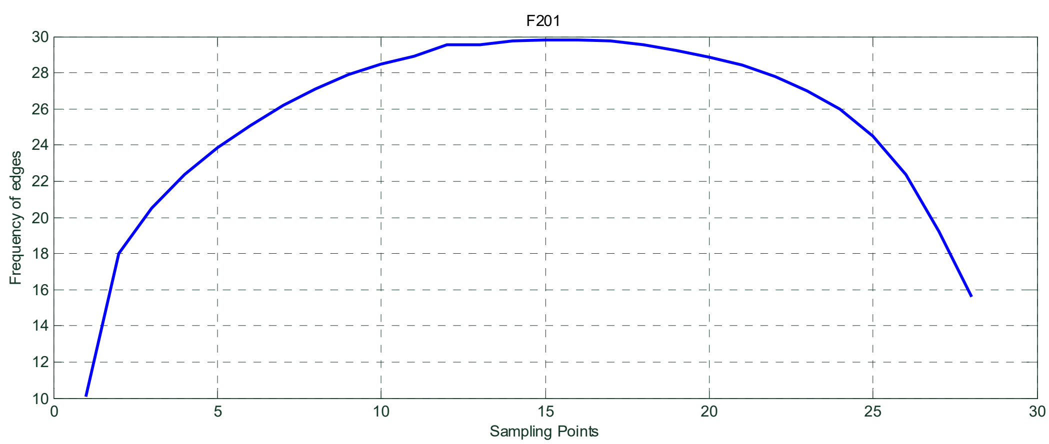
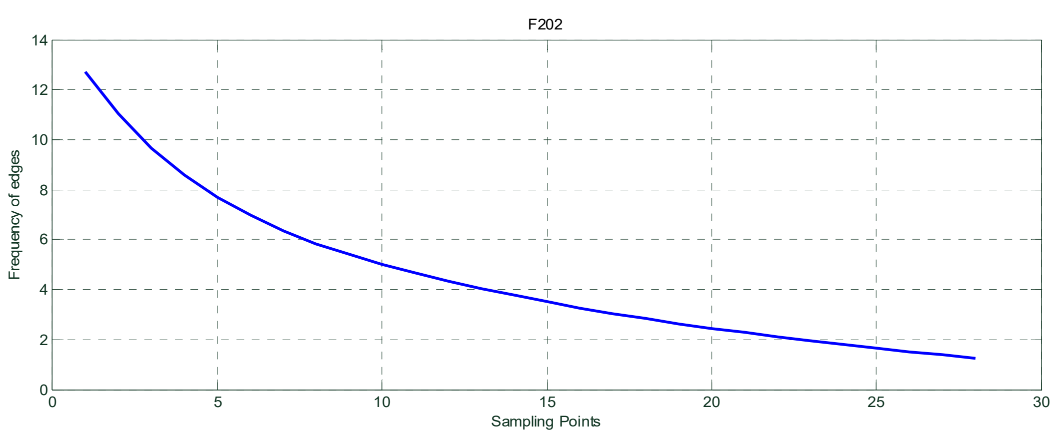



**Figure 3-3 Worn-out wheel profile**



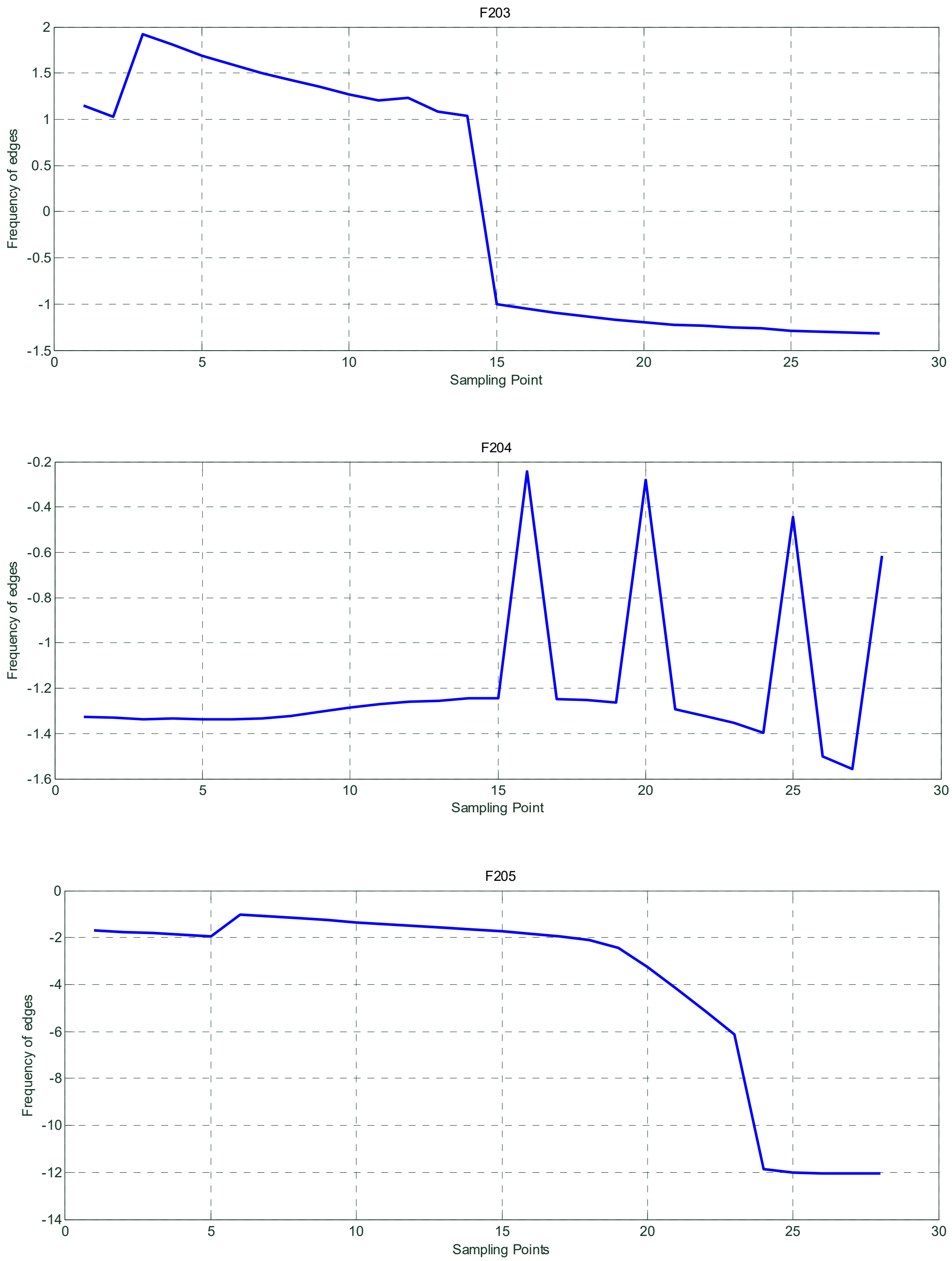



**Figure 3-4 Worn-out wheel profile signals**

Here also as shown in figure 3.3 (F200) above, the worn-out wheel profile curve is smooth especially up to around 59 sampling point then there is some difference from normal-wheel profile so to distinguish worn-out position from normal, sampling points are divided to suitable amount in which each graphs include 28 sample points from 1 to 140 respectively.

F204 curve shows exaggerated picture of worn-out wheel profile from around 60 to 120 sampling points where the damage is great.

## 3.3 Signal Preprocessing

The original signals from data acquisition need to be reformed before any analysis. The arrangement is to improve the reliability of data, and check the randomness of signals, so as to correctly perform the analysis and process, zero-mean processing is selected.

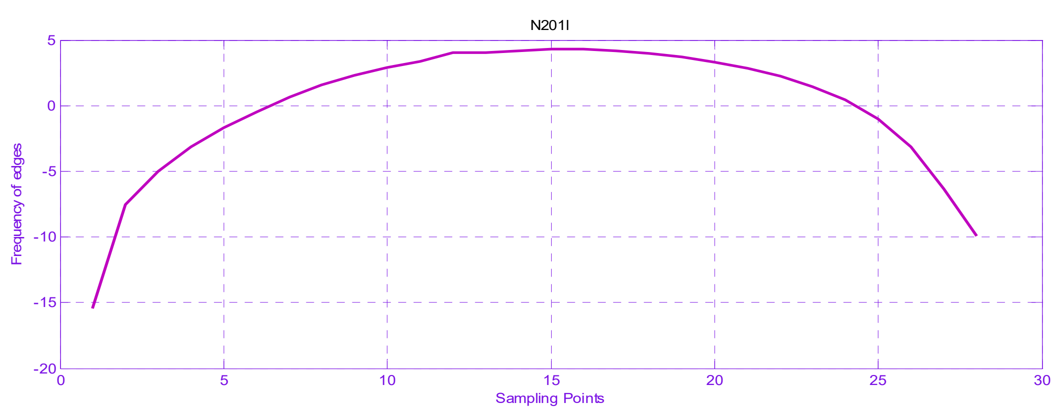
Zero-mean processing is also called centralization processing. The mean value of signal as a DC component, and its Fourier transformation is impulse function at $\omega = 0$ .So when we do processing in spectrum analysis, if the mean is not removed, it will appear a big peak at $\omega = 0$ ,and will affect spectrum curves around $\omega = 0$ which may produce higher error. Therefore the profile data for normal and fault wheel after zero-mean processing is shown in the figure below. Sample data is assumed to be $X_n$ $X_n$ （n=1, 2, …, *N*. Its mean value is calculated by the following formula:

$$\bar{x} = \frac{1}{N}\sum_{n=1}^{N} x_n \quad \text{……Eq 3.1}$$

With the following formula to do zero-mean processing results in

$$u_n = x_n - \bar{x} \quad (n=1, 2, \ldots, N) \text{……Eq 3.2}$$

$x_n$ becomes a new signal $u_n$ with zero mean after processing:



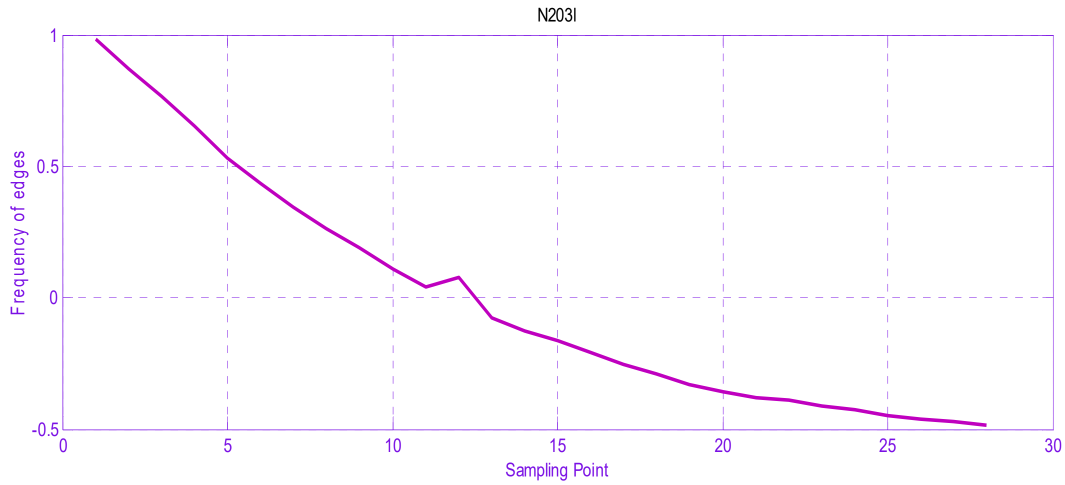



**Figure 3-5 Profile data for normal wheel after zero-mean processing**

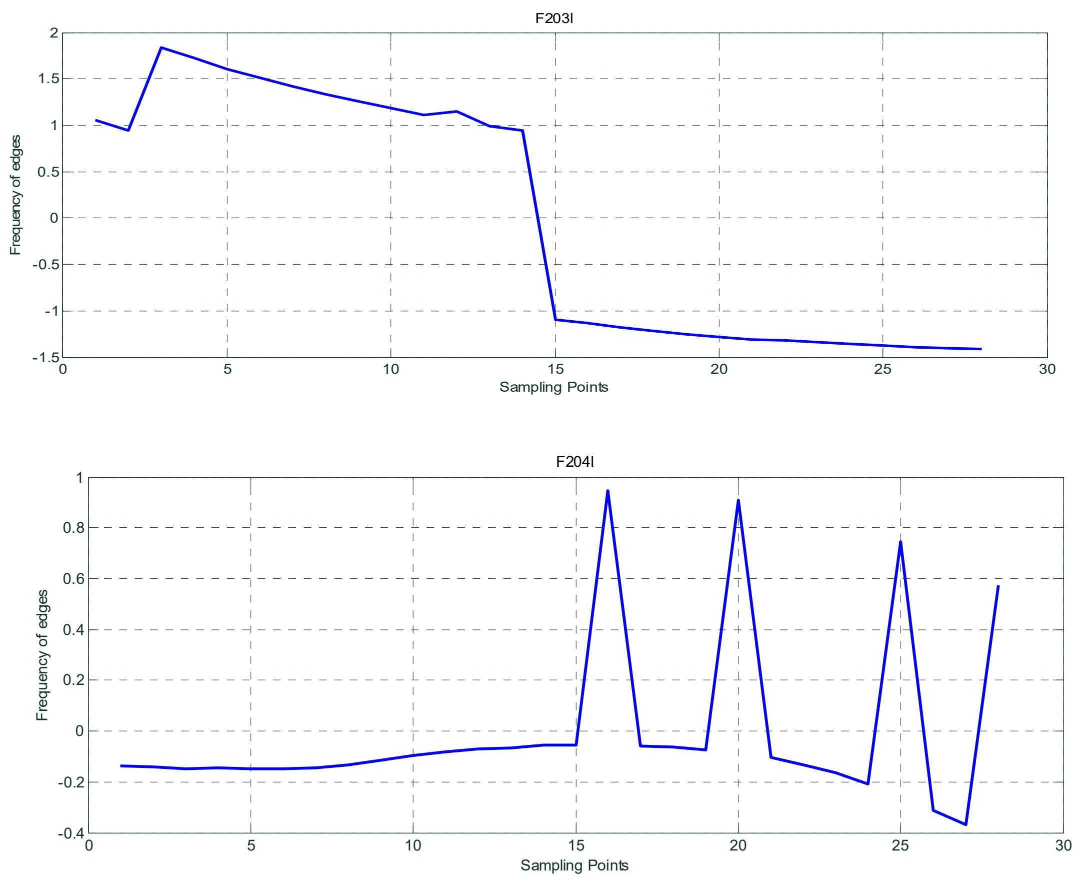



**Figure 3-6 Profile data for failure wheel after zero-mean processing**

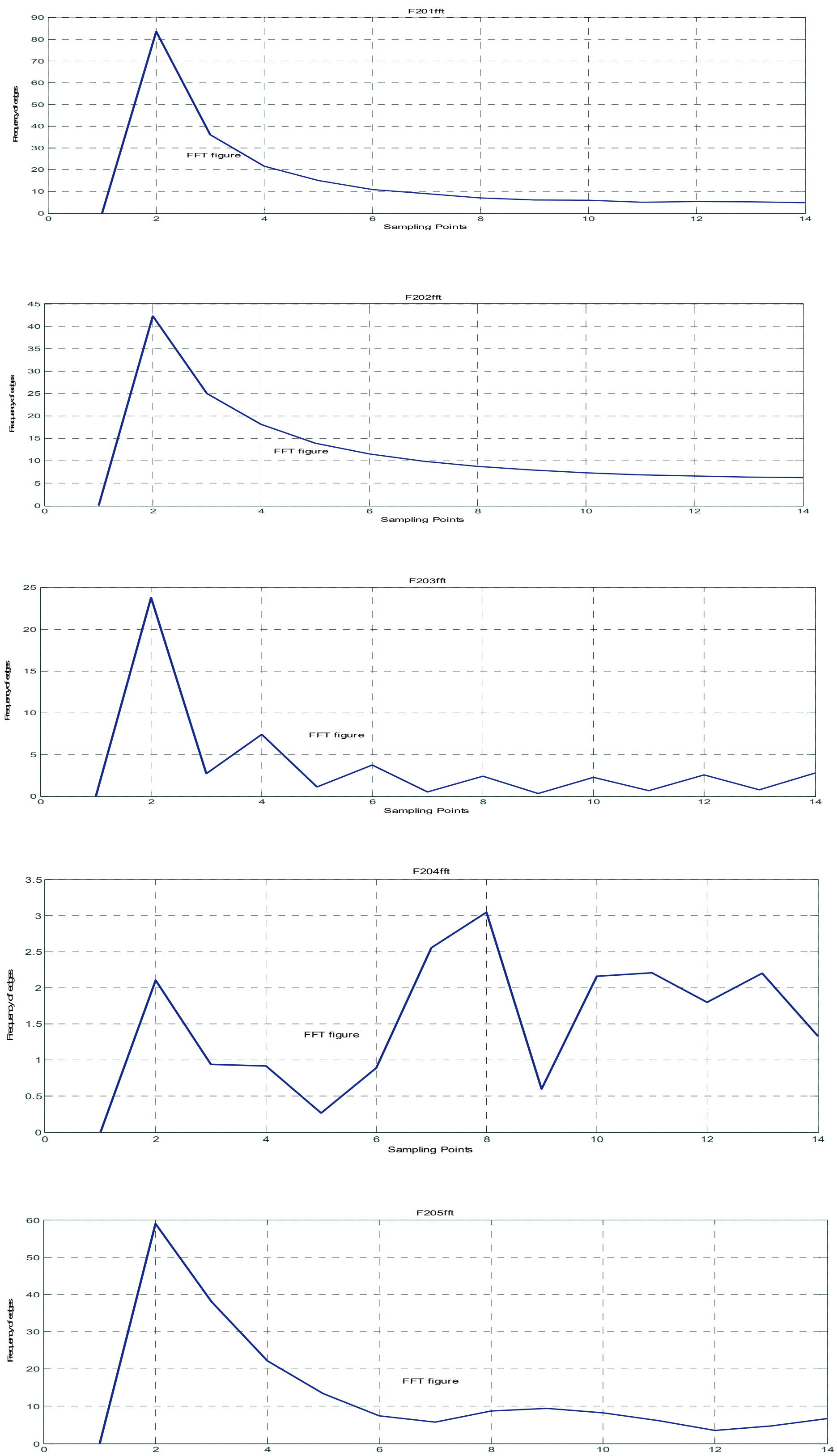



**Figure 3-7 Profile data for failure wheel after Fast Fourier Transformation**

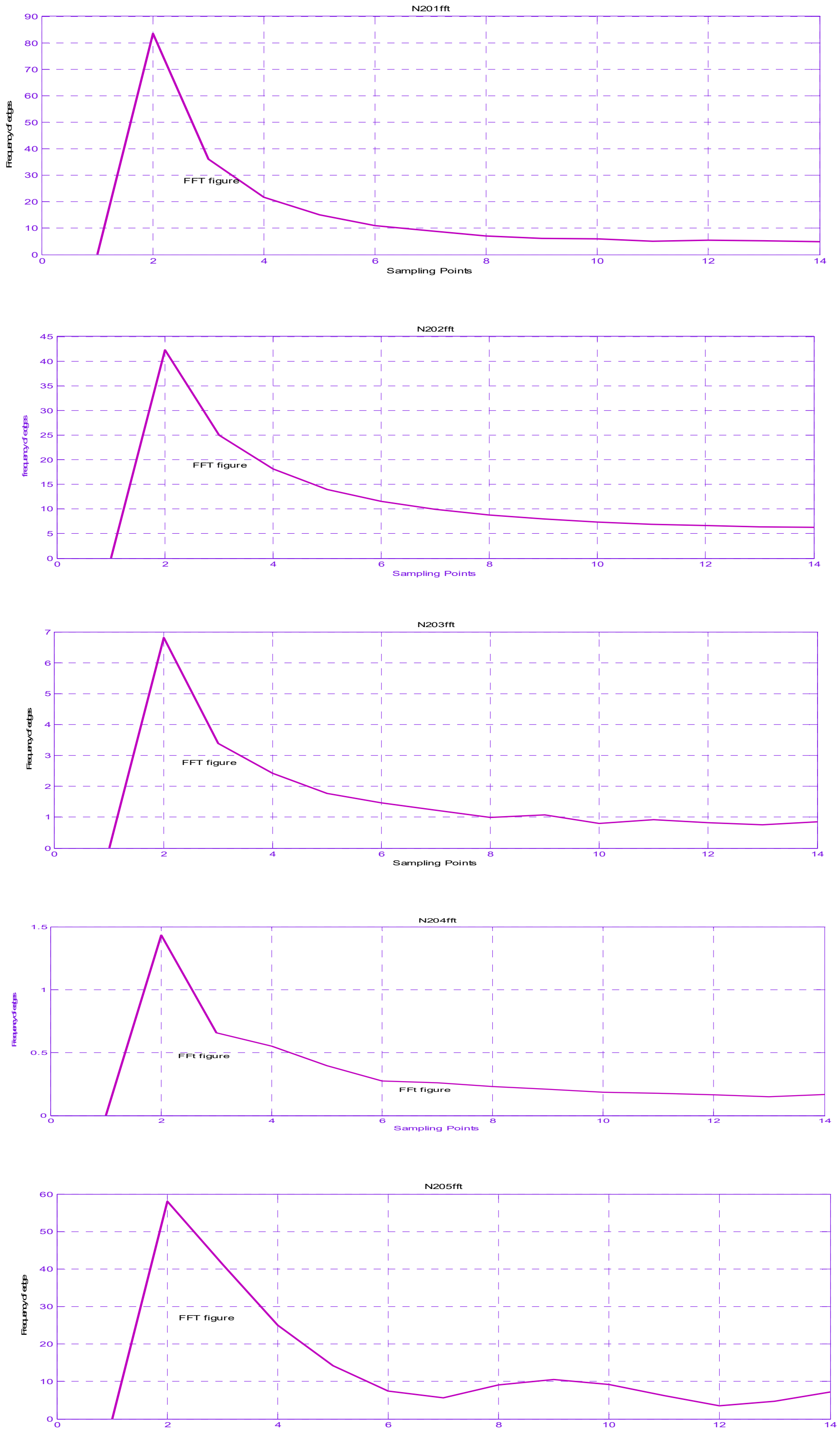



**Figure 3-8  Profile data for normal wheel after Fast Fourier Transformation**

## 3.4 Feature Extraction

From the various diagnostic techniques in the literature, the experiments conducted, here, are limited to time-domain and frequency feature extraction monitoring methods. They include the variance, peak, kurtosis factor, clearance factor, impulse factor, shape factor, and center frequency FC, mean-square frequency MSF, and variance frequency VF. All the diagnostic algorithms are coded in matlab environment, where the syntax used to drive this all feature is shown in the appendix section of this paper. The formulation and implementation of each method is explained in detail in the next chapter.

## 3.5 Fault Diagnosis Method Based on Back propagation (Bp) Neural Network

Neural network could be implemented as computer algorithms that could be used to describe a system in term of relations between input and output. They represent an alternative method of describing systems when it was very difficult or impossible to use analytical approaches. They had been used in a wide variety of applications related to manufacturing. These applications include process control, quality control, industrial inspection, optimization, and modeling.

A neural network in its basic form was composed of several layers of neurons; an input layer, one or more hidden layers and an output layer. Output of each layer becomes the input to the next layer. The first layer was an input layer that distributes the inputs to the hidden layer.

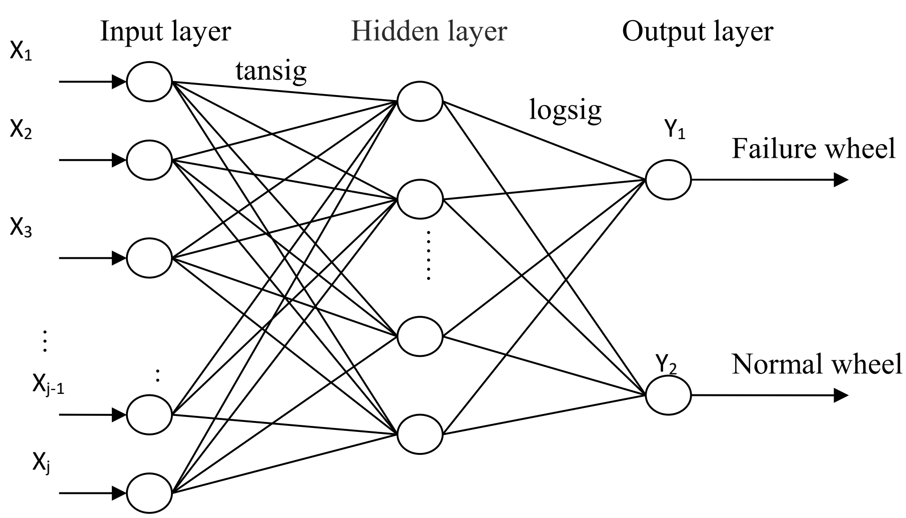



**Figure 3-9 Structure of Bp Neural Network**

There were many kinds of neural network model in different applications. Bp neural network is used in this paper. Bp neural network is a kind of single forward propagation network with structure of multilayer, which is usually composed of input layer, hidden layer and output layer. In the process of information forward propagation, the input information translated from input layer to output layer with weighting computation in hidden layer. The error is defined as the difference of output value computed with action function and expectation of output. If the error isn't equal to an expected value, then the error would be backward propagated. With the modification of weighting coefficients of every layer, the error would be decreased. The calculation process would be repeated until the error becomes less than the expectation error.

# Chapter 4

# Results and Discussion

## 4.1 Feature Extraction

From the various diagnostic techniques in the literature, the experiments conducted, here, are limited to time-domain and frequency feature extraction monitoring methods. They include the variance, peak, kurtosis factor, clearance factor, impulse factor, shape factor, and center frequency FC, mean-square frequency MSF, and variance frequency VF. All the diagnostic algorithms are coded in matlab environment, where the syntax used to drive this all feature is shown in the appendix section of this paper. The formulation and implementation of each method is briefly explained below.

### 4.1.1 Time-domain Features Extraction

Feature selection has a significant impact on the success of pattern recognition. Following time domain statistical parameters are used in this paper to detect incipient wheel damage:

Peak value, $Pv = (1/2)\,[\max(x_i) - \min(x_i)]$……………………………………........Eq 4.1.1.1

where $x_i$, (i = 1, ..., N) is the amplitude at sampling point i and *N* is the number of sampling points.

RMS value, $RMS = \sqrt{\dfrac{1}{N\sum_{i=1}^{N}(X_i)^2}}$ …………………………………………………….Eq 4.1.1.2

Standard deviation, $SD = \sqrt{\dfrac{1}{N}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2}$ ……………………………………………Eq 4.1.1.3

Kurtosis value, $K_v = \dfrac{\frac{1}{N}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^4}{\text{RMS value}}$ …………………………………………….....Eq 4.1.1.4

Crest factor, Crf = Peak value / RMS value ………………………………………...Eq 4.1.1.5

Clearance factor, $\mathrm{Clf} = \dfrac{\text{Peak value}}{\left(\dfrac{1}{N}\sum_{i=1}^{N}\sqrt{|x_i|}\right)^2}$ ……………………………………………Eq 4.1.1.6

Impulse factor, $\mathrm{Imf} = \dfrac{\text{Peak value}}{\dfrac{1}{N}\sum_{i=1}^{N}|x_i|}$ ………………………………………………...Eq 4.1.1.7

Shape factor, $\mathrm{Shf} = \dfrac{\text{RMS value}}{\dfrac{1}{N}\sum_{i=1}^{N}|x_i|}$ ………………………………………………….Eq 4.1.1.8

Finally, the time-domain features are extracted from the raw profile data for wheel fault diagnosis. The extracted features values are show in Table 4.1

**Table 4-1 Time-domain parameters from wheel profile signal**

| Condition | Sample | Time-Domain frequency | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean value | Variance | RMS | Peak | Kurtosis factor | Crest factor | Clearance factor | Impulse factor | Shape factor |
| **Normal** | N201 | 4.6947e-15 | 24.0075 | 4.8997 | 9.8635 | 2.0131 | 4.6488 | 1.2749 | 2.5665 | 2.9391 |
| | N202 | -4.1237e-16 | 9.0597 | 3.0099 | 5.7280 | 1.9030 | 3.4184 | 1.2486 | 2.3762 | 2.7491 |
| | N203 | 2.3790e-17 | 0.1945 | 0.4410 | 0.7330 | 1.6622 | 2.3666 | 1.1712 | 1.9468 | 2.1577 |
| | N204 | 3.1721e-17 | 0.0085 | 0.0924 | 0.1816 | 2.0133 | 5.0185 | 1.4471 | 2.9135 | 3.9479 |
| | N205 | 6.3441e-16 | 16.3654 | 4.0454 | 5.6760 | 1.4031 | 3.1793 | 1.2470 | 1.7496 | 1.9731 |
| **Worn-out** | F201 | 4.6947e-15 | 24.0075 | 4.8997 | 9.8635 | 2.0131 | 4.6488 | 1.2749 | 2.5665 | 2.9391 |
| | F202 | -4.1237e-16 | 9.0597 | 3.0099 | 5.7280 | 1.9030 | 3.4184 | 1.2486 | 2.3762 | 2.7491 |
| | F203 | -3.1721e-17 | 1.7099 | 1.3076 | 1.6235 | 1.2416 | 1.1108 | 1.0131 | 1.2578 | 1.2659 |
| | F204 | -4.6788e-17 | 0.1130 | 0.3361 | 0.6570 | 1.9548 | 5.4247 | 1.4814 | 2.8958 | 3.5815 |
| | F205 | -2.5377e-16 | 15.4665 | 3.9327 | 5.4970 | 1.3978 | 3.2474 | 1.2516 | 1.7495 | 1.9755 |

## 4.1.2 Frequency-domain Feature Extraction

Of all frequency-domain features, in this problem only the major parameters are used: center frequency FC, mean-square frequency MSF, and variance frequency VF. Each value is formulated and implemented as briefly explained below:

Centre Frequency $$FC = \frac{\sum_{i=1}^{N} f_i p_i}{\sum_{i=1}^{N} p_i}$$ ……………………………………..Eq 4.1.2.1

The variance frequency $$VF = \frac{\sum_{i=1}^{N} (f_i - fc)^2 p_i}{\sum_{i=1}^{N} p_i}$$ ……………………………..…Eq 4.1.2.2

Mean-square frequency $$MSF = \frac{\sum_{i=1}^{N} f_i^2 p_i}{\sum_{i=1}^{N} p_i}$$ ……………………………………...Eq 4.1.2.3

Where, $f_i$ is the frequency value responding to power spectrum at time i. $p_i$ is the amplitude of power spectrum at time i.

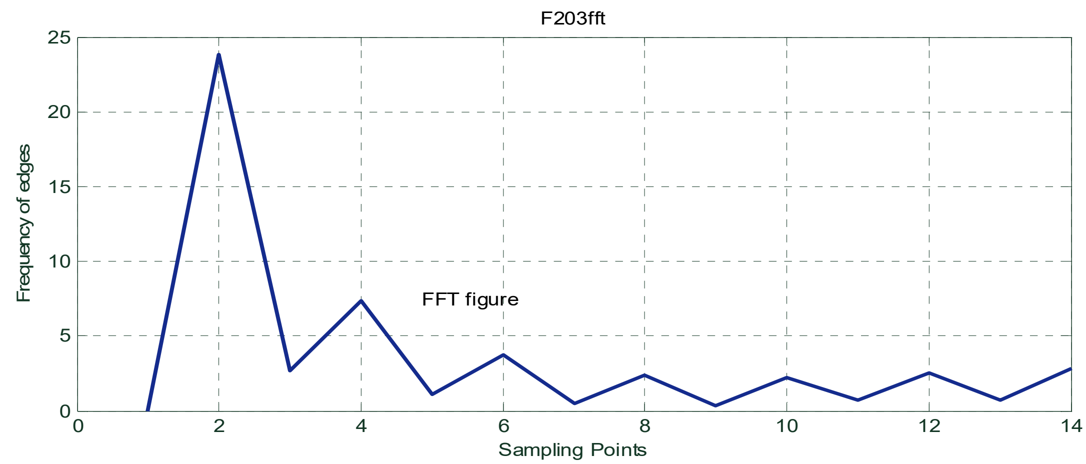
The extracted frequency-domain features values are shown in Table 4.2 for the normal and fault wheel data and the matlab algorithm is at appendix.

**Table 4-2 Frequency-domain parameter from wheel profile signal**

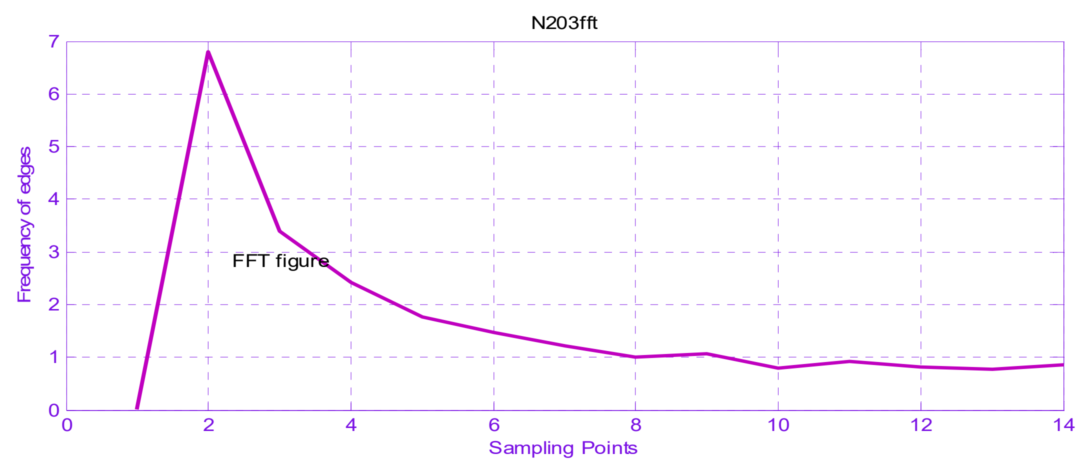
| **Condition** | **Sample** | **Frequency-domain parameter features** | | |
|---|---|---|---|---|
| | | Center frequency | Variance frequency | Mean-square frequency |
| **Normal** | N201 | 421380 | -33.1217 | 420280 |
| | N202 | 90379 | -146.0952 | 69035 |
| | N203 | 60327 | -88.6479 | 52469 |
| | N204 | 186730 | 323.5379 | 82053 |
| | N205 | 200830 | 165.8542 | 173320 |
| **Worn-out** | F201 | 421380 | -33.1217 | 420280 |
| | F202 | 90379 | -146.0952 | 69035 |
| | F203 | 268850 | 99.0101 | 259050 |
| | F204 | 5554300 | 1823.3 | 2229900 |
| | F205 | 217480 | 179.7070 | 185190 |

### 4.1.3 Fast Fourier Transformation

The raw wheel profile data is transformed into frequency (spectral) domain using fast Fourier transformation (FFT), and a matlab algorithm is used for both normal and fault wheel conditions. And these diagrams are shown below in fig. 4.1

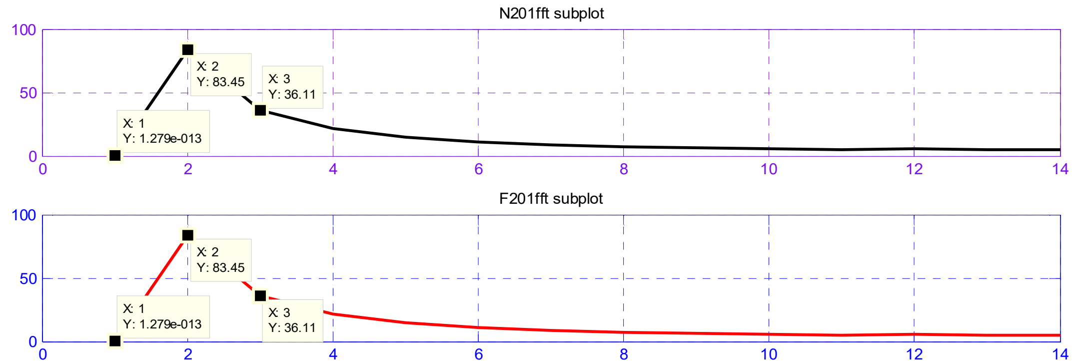


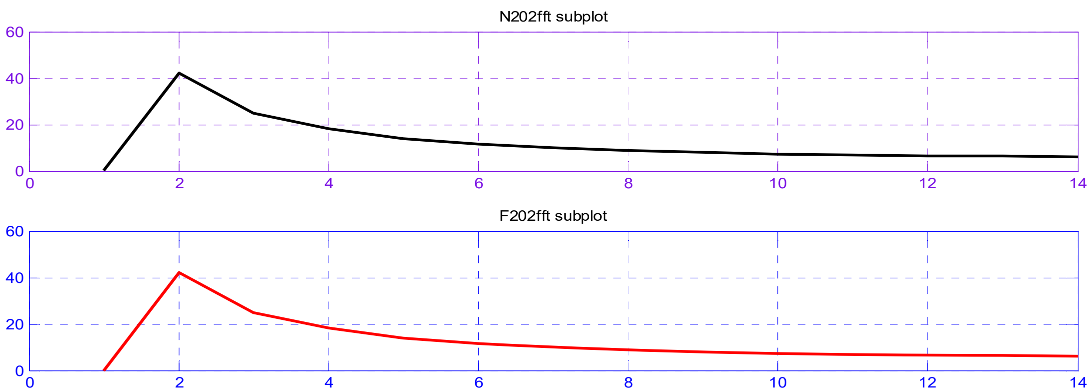

Exaggerated worn-out condition diagram

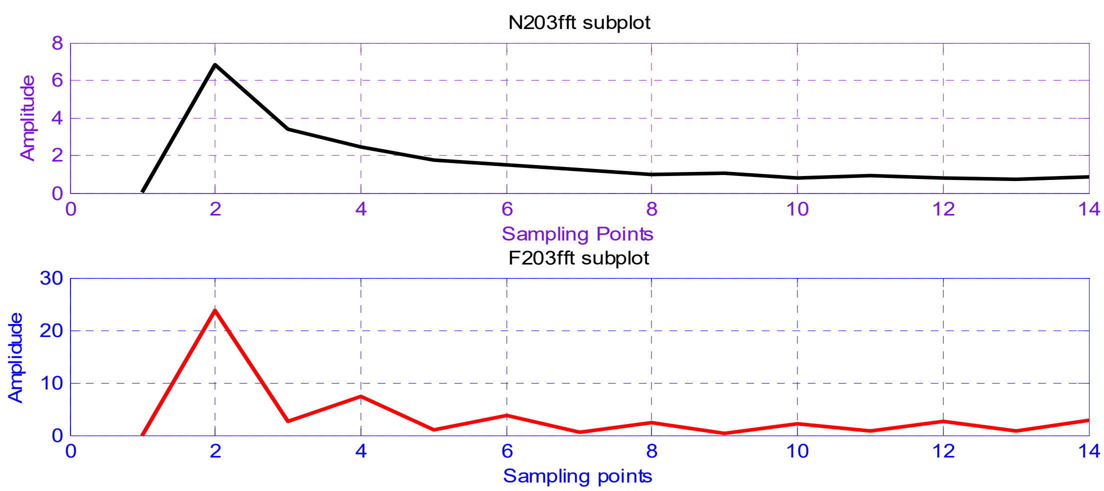



Normal condition diagram

**Figure 4-1 Sample FFT diagram of worn-out and normal condition of wheel**


N201fft subplot
X: 1
Y: 1.279e-013
X: 2
Y: 83.45
X: 3
Y: 36.11
F201fft subplot
X: 1
Y: 1.279e-013
X: 2
Y: 83.45
X: 3
Y: 36.11


N202fft subplot
F202fft subplot


N203fft subplot
Amplitude
Sampling Points
F203fft subplot
Amplitude
Sampling points

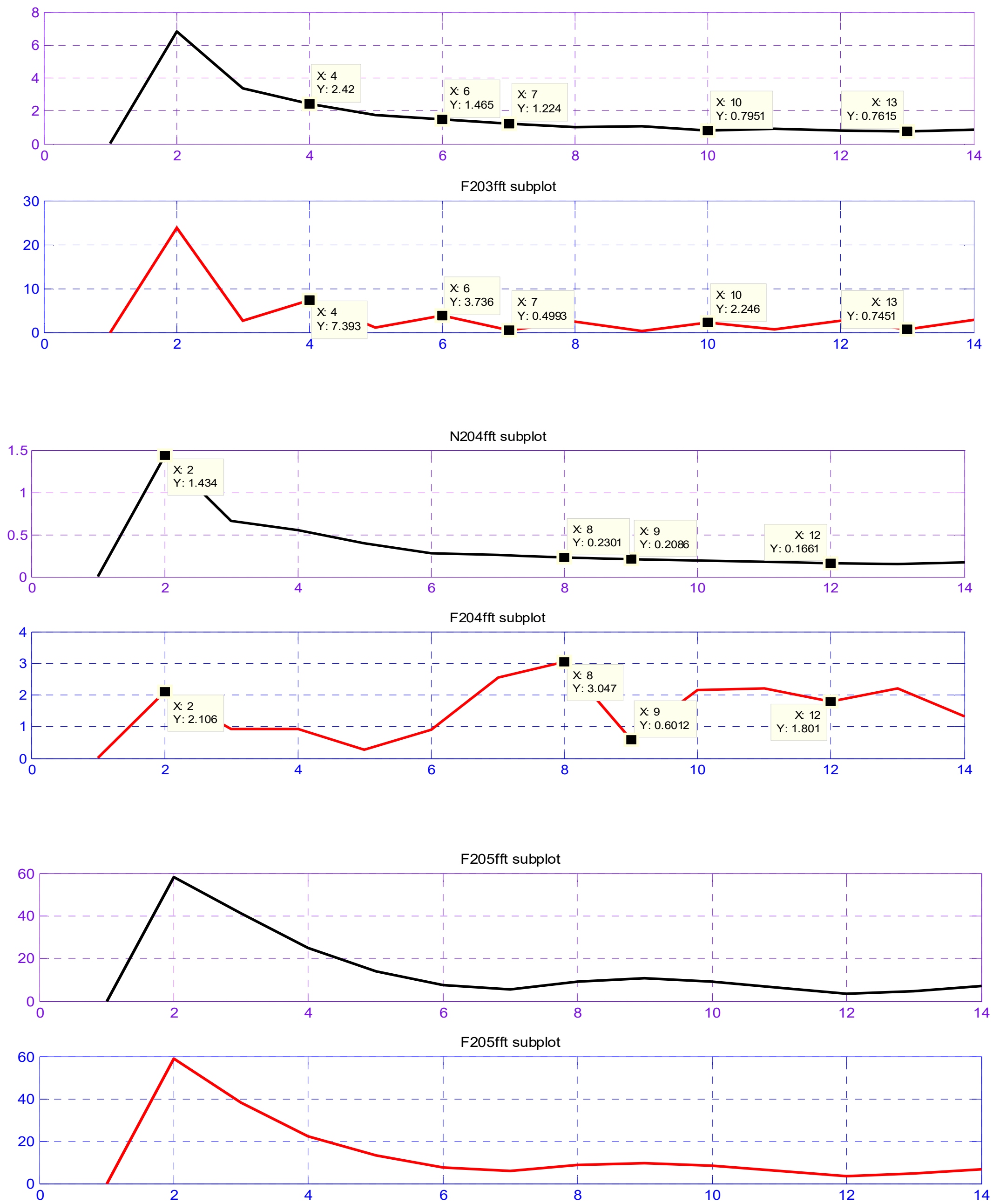



**Figure 4-2 FFT subplot diagram for both conditions of wheel**

By having a very close and careful look in the above FFT figure for faulty and normal wheels' profile data, it can be noticed that we can still extract features to diagnosis the wheels. Therefore two peak points and three areas are taken after visual inspection which is quiet depends on our skill (maximum difference in peak value). The extracted features are observed below and tabulated as follows.

**Table 4-3 FFT parameters from wheel profile signal**

| **Condition** | **Sample** | **FFT features** | | | | |
|---|---|---|---|---|---|---|
| | | (4,1) | (5:6,1) | (8,1) | (9:10,1) | (12:13,1) |
| Normal | N201 | 21.6641 | 26.0040 | 7.0108 | 12.2307 | 10.6777 |
| | N202 | 18.0897 | 25.4781 | 8.7560 | 15.2797 | 12.9958 |
| | N203 | 2.4204 | 3.2272 | 0.9969 | 1.8652 | 1.5816 |
| | N204 | 0.5507 | 0.6716 | 0.2301 | 0.3949 | 0.3172 |
| | N205 | 24.9816 | 21.5482 | 9.0453 | 19.7381 | 8.1684 |
| Worn-out | F201 | 21.6641 | 26.0040 | 7.0108 | 12.2307 | 10.6777 |
| | F202 | 18.0897 | 25.4781 | 8.7560 | 15.2797 | 12.9958 |
| | F203 | 7.3932 | 4.8432 | 2.4083 | 2.5689 | 3.3037 |
| | F204 | 0.9190 | 1.1559 | 3.0471 | 2.7623 | 3.9987 |
| | F205 | 22.1575 | 20.8506 | 8.7564 | 17.6535 | 8.1967 |

## 4.1.4 Feature Normalization

As shown in the above three tables (Table 4.1 to 4.3) the values of different features varies very extremely. Hence, during training of the neural network, higher valued input variables may tend to suppress the influence of the smaller one. To overcome this problem and in order to make neural networks perform well, the data must be well processed and properly scaled before inputting to the ANN. The Colum data are normalized in the range 0 to 1 to minimize the effect of input variable. All the component of feature vector is normalized using the following equation:

$$X = \left( \frac{x - \min(x)}{\max(x) - \min(x)} \right) \qquad \text{Eq 4.1.4.1}$$

Where, $X$ is normalized data, x actual data, min(x) & max (x) minimum and maximum in the respective data set. Therefore the normalized data for all the seventeen features are shown in one table as follow:

**Table 4-4 Normalized features parameters for normal wheel**

| | Normal wheel profile N201 to N205 | | | | |
|---|---|---|---|---|---|
| **Time-domain frequency** | 1 | 0 | 0.0854 | 0.0870 | 0.2050 |
| | 1 | 0.3771 | 0.0078 | 0 | 0.6816 |
| | 1 | 0.6067 | 0.0725 | 0 | 0.8223 |
| | 1 | 0.5729 | 0.0570 | 0 | 0.5675 |
| | 0.9997 | 0.8559 | 0.5412 | 1 | 0.2031 |
| | 0.8201 | 0.5349 | 0.2911 | 0.9058 | 0.4795 |
| | 0.5590 | 0.5029 | 0.3376 | 0.9268 | 0.4995 |
| | 0.7904 | 0.6755 | 0.4161 | 1 | 0.2970 |
| | 0.6239 | 0.5530 | 0.3325 | 1 | 0.2637 |
| **Frequency domain parameters** | 0.0657 | 0.0055 | 0 | 0.0230 | 0.0256 |
| | 0.0574 | 0 | 0.0292 | 0.2385 | 0.1584 |
| | 0.1689 | 0.0076 | 0 | 0.0136 | 0.0555 |
| **FFT parameters** | 0.8642 | 0.7179 | 0.0765 | 0 | 1 |
| | 1 | 0.9792 | 0.1009 | 0 | 0.8241 |
| | 0.7692 | 0.9672 | 0.0870 | 0 | 1 |
| | 0.6119 | 0.7695 | 0.0760 | 0 | 1 |
| | 0.8015 | 1 | 0.0226 | 0 | 0.5866 |

**Table 4-5 Normalized features parameters for worn-out wheel**

| | Worn-out wheel profile F201 to F205 | | | | |
|---|---|---|---|---|---|
| **Time-domain features** | 1 | 0 | 0.0745 | 0.0716 | 0.0311 |
| | 1 | 0.3771 | 0.0709 | 0.0044 | 0.6441 |
| | 1 | 0.6069 | 0.2528 | 0.0507 | 0.7988 |
| | 1 | 0.5729 | 0.1489 | 0.0491 | 0.5490 |
| | 0.9997 | 0.8559 | 0 | 0.9229 | 0.1962 |
| | 0.8201 | 0.5349 | 0 | 1 | 0.4953 |
| | 0.5590 | 0.5029 | 0 | 1 | 0.5093 |
| | 0.7904 | 0.6757 | 0 | 0.9893 | 0.2970 |
| | 0.6239 | 0.5530 | 0 | 0.8634 | 0.2646 |
| **Frequency-domain parameters** | 0.0657 | 0.0055 | 0.0380 | 1 | 0.0286 |
| | 0.0574 | 0 | 0.1245 | 1 | 0.1654 |
| | 0.1689 | 0.0076 | 0.0949 | 1 | 0.0610 |
| **FFT features** | 0.8642 | 0.7179 | 0.2801 | 0.0151 | 0.8844 |
| | 1 | 0.9792 | 0.1647 | 0.0191 | 0.7966 |
| | 0.7692 | 0.9672 | 0.2471 | 0.3196 | 0.9672 |
| | 0.6119 | 0.7695 | 0.1124 | 0.1224 | 0.8922 |
| | 0.8015 | 1 | 0.1701 | 0.2296 | 0.5891 |

## 4.2 Fault Diagnosis Method Based on Back propagation (Bp) Neural Network

Neural network could be implemented as computer algorithms that could be used to describe a system in term of relations between input and output. They represent an alternative method of describing systems when it was very difficult or impossible to use analytical approaches. They had been used in a wide variety of applications related to manufacturing. These applications include process control, quality control, industrial inspection, optimization, and modeling.

A neural network in its basic form was composed of several layers of neurons; an input layer, one or more hidden layers and an output layer. Output of each layer becomes the input to the next layer. The first layer was an input layer that distributes the inputs to the hidden layer.

There were many kinds of neural network model in different applications. BP neural network is used in this paper. BP neural network is a kind of single forward propagation network with structure of multilayer, which is usually composed of input layer, hidden layer and output layer. In the process of information forward propagation, the input information translated from input layer to output layer with weighting computation in hidden layer. The error is defined as the difference of output value computed with action function and expectation of output. If the error isn't equal to tolerable value, then the error would be backward propagated. With the modification of weighting coefficients of every layer, the error would be decreased. The calculation process would be repeated until the error becomes less than the expectation error.

The output value $y_i$ of unit i is defined as follows

$$y_i = f\left(\sum_{j=1}^{n} w_{ij} x_j + \theta_i\right) \qquad \text{…Eq 4.2.1}$$

Where $w_{ij}$ is the connection weight of node j of upper layer and node $i$ of the current layer.

$x_j$ is the output value of node $j$ of the upper layer.

$\theta_i$ is the threshold value of node $i$

$n$ is the number of upper layer node

$f$ is the action function. In this paper, the action function f(x) defined as follows

$$f(x) = \frac{1}{1+e^{-x}} \qquad \text{…Eq 4.2.2}$$

Suppose the output value of node $i$ of sample p in the process of training is $y_{pi}$, expectation output would be $d_{pi}$, then the error was defined as follows

$$E_p = \frac{1}{2}\sum_{i=1}^{n}\left(d_{pi} - y_{pi}\right)^2 \qquad \text{…Eq 4.2.3}$$

With self-learning the weighting value of $w_{i\,j}$ would be modified. The learning goal was to make $E_p$<**ε** (**ε** is preset network accuracy).

Gradient descending method is used to modify the weight $w_{ij}$.

$$\Delta w_{ij} = -\alpha\left[\frac{\partial E_p}{\partial w_{ij}}\right] \qquad \text{Eq 4.2.4}$$

Where $\alpha$ is the learning rate.

With mathematic transformation equation 4.2.4 is rewritten as follows,

$$\Delta w_{ij} = \alpha \delta_i x_j \qquad \text{Eq 4.2.5}$$

If node $i$ is output node, then

$$\delta_i = y_i(1 - y_i)(d_i - y_i) \qquad \text{Eq 4.2.6}$$

In equation (4.2.6), $y_i$ is output value of node $i$;$d_i$ is expectation of node $i$

If node $i$ is hidden node, then

$$\delta_i = x_i(1 - x_i)\sum_{j=1}^{n}\delta_j w_{ij} \qquad \text{Eq 4.2.7}$$

In equation 4.2.7, $n$ is the number of node that is located in the upper layer of node $i$, $x_i$ is the output of node $i$ of hidden layer.

### 4.2.1 Design of Input and Output Layers

During wheel condition monitoring, the samples come from experiment with extracted features. So the number of input neuron is 14. It is extracted to make the job easy but we can take as it is. The network output is wheel condition which is divided into failure wheel and normal wheel, with（0 1）expressing failure wheel and（1 1）expressing normal wheel. Therefore the network is design only for two output neurons expressing the two conditions. This BP network has 14 neurons at input layer and 2 neurons at output.

` 
### 4.2.2 Selection of Hidden Layer

Hidden layer's number is defined by the below formula:

$n_2 = 2n_1 + 1$,………………………….……………………………..……….Eq 4.2.2.1

Where, $\mathbf{n_1}$ is the number of the first layer, and

$\mathbf{n_2}$ is the number of Hidden layer.

So in this article with the wheel conditions recognition, because input layer has 14 neurons and output layer has 2 neurons, hidden layer has about 29 neurons from the formula. Then we design a Bp neural network which the hidden layer can be changed optionally, and determine the hidden layer's number by error comparison. The hidden layer's neurons are compared within 25 to 32.

There are 10 samples we have selected. We can choose 6 samples for training ("tr").

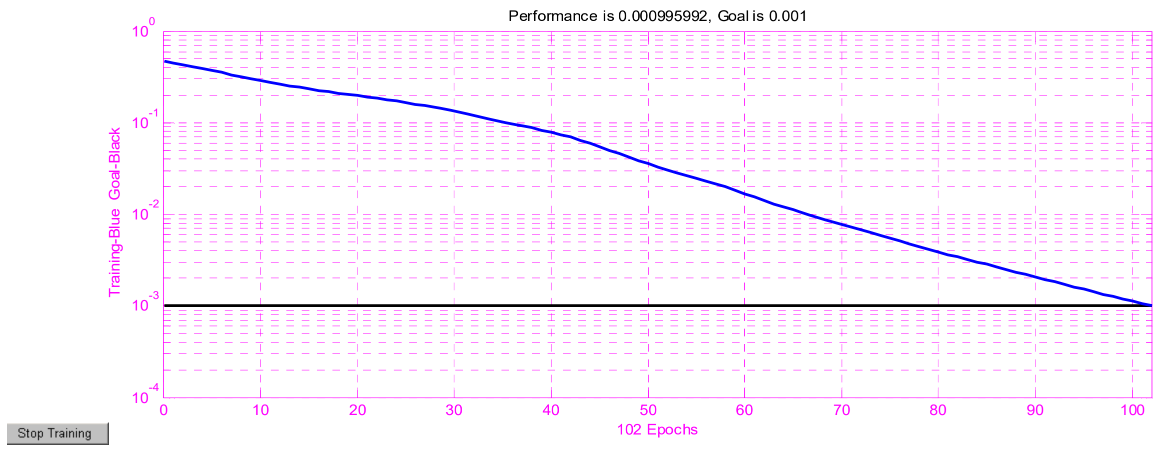



**Figure 4-3 Training curve for selected samples**

TRAINGDX, Epoch 0/1000, MSE 0.475174/0.001, Gradient 0.460348/1e-006

TRAINGDX, Epoch 25/1000, MSE 0.166251/0.001, Gradient 0.164284/1e-006

TRAINGDX, Epoch 50/1000, MSE 0.0354881/0.001, Gradient 0.0500373/1e-006

TRAINGDX, Epoch 75/1000, MSE 0.00544079/0.001, Gradient 0.00953997/1e-006

TRAINGDX, Epoch 100/1000, MSE 0.00112251/0.001, Gradient 0.00219927/1e-006

TRAINGDX, Epoch 102/1000, MSE 0.000995992/0.001, Gradient 0.00196834/1e-006

TRAINGDX, Performance goal met.

From the above command it can be seen that the transfer-function of hidden layer neuron is "tansig", and the transfer-function of output layer neuron is "logsig". The goal error is set to be 0.001. Since we can't avoid error we assume an affordable amount of error. So in our case, it set to be acceptable with an error of less than this.

The content of Bp learning algorithm is to change the output of training sample and expectation of output into an optimum non-linear function. Gradient descending method is used to calculate the weighting coefficients of nodes, which showed the map relationship of input vectors and output vectors with weighting coefficients. Fourteen features are used as input vectors of Bp neural network. So the neuron number of input layer is $n_1 = 14$. Considering the diagnosis conclusion, whether there was fault in rail-wheel, the neuron number of output layer is defined as 2, which meant good status or fault status of the rail-wheel.

The neuron number of hidden layer has great influence on the performance of the neural network. With simulation research, the neuron number of hidden layer is set as $n_2 = 25$. So the structure of the Bp neural network is defined as N (14, 25, 2).When the structure of neural network is defined, classic sample are needed to train the neural network. The following two principles are used to choose sample. (1) Integrity, which meant the status of sample should include normal status and fault status. (2) Number of the sample should be big enough.

From res (i) we get the table as follow:

**Table 4-6 Status of sample**

| Hidden layer's number | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 |
|---|---|---|---|---|---|---|---|---|
| error | 0.1039 | 0.1061 | 0.1023 | 0.1041 | 0.1068 | 0.1085 | 0.1043 | 0.1043 |

From the above table it can be seen that it's 27 neurons in hidden layer of Bp network which has a good effect of approximation for function after 1000 times of training (The training function is "traingdx"). Because it's error is the minimum. We define the hidden layer's number as 27.

## Testing Network

The testing program of neural network is as follow:

y=sim(net,testing data);

Expecting result is:

| | | |
|---|---|---|
| 0 | 1 | Worn-out wheel |
| 1 | 1 | Normal wheel |

Testing result is:

| | | | |
|---|---|---|---|
| 0.0427 | 0.048 | 0.9919 | 0.9931 |
| 0.9968 | 0.9959 | 0.9776 | 0.9549 |

From the above testing it can be seen that the classification of data is exactly correct, that is, the network established above for recognition system of wheel conditions is right. So when making pattern recognition, we put measured data into this network and then according to its output result correctly recognize the rail-wheel's conditions.

# Chapter 5

# Conclusion and Recommendation

## 5.1 Conclusions

Profile monitoring feature extraction techniques are improving all the time given advances in disciplines such as statistics, signal processing, and computing science. Time domain techniques include raw signals, filter based signals, stochastic and model based methods. The statistical moments such as mean, co-variance, and kurtosis have be calculated and compared with a threshold to detect rotating machinery faults. Statistical parameters are being researched to improve their sensitivity to faults when detecting machinery faults.

Frequency domain features are generally more consistent in the detection of damage than time domain parameters. Frequency techniques and time frequency techniques are being investigated by increasing the order of transformation parameters. Moreover, time frequencies techniques are also being investigated to solve problems such as inter term components between neighboring frequency bands. In addition, time frequency techniques are also being researched to analyze certain component information required for specific applications.

The thesis covers detail of literature review done for condition monitoring of different rotating machineries, such as gear, bearing, rail pad, and wheel. From these literatures it is obtained that the best and successful way (in terms of data and resource reviewed) for rail vehicle wheel condition monitoring is based on rail vehicle wheel profile analysis. So it is done by mathematical analysis and matlab algorithm for different feature extraction such as time-domain feature extraction and frequency-domain extraction. To change these wheel profile parameters to more readable form of fast Fourier transformation is done by matlab algorithm for both normal and damaged wheel conditions.

During training of the neural network, higher value input variables of different feature, may tend to suppress the influence of the smaller variables. Therefore, to avoid this feature, feature normalization has been done. The neural network training has been done and the output shown graphically which is almost exact to the target. So fast diagnosis method based on Bp neural network and time domain and frequency domain parameters of wheel profile was used to monitor a rail wheel condition.

## 5.2 Recommendations

The present work provided significant insights on the issues associated with rail-wheel impact accelerations in the presence of normal and fault (worn-out) wheel conditions. Although this study clearly demonstrates reasonably accurate results compare to the experimental data, the potential usefulness and accuracy can be further enhanced upon some other more considerations.

In view of the potential benefits of the present research, further detailed modeling and through investigations are required in order to improve accuracy of the prediction tools to ensure safe operation and low cost maintenance.

The paper include all defects on rail-wheel in on simulation program because of different matters; to get more precise and accurate result, it can be recommended the simulation program to up-grade for the identification of the defects that shown on the rail-wheel separately. The simulation program developed here is limited to identify normal condition from fault (defected) condition using rail-wheel profile signal as an input. It can be also recommended to formulate the program that can identify what types of problem is it whether it is crack, fatigue, shelling, wheel flat and so on.

Another and may be more important recommendation is improvement of data. Data is more important in one way another. Using more relevant data to specific problem can help as to get more accurate result that can identify the defects.

## 5.3 Future Works

More works following this thesis should be done along two major directions, data and modeling. From data side more work need to be done to provide better data. First it is obvious that large sample is always desired for better modeling analysis. Second maintenance consideration should be reflected in sample design.

As it is mentioned in the scope of this paper the work is limited to wheel profile analysis but it can be extended to other parameters such as temperature based analysis and sound based condition monitoring analysis. So in addition to improve the quality of data and modeling the program; these above mentioned parameters can be used for farther work of condition monitoring of rail-wheel.

Another way of developing this research is to formulate or create the program that can identify specific type of the problem for example this paper can help to identify normal rail-wheel condition from fault rail-wheel condition but we can increase the ability of program to distinguish which types wheel defect is occur whether it is spalling, wear and another.

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# APPENDIX

**Import data into Matab**

First of all click MATLAB icon on the desktop .Then click and load N25610 data of normal wheel profile and F25610 data of worn-out wheel profile respectively.

**Divide the data**

Divide the normal and worn-out data N25610 and F25610 respectively into five groups using the input command like this:

```
N201= N25610 (1:28,1); plot(N201);
N202= N25610 (29:56,1); plot(N202);
N203= N25610 (57:84,1); plot(N203);
N204= N25610 (85:112,1); plot(N204);
N205= N25610 (113:140,1); plot(N205);

F201= F25610 (1:28,1); plot(F201);
F202= F25610 (29:56,1); plot(F202);
F203= F25610 (57:84,1); plot(F203);
F204= F25610 (85:112,1); plot(F204);
F205= F25610 (113:140,1); plot(F205);
```

**Zero mean processed data**

We need the zero mean processed data on wards for our analysis, therefore input a command like this in matlab

N201l=N201-sum(N201)/28; plot(N201l);%N201l is the zero-mean processed data for normal profile。'28' is sample points。

F201l=F201-sum(F201)/28; plot(F201l);%F201l is the zero-mean processed data for worn-out profile。'28' is sample points

**Time-domain Features Extraction**

In order to get the N201's time-domain features input a command like below. Then we can also obtain the time-domain features of from N201 to N205 and from F201 to F205 in the same manner only by changing the corresponding variables in the work space of matlab.

```
N201m=sum(N201l)/28; %N201m is mean value,

N201f=sum((N201l-N201m).^2) /28;  %N201f is variance

N201rms=sqrt(sum(N201l.^2)/28);    %N201rms is root-mean-square value

N201peak=(max(N201l)-min(N201l))/2;   %N201peak is peak

N201c= N201peak/N201rms;                %N201c is peak factor

N201k=sum(N201l.^4)/((N201rms.^4)*28);  %N201k is kurtosis factor

N201s=(N201rms*28)/sum(abs(N201l));    %N201s is shape factor

N201i=(N201peak*28)/sum(abs(N201l));    %N201i impulse factor

N201cl=N201peak/(sum(sqrt(abs(N201l)))/28).^2;%N201cl is clearance factor
```

**Frequency-domain Feature Extraction**

To get frequency-domain features for the all groups input a command like this:

```
fori=2:28

G201n(i)=(N201l(i)-N201l(i-1))/(1/10000);

end

 fori=2:28
```

```
N201nn(i)=N201n(i)*N201l(i);
end
N201msf=(sum((N201n).^2))/(4*(pi^2)*sum(N201l.^2));%N201msf is mean-square frequency
N201fc=(sum(N201nn))/(2*pi*sum(N201l.^2));%N201fc is centre frequency
N201vf=N201msf-N201fc.^2;            %N201vf is variance frequency
```

**Note that**: this brings up the N201's frequency-domain features. Then we can obtain the frequency-domain features of from N201 to N205 and from F201 to F205 by varying the variables for each group.

FFT **Feature Extraction**

First to extract the FFT input a command like this:

```
N=28;  %sampling points
fs=10000; %sampling frequency
N201fft=abs(fft(N201l)); %FFT,N201fft is the result of N201l making FFT
N201fft=N201fft(1:N/2,1);
subplot(2,1,1);plot(N201fft);
subplot(2,1,2);plot(N201fft);
```

Use the below command to extract the points and areas of FFT features which is from N201 to N205 and from F201 to F205.

```
N201ffttz=[N201fft(4,1),sum(N201fft(5:6,1)),N201fft(8,1),sum(N201fft(9:10,1)), sum(N201fft(12:13,1))];%N201ffttz is the features which N201l is made FFT.
```

**Features Normalization**

Input a command like this:

```
fori=1:17
for j=1:10
```

gy(i,j)=(tz(i,j)-min(tz(i,:)))/(max(tz(i,:))-min(tz(i,:)));% The tz is original feature matrix, the gy is the feature matrix after normalization. The 17 is the number of original feature. The 10 is the number of samples.

end

end

**Number of Hidden layers**

To determine the number of hidden layer, input a command like this:

```
t=[0 1;0 1;0 1; 1 1;1 1;1 1];
t=t';
s= 1:8;
res=1:8;
fori=1:8
net=newff(minmax(tr),[s(i),2],{'tansig','logsig'},'traingdx');
net.trainParam.epochs =1000;%training times
net.trainParam.lr = 0.1;
net.trainParam.goal = 0.001; % training error
net=train(net, tr,t);        % "train" is the training sample after normalization,t is goal output of training sample
y=sim(net, tr);
error=y-t;
res(i)=norm(error);
end
```

**Training the BP NN**

The training program is as follow:

```
net=newff(minmax(gy),[27,2],{'tansig','logsig'},'traingdx');
```

```
net.trainParam.epochs =1000;

net.trainParam.lr = 0.1;

net.trainParam.goal = 0.001;

 net=train(net,gy,t);
```

**Test the NN**

The testing program of neural network is as follow:

```
 y=sim(net,testing data);
```