

FAULTY GEAR VIBRATION DIAGNOSTIC AND MONITORING



BACHELOR OF MECHANICAL ENGINEERING TECHNOLOGY (MAINTENANCE TECHNOLOGY) WITH HONOURS

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FACULTY OF MECHANICAL AND MANUFACTURING ENGINEERING TECHNOLOGY



UNIVERSITI TEKNIKAL MALAYSIA MELAKA

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Faculty of Mechanical and Manufacturing Engineering Technology

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2022

DECLARATION

I declare that this research report entitled "Faulty Gear Vibration Diagnostic And Monitoring" is the result of my own research except as cited in the references. The report has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.



APPROVAL

I hereby declare that I have checked this research report and in my opinion, this report is adequate in terms of scope and quality for the award of the Bachelor Of Mechanical Engineering Technology (Maintenance Technology) With Honours.



DEDICATION

To my beloved parents Anbualagan A/L Sinakaundan and Tang Siew Eng, I would be honour to dedicate this report for both of them as they are my courage, inspiration, dedication, and strength to complete my research until the end. I would also like to thanks to my brother, sister and friends because they also help me in term of financial during my year of study.



ABSTRACT

Vibrations are an inherent part of machinery. If not monitored or lowered to a safe level, the magnitude of this vibration rises over time and becomes damaging to the apparatus. Researchers worldwide are always conducting research on gear vibrations in order to enhance or suggest solutions to difficulties caused by the vibrations. Numerous components, particularly gears, can create these vibrations, which cause the machinery to shake at a specific frequency and might impair the machine's function if left unnoticed and undiagnosed. Vibrations of a high magnitude indicate that the gear is malfunctioning and should be evaluated; if left untreated, they can raise the cost of repairing the failure and shorten the machine's life. Gears typically face an increase in vibration magnitude when they sustain damage over time due to continual motion during operation. When a defective rolling element makes contact with another element's surface, impact force is generated, resulting in an impulsive gear response. Machinery performs poorly as a result of this increase in vibration magnitude. As a result, it is critical to monitor the gear's vibration status at all times and to diagnose any increase in its vibration amplitude immediately. To address this, vibration signal analysis can be used as an effective vibration monitoring technique, as demonstrated in this thesis. This thesis examines spur gear and helical gear vibrations under normal and fault conditions by conducting an experiment at speeds of 500 rpm, 1000 rpm, 1500 rpm, and 2000 rpm under four different gear conditions to determine the vibration levels associated with each condition. Vibration Statistical Analysis (VSA) was then used to examine the vibration of this gear using MATLAB and Excel tools. As a result of the results, there is an increase in the transient components, which increases in lockstep with the running speed. Additionally, the graphs demonstrate that as the speed increases, the vibration with frequency increases in amplitude. By examining the scattering of z-freq data and its coefficient. It is visible that the dots spread throughout the affix and annex frequency, indicating that the scattered data exhibits a distinct pattern when the RMS speed increases for all conditions. To summarise, time domain is less suitable for fault prediction than the R-Squared approach because the graph difference between the defective and excellent situations is similar to the graph difference between the frequency domain graphs. The RMS and R-squared values in this thesis are used to predict the condition that creates the specific vibration.

ABSTRAK

Getaran adalah sebahagian daripada peralatan mesin. Jika tidak dipantau atau diturunkan ke tahap yang selamat, magnitud getaran ini meningkat dari semasa ke semasa dan menjadi merosakkan radas. Penyelidik di seluruh dunia sentiasa menjalankan penyelidikan tentang getaran gear untuk meningkatkan atau mencadangkan penyelesaian kepada kesukaran yang disebabkan oleh getaran. Banyak komponen, terutamanya gear, boleh mencipta getaran ini, vang menyebabkan jentera bergegar pada frekuensi tertentu dan mungkin menjejaskan fungsi mesin jika dibiarkan tanpa disedari dan tidak didiagnosis. Getaran dengan magnitud tinggi menunjukkan bahawa gear tidak berfungsi dan harus dinilai; jika tidak dirawat, mereka boleh meningkatkan kos membaiki kegagalan dan memendekkan hayat mesin. Gear biasanya menghadapi peningkatan dalam magnitud getaran apabila ia mengalami kerosakan dari semasa ke semasa akibat gerakan berterusan semasa operasi. Apabila elemen gelek yang rosak bersentuhan dengan permukaan elemen lain, daya hentaman dijana, menghasilkan tindak balas gear impulsif. Jentera berprestasi lemah akibat peningkatan magnitud getaran ini. Akibatnya, adalah penting untuk memantau status getaran gear pada setiap masa dan untuk mendiagnosis sebarang peningkatan dalam amplitud getarannya dengan segera. Untuk menangani perkara ini, analisis isyarat getaran boleh digunakan sebagai teknik pemantauan getaran yang berkesan, seperti yang ditunjukkan dalam tesis ini. Tesis ini mengkaji getaran gear memacu dan gear heliks di bawah keadaan normal dan kerosakan dengan menjalankan eksperimen pada kelajuan 500 rpm, 1000 rpm, 1500 rpm dan 2000 rpm di bawah empat keadaan gear yang berbeza untuk menentukan tahap getaran yang berkaitan dengan setiap keadaan. Analisis Statistik Getaran (VSA) kemudiannya digunakan untuk memeriksa getaran gear ini menggunakan alat MATLAB dan Excel. Hasil daripada keputusan, terdapat peningkatan dalam komponen sementara, yang meningkat dalam lockstep dengan kelajuan berjalan. Selain itu, graf menunjukkan bahawa apabila kelajuan meningkat, getaran dengan frekuensi meningkat dalam amplitud. Dengan meneliti taburan data z-freq dan pekalinya. Kelihatan bahawa titik-titik tersebar di seluruh frekuensi imbuhan dan lampiran, menunjukkan bahawa data yang berselerak mempamerkan corak yang berbeza apabila kelajuan RMS meningkat untuk semua keadaan. Ringkasnya, domain masa kurang sesuai untuk ramalan kesalahan berbanding pendekatan R-Squared kerana perbezaan graf antara situasi rosak dan cemerlang adalah serupa dengan perbezaan graf antara graf domain frekuensi. Nilai RMS dan R kuasa dua dalam tesis ini digunakan untuk meramalkan keadaan yang mewujudkan getaran tertentu.

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## LIST OF SYMBOLS AND ABBREVIATIONS

Hz	-	Hertz
СРМ	-	Cycles Per Minute
RPM	-	Revolution Per Minute
FFT	-	Fast Fourier Transform
DAQ	-	Data Acquisition
FDD	-	Fault Detection and Diagnostics
DWT	-	Discrete Wavelet Transform
ANN	-	Artificial Neural Network
AC	- 10	Alternating Current
FDTW	Ser.	Fast Dynamic Time Warping
СК	3-	Correlated Kurtosis
AI	-	Artificial Intelligent
R&D	See.	Research And Development
RMS		Root Mean Squared
RMSE	ملاك	Root Mean Squared Error
MAPE	-	Mean Absolute Percentage Error
MATLAB	UNIVE	Matrix Laboratory KAL MALAYSIA MELAKA
LabVIEW	-	Laboratory Virtual Instrumentation Engineering Workbench
Lf	-	Large Fault
Ln	-	Large Normal
Sf	-	Small Fault
Sn	-	Small Normal

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#### **CHAPTER 1**

#### **INTRODUCTION**

#### 1.1 Background

In engineering, Vibration is a crucial topic to examine since it occurs as a result of movement. This oscillatory movement exhibits features such as frequency, velocity, amplitude, displacement, acceleration, phase, and period. Physical vibration components include mass, stiffness, and damping, which are all comparable to acceleration, amplitude, velocity, and displacement, respectively. Vibration is classified into three types: forced vibration, free vibration, and damped/undamped vibration. Vibration are being quantified using frequency and amplitude measurements. The frequency specifies the duration of one single rotation. While amplitude can be defined as the range of motion of a weight all over a rotation. The frequencies of a vibration is measured in Hertz (Hz) units, or the number of cycles divided by time (second). The frequency of a vibration can also be expressed in cycles per minute. Additionally, cycles per minute is referred to as revolution per minute. Large or extreme vibration can have a detrimental effect on the effectiveness of a system or piece of equipment, and if not addressed or controlled, excessive vibration can result in errors. Reduced it can result in catastrophic failure, and increasing unnecessary costs (Systems & Bone, 2017).

Statistical signal process is an approach that treats signals as stochastic processes and uses their statistical features to perform signals. In signal processing applications, statistical techniques are widely used. For example, when you photograph an image you can map the probability distribution of noise and build techniques using the image model to reduce noise(Hong & Singh, 2014).

Machine learning is a type of data analytics that automates the process of developing analytical models. It is a subfield of artificial intelligence predicated on the premise that systems could exhibit intelligent behavior, recognize designs, and make decisions without much human interaction. According to advancements in information technology, modern machine learning is not comparable to previous machine learning. It was predicated on object recognition and the assumption that computers may learn to execute particular jobs without being instructed; the creators, who were concerned in artificial intelligence, sought to determine whether computers can learn from data. The iterative nature of machine learning is critical because it allows models to alter independently as they are exposed to fresh data. If prior calculations yielded dependable, reproducible results. It is not a true technology, but one that is gaining new traction. While numerous machine learning methods have existed for a long period of time, the capacity to apply sophisticated mathematical computations to large amounts of data automatically and rapidly is a relatively recent development (Szymański, 2020).

#### **1.2 Problem Statement**

Gears are a major element of rotating equipment and may be classified into three types: tooth, manufacturing method, and material. To identify a defective gear, it is nearly difficult to do so using simply human ears. Misalignment, out of position, fractures, and fractured gears are all frequent gear defects that must be detected prior to failure. When all of the machinery's parts and components are fully operational, noise and vibration may occur. In the long term, this condition may have a direct effect on the regular operation of all of the equipment.

Additionally, not everyone has access to appropriate equipment or machinery capable of tracking down a malfunctioning piece of equipment in a timely manner. Vibration Analysis (VA) is a technique that may be used to discover early failures of parts or components such as gears, shafts, bearings, and belts. Gears, on the other hand, are prone to deteriorate over time if left untreated. If the spinning machinery breaks in this situation, it may quickly result in significant injuries and jeopardise the personal safety of the employees involved. Thus, severe loss of life and property can be avoided if the rotor system's noise and vibration can be detected and analysed.

#### **1.3** Research Objective

- i). To measure the vibrations of normal and faulty gear using accelerometer sensor.
- To analyze the vibration data of the gears via various of vibration Statistical Analysis Methods.
- iii). To verify the analysis done by R-squared and Distribution method via Z-freq.

#### **1.4** Scope of Research

The following are the scope of this Faulty Gear Vibration Diagnostic and Monitoring research:

- Helical gears and spur gears are all utilised in this research.
- Two different gear situations were chosen for this research: a regular gear and a malfunctioning gear, in order to compare the outcomes between them.
- Create a simulation model in MATLAB.
- Conduct a vibration analysis utilising the Vibration Signal Analysis (VSA), the Fast Fourier Transform (FFT), the Time Domain, the Root Mean Square (RMS), and the Z-Freq Coefficient.



#### **CHAPTER 2**

#### LITERATURE REVIEW

#### 2.1 Introduction

The literature review on condition monitoring and diagnostics, fault detection, signal processing, and vibration analysis will be discussed in this chapter. This study's references come from journals, books, and the internet. The goal of going over prior articles about faults in spur gear and helical gear is to obtain a better grasp of how to conduct faulty gear vibration diagnostic and monitoring.





Figure 2.1 Literature Review K-Chart

#### 2.2 Gears Variety

Gears are widely used in industrial machinery, vehicles, and a variety of other applications. Mechanics can then be used to categories gear. It is most commonly categorized by the shape and size of the teeth, as well as the manufacturing process and the substance. In addition, shifting the axis position of the gears could be used. Spur Gear, Helical Gear, Worm Gear, Bevel Gear, and Rack and Pinion Gears are the most commonly used gears.

#### 2.2.1 Spur Gear

Gears with direct teeth are built on circular or cylindrical bodies with teeth inserted in parallel to the shaft. Transmission of motion and power is accomplished through the mating of parallel axes in matted pairs. For example, if the application is a planetary gear system or rack and pinion gear pair, then a Spur Gear can be used in conjunction with another Spur Gear, such as an internal gear (OuYang et al., 2015). Because of the spur gears' simple tooth design, they are both extremely accurate and simple to produce. Because of its simplicity, it is also one of the most commonly used gears in the manufacturing industry. For axial loads such as thrust power parallel to the shaft, high speeds and bulky maneuvers, and high efficiency ratings, spur gears are an excellent choice.

The teeth of spur gears are subjected to more stress and vibration when operating at high speeds. When operating at high speeds, spur gears produce a high-pitched squealing noise. With their multiple speed ratios (see Fig. 2.2), spur gears can be used in many mechanical applications. There are many uses for this technology, including clocks, watering systems for pumps, washers, dryers, and other pumps, as well as gear trains that can provide a higher gear reduction.



Figure 2.2 Spur Gear

#### 2.2.2 Helical Gears

It is possible to use helical gears to drive shafts that are not parallel or intersecting, just like spur gears. Due to the fact that helical gears have teeth curved around the cylindrical transmission at an angle to its front. The teeth of the helical gear are angled in the same direction on both the right and left gears in each gear pair. Because of the helical teeth' angled design, they work differently than the significant teeth of the spur gears when paired with other gears(Wei & Lin, 2011). When helical gears make contact, the total number of tooth-to-tooth contact gradually increases rather than using the entire tooth at once. Allows the teeth to be loaded less and the operation to be smoother and smoother. Additionally, helical gears can be far more efficient than spur gears when it comes to distributing the load. They have a lower level of productivity.

Because of the helical design's complexity and the axial thrust it generates, helical gears (Figure 2.3) have a number of drawbacks, such as the need for thrust bearings in every application where a single helical gear is used. As a result, the overall cost of using helical gears is also increased. Due to helical gears' ability to handle high speeds and heavy loads,

they are ideal for pump and generator applications. The smooth, leisurely operation of this gear is also well-suited to automobile transmissions when spur gears aren't present.



Figure 2.3 Helical Gear

#### 2.2.3 Bevel Gears

Cone-shaped gears with cone-shaped teeth are known as bevel gears. Power and movement are transferred between shafts using these devices in applications where the rotational axis must be adjusted. For 90-degree shaft combinations, bevel gears are typically used, but they can also be used for less- and larger-angled combinations. Many of its tooth shape distinguishes between bevel gears of the same type. Figure 2.4 shows the most common type of bevel gear: the straight and spiral. In terms of bevel gear designs, straight bevel gears are most common because of their simplicity and ease of production.

A significant impact on noise levels, load pressure on gears, and overall gear reliability and performance can be expected when straight bevel gears are used. It's easier for teeth to come into contact with each other in spiral-shaped bevel gears because the teeth are curved, allowing for more gradual contact and engagement between teeth. Similarly, spiral bevel gears with teeth that are either right or left angled are open. Helical gears, which are more difficult and expensive to make because of their complexity, are also a challenge (Padmanabhan et al., 2011). However, it is quieter and has a higher tooth strength than straight bevel gears when in operation.



Figure 2.4 Bevel Gear

#### 2.2.4 Worm Gears

AALAYSI.

Using a worm wheel or a cylindrical gear, which is then attached to a worm and a scaffolded gear, worm gear pairs are created for various applications. Non-parallel shafts can be moved and powered together with this gear by turning it counter-clockwise. They have large gear ratios and the ability to reduce speed significantly while maintaining quiet and smooth operation. Due to differences in the worm gears' angular positions, the worm wheel may not be capable of rotating around the worm, and vice versa (Melnikov & Schegoleva, 2019).

Self-locking devices benefit from this feature. Worm gears have a number of drawbacks, including low signal transmission and the need for constant lubrication between the worm wheel and the worm gears (Figure 2.5).



Figure 2.5 Worm Gear

#### 2.2.5 Rack and Pinion Gears

There are two gears in the rack and pinion gear (Figure 2.6), which are referred to as both the rack and the pinion. The gear shelf could be used as a straight-toothed unending gear, whether cut out or mounted on the plate's surface. When mating a spur gear to a helical gear, the teeth of the gear rack are either parallel or cornered, depending on the spindle gear. It is possible to convert rotational motion into linear motion or the other way around for either of these rack designs. A rack and pinion gear combination's ease of construction, low development costs, and lower load capacity are some of its advantages (Vempati et al., 2021). Gears using this approach are limited in number due to its advantages. The distance of the gear rack, for example, limits the transmission's ability to move in any direction.



Figure 2.6 Rack and Pinion Gears

#### 2.3 Condition Monitoring and Diagnostics

The electrical control components, the tooth, and the gearbox itself are the areas where gear systems have been documented to have suffered the most damage. This will demonstrate that the monitoring of gears utilising vibration condition is a significant advantage to the gear systems in operation. Vibration analysis methods are widely used for condition monitoring, and they aid in the diagnosis of machine damage as well as the prevention of unwanted and expensive consequential damages by detecting them in a timely manner.

There were a number of conventional methods that were used most frequently in early studies for condition monitoring that were based on the cumulative probability characteristics of the vibration, such as the Fourier spectrum method (Inalpolat & Kahraman, 2010), modulation sidebands, skewness, kurtosis (Zhang et al., 2016), and finally a Cestrum Analysis Method (CAM). This explains why such approaches were extensively employed for monitoring systems in the past, and why they have been found to perform effectively in such circumstances. The gear system for the gearboxes was subjected to constant loading under these conditions. It goes without saying that a gearbox signal, for example, will have spectral characteristics that change over time in the majority of instances. Because the Fourier transform basically extends a signal as a linear combination of single frequencies that occur across time, the output will not be accurate when employing the Fourier transform.

The monitoring of vibratory conditions, on the other hand, is primarily based on the concept that the rotating machinery has a specific vibration pattern for its usual state, which varies with the progression of damage over time (Antoni, 2006). To give an example, the gearboxes inside a wind turbine will have a vibration pattern that will change when the environment changes, such as when the wind speed, turbulence, and temperature change, as well a time fluctuation in the loads while the wind turbine operates (Ertek & Kailas, 2021).

Furthermore, it can be concluded that when the gear system is working in a steady state, it will be a quick and convenient method for monitoring the vibration conditions. In general, condition monitoring methods are similar to other ways of harm detection in that they do not require the knowledge of correct conclusions about the frequency bands associated with the damage of the gears or any other components to be used in conjunction with them.

#### 2.3.1 Vibration Analysis

The vibration analysis approach is among the condition monitoring strategies It is the principal diagnostic tool for the vast majority of mechanical systems, regardless of whether they are spinning, reciprocating, or exhibiting other mechanical movement. There are many different types of vibration analysis techniques that can be used depending on their function. Many researchers have used various types of vibration analysis, as shown in Table 2.1. Vibration analysis is a technique for determining the operational and mechanical condition of rotating machinery. Several studies have used vibration analysis to monitor the condition

of a machine, whether it is rotating or reciprocating, such as a gear, motor, pump, or vehicle engine.

No	Types of vibration analysis
1	Frequency Domain Analysis
2	Time-Domain Analysis
3	Time-Frequency Analysis
4	Non-Linear Analysis
5	Cepstral Analysis

Table 2.1 Types of vibration analysis

The advantages of vibration analysis include a quick response to changes, the ability to be used for both continuous and periodic monitoring, pointing to the real faulty component, and identifying developing problems before they become too significant and cause unplanned downtime. Finally, vibration analysis can be used as part of a larger programmed to improve equipment reliability dramatically. On a larger number of machines, periodic monitoring is used to provide long-term warning of developing faults. The factor of implementing periodic monitoring technique focuses on productivity losses rather than equipment cost.

The vibration signal was measured using two different type of gear. The frequency spectrum and time waveform are the two main components used in vibration analysis. Understanding the relationship between time waveform and frequency spectrum is critical because it will aid in the analysis of vibration energy. The time waveform is a complex vibrational indication that shows how alternating current (AC) varies with time (Jiang et al., 2017).

As a result, the vibration spectrum is used to represent the vibration waveform in a more understandable way by displaying the frequency on the x-axis and the amplitude on the y-axis. The use of the Fast Fourier Transform can be used to convert a time waveform to a frequency spectrum (FFT). FFT as the number of resolution lines (Peters, n.d.). The use of

FFT to study the vibration behavior of an faulty gear for condition monitoring has been proposed (Sun & Han, 2020). Time waveform analysis can be used to detect faulty gears, engine, looseness, rubs, and beats. The use of fast dynamic time warping and correlated kurtosis has resulted in the development of a new time-domain diagnostic technique for fault identification (Sun & Han, 2020).

#### 2.4 Machine Learning

Since this world progresses continually to improve humanity, many scientists explore a technology that requires less human effort, or better. This means that the world is directed towards the intelligence (robotic systems and machineries), or that other people can say that they are "artificial intelligent" (AI). AI is like a machine or computer which has a human nature that can think like human beings and make decisions like human beings. Machine learning is, on the other hand, the subset of AI that forms a learning machine. Machine learning model searches the recognition of patterns in a data for conclusion determination. The example input in your system helps you to learn.

Mechanical learning is also used in the industry as a tool to identify the problem in a machine. As a tool for conditionally maintained maintenance, Machine learning and data mining algorithm can detect abnormalities on a machine before failure happens. Machine training, supervised learning, unattended learning and strengthened training exist in three different ways. Learning is monitored when an algorithm is learned by example. Uncontrolled learning is a self-contained learning in which no response is provided. A simple example shows the algorithm itself. While enhancement is an algorithm, this example shows that there are no data or that there's no human trial or error (Accorsi et al., 2017).

#### 2.5 Statistical Analysis

Data collection and interpretation to uncover patterns and trends is statistical analysis. It is a data analysis component. In situations such as research interpretations collection, statistical modelling or survey and studies design, the statistical analysis can be used. The statistical analysis is used to calculate the measured signal coefficient (Nuawi et al., 2013). During gear operation, the input data is obtained during signal acquisition. The vibration statistical analysis is a mathematical platform approach. Applied statistical method in real time to analyze the performance of the proposed technique for irrelevant environment failure detection. The following are certain statistical measurements.

#### 2.5.1 Mean

The average of whole data points as shown in Equation 2.1 is known more commonly. It can be calculated by adding together all data numbers and dividing them with the total numbers. In other words it is the sum divided by the count (Sharma et al., 2014).

# UNIVERSITI TEKNIKAL MALAYSIA MELAKA $\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$ (2.1)

Where  $\bar{x}$  is indicating the mean value,  $\sum_{i=1}^{n} x_i$  total numbers of data and n are the total numbers amounts.

#### 2.5.2 Median

Median is the value that separates the higher half from the lower half of the statistical analysis data sample, populations or distribution of probabilities. It can be considered as a "middle" value for a data set. The median's basic feature when describing data is that it is not skewed by an extremely more or less proportion and provides more accurate analysis of a "typical" value. For example, middle income could be better for suggesting what is a "typical" income, as distribution of income can be very skewed. The median, as the most resistant statistical median with a breakdown point of 50%, is of central importance in statistical data. If less than half of the data is tainted, the median would not be excessively large or tiny (Sharma et al., 2014).

#### 2.5.3 Mode

The mode is the value that occurs most frequently in a collection of data values. When X becomes a random discrete variable, mode indicates the value of the probability mass function that is closest to its greatest value. In other words, it is the most frequently sampled value. Like the mean and median, mode means that important information on a random variable or a population is expressed in a usual single number. The mode value is identical to the mean and median values in a normal distribution, but may be significantly different in highly skewed distributions (Sharma et al., 2014).

#### 2.5.4 Variance

Variation is the expectation in statistics analysis that a random variable deviates squarely from its mean. In other words, it measures the extent to which a number is divided between its average value (Jiang et al., 2017). Variance as stated in Equations 2.2 and 2.3 is the measure of how the data sets are distributed.

$$\sigma^2 = \frac{\sum (x - \mu)^2}{n}$$
(2.2)

Where  $\sigma^2$  is the variance in population, *x* is the data value,  $\mu$  the mean population and *n* the total point of data quantities.

$$s^{2} = \frac{\sum (x - \bar{x})^{2}}{n}$$
(2.3)  
the standard variance in sample, x is the data value,  $\bar{x}$  is the sample mean of

Where  $s^2$  is the standard variance in sample, x is the data value,  $\overline{x}$  is the sample mean of data point, and n is the total quantities of data points.

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#### 2.5.5 Standard Deviation

In statistical analysis, the standard deviation is used to calculate the extent of variation or dispersion of values. The lower number indicates that the values are often close to the set's mean, whereas a higher number indicates that the values span a greater range (Sharma et al., 2014). As shown in Equation 2.4 and 2.5, the standard deviation is the measure of distribution. It shows the extent of variety provided in the sets of data. It indicates variation.

$$\sigma = \sqrt{\frac{\sum (x - \mu)^2}{n}}$$
(2.4)
he population standard deviation, x is the data value,  $\mu$  is the mean of population

Where  $\sigma$  is the population standard deviation, x is the data value,  $\mu$  is the mean of population data point, and n is the total quantities of data points.

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UNIVERSITI TEK  
$$S = \sqrt{\frac{\sum(x_1 - M\bar{x}_1)^2 \text{YSIA MELAKA}}{n-1}}$$
 (2.5)

When S is the standard deviation in sample, x is the data value, x is the mean of sample data point and n are the total quantities of data points.

#### 2.5.6 Standard Error

The standard error of a statistical is that a statistical sample population standard deviation approximately by default. The standard error is a statistical term used to refer to the correctness of a sample distribution and population as measured by the standard deviation. Statistics demonstrate that the sample mean deviates from the population mean (Sharma et al., 2014). The population standard error is shown in Equation 2.6, and Equation 2.7 is the sample standard error.

$$\sigma_{\bar{\chi}} = \frac{\sigma}{\sqrt{n}} \tag{2.6}$$

Where  $\sigma$  is standard deviation of the population and *n* is the size of sample.


## 2.5.7 Crest Factor

The Crest Factor is a waveform parameter that shows the ratio of summit values to actual value, for example the alternative current and sound. Higher crest factors indicate high peaks, such as high crest, for example sound waves. The Crest factor is the connection between current peak and current RMS (Taghizadeh-alisaraei et al., 2016). Crest factor is also referred to as the ratio of peak to rms, or the factor of peak or amplitude. A crest factor of 1.414 is the perfect sine wave. Crest factor can be used to monitor the trend of machine condition. Equation 2.8 shows the Crest factor formula (Alkhadafe et al., 2016).

$$CF = \begin{vmatrix} X_{i max} \\ r.m.s \end{vmatrix}$$
(2.8)

#### 2.5.8 Skewness

The degree of asymmetry in the probability distribution is skewness in statistics (Sharma et al., 2014). Apart from positive and negative skew, distributions are also stated to have null or undefined skew on the normal distribution. Data mostly on right side of the curve can drop in a different direction than the data on the left side of the curve. The "tails" is known as these tapering's. Negative skew indicates a longer or fatter tail on the left, whereas positive skew indicates a longer or fatter tail on the left, skewness of Equation 2.9 shows whether the average number of data is positive or negative.

$$S_K = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{x_i - \bar{x}}{\sigma} \right)^3 \tag{2.9}$$

## 2.5.9 Kurtosis

Kurtosis is a statistical term that refers to the difference between a distribution's tails and the tails of a normal distribution. In other terms, kurtosis indicates rather or not a distribution's tails contain extreme values. If it is a positive kurtosis the normal distribution can be described as pointer or flatter, it will have a pointer bell form, and if it is negative it will be shaped flatter. The formula of kurtosis is shown in equation 2.10 (Alkhadafe et al., 2016). Noise is very sensitive to it and can be detected by Kurtosis. In the direction of these overall performance indicators, signal filtering however is extremely important.

$$K = \frac{1}{n\sigma^4} \sum_{i=1}^{n} (x_i - \bar{x})^4$$
(2.10)  
Ican Squared (RMS)

## 2.5.10 Root M

In statistics, the root mean square is the square root of the mean square. The RMS is sometimes known as the quadratic mean, whereas the generalized mean would be special instance with an exponent of two. For a continuously variable function, RMS can also be defined as an integral of the squares of peak value throughout a cycle. For the sine wave, the root mean value is 0.707. It provides a way to analyses a signal in a vibration analysis instantly. The area under the curve also increases when the RMS value increases. In general, the positive peak is the negative curve of a sinus wave, which averages the RMS value. The root mean square (RMS) shown in Equation 2.11 (John Mathey, 2013).

$$RMS = \sqrt{\left[\frac{1}{n}(x_1^2 + x_2^2 + \dots + x_n^2)\right]}$$
(2.11)

## 2.5.11 Root Mean Squared Error (RMSE)

Root Mean Square Error is the standard deviation of residuals (prediction error). The term "residuals" refers to the distance between the data points and the regression line; the term "RMSE" refers to the spread of the residues. In other words, it indicates how the facts are organised optimally (Hong & Singh, 2014). The root mean square error (RMSE) shown in Equation 2.12.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{n}}$$
(2.12)

Where n is the size of sample,  $\hat{y}_i$  is the value of predicted, and  $y_i$  is value of observed.

# 2.5.12 Mean Absolute Percentage Error (MAPE)

The mean absolute percentage error is a metric used to determine the accuracy of a forecasting system. This accuracy is expressed as a percentage and can be calculated by dividing actual data by the absolute average percent inaccuracy by each time. Using Equation 2.13, MAPE may be calculated.

$$M = \frac{1}{N} \sum_{t=1}^{N} \left| \frac{A_t - F_t}{A_t} \right|$$
(2.13)

Where  $A_t$  is actual value,  $F_t$  is the value of forecast, and N is the observation number.

## 2.5.13 Z-Freq Coefficient

Numerous regular measurement signals are random or exhibit non-deterministic properties, posing a barrier for analysis using signal processing techniques. The majority of gear vibration signals are non-deterministic, meaning that the statistical value over a time range is more essential than a value at a specific instantaneous time. To extract information from this random signal, the Z-freq statistical approach was suggested. The signal generated by the acquired data is then converted to the frequency domain using the Fast Fourier Transform (FFT) and evaluated using the derived statistical approach to determine the Z-freq coefficient value. The Z-freq approach generates a two-dimensional graphical representation of the observed signal's frequency distribution based on its kurtosis value. The time domain signal is divided into two frequency bands, with the x-axis representing low frequency (affix) and the y-axis representing high frequency (affix) (annex). Affix mob is composed of frequencies ranging from 0 to 0.5fmax, whereas annex mob is composed of frequencies ranging from 0.5fmax to 1.0fmax. The Z-freq coefficient measures the distance between each data point and the signal centroid in order to determine the distribution of the scattered data. The coefficient of Z-freq is defined as follows:

$$Z^f = \frac{1}{n} \sqrt{K_{afx} s^4_{afx} + K_{anx} s^4_{anx}}$$
(2.14)

where  $K_{afx}$  and  $s_{afx}$  are the kurtosis and standard deviation, respectively, for the low-frequency range, and  $K_{anx}$  and  $s_{anx}$  are the kurtosis and standard deviation, respectively, for the high-frequency range. On the basis of the normal order of Daubechies signal decomposition, the  $Z^f$  coefficient is derived.

## 2.6 Software

Software is used widely for vibration analysis in numerous engineering industries including manufacturing, automotive industry, machinery, and even structural engineering. The use of software for vibration analysis is also important since it can be used to analyze the system's vibrational behavior and to detect early fault prior to severe damage. There is a lot of software that manufacturers can use to perform vibration analysis. For example, the most popular researchers recommend MATLAB (Matrix Laboratory) and LabVIEW (Laboratory Virtual Instrumentation Engineering Workbench) because it could integrated with the DAQ system in which vibration data from various machine elements can be acquired, analysed and interpreted.

# 2.6.1 MATLAB (Matrix Laboratory)

MATLAB is an engineering and scientist programming platform designed to analyses and design systems and products which are transforming our world. MATLAB's core is the MATLAB language, a matrix language that allows computational mathematics to be most naturally expressed like the manipulation of metrics, function plotting and algorithm data implementation. Researchers use the MATLAB software to analyse the signal response time- and frequency domain in engineering perform a vibration analysis of the rotating shaft. In applicational areas like embedded systems, data analytics, robotics, wireless communication, image processing and computer vision, the MATLAB can also be used (Gopinath & Periyasamy, 2016). Data processing using MATLAB is widely used in engineering, in which data collected can be easily understood and processed in a much simpler form. Uses MATLAB to convert the time domain to the Fast Fourier transform domain (Nuawi et al., 2013).

## 2.6.2 LabVIEW (Laboratory Virtual Instrumentation Engineering Workbench)

LabVIEW is a platform for system design and development for visual programming. LabVIEW function for data acquisition systems testing and measurement (Hamel & Mohellebi, 2020). Otherwise, the device and instrument can be controlled, data processed, data analysed and the instrument can acquire data. This great feature is achieved through graphical programming techniques in a simple environment. To detect breakage in materials using LabVIEW to acquire data in real time (Hamel & Mohellebi, 2020). This could make very complex routines relatively easy for engineers and researchers to use.



## **CHAPTER 3**

## METHODOLOGY

## 3.1 Introduction

A flow chart shows the process of this research in Figure 3.1. As mentioned in the preceding chapter, the gear fault may occur over time. Consequently, if a fault has not been previously recognized, it becomes a serious concern if the gear is failing or if it fails. The costs of upkeep will be increased. There were a lot of explanations about how this project went from the start to the end in this chapter. It took a long time to find the best way to do this research. There are programme called MATLAB that can help us do this variable analysis on gear faults. We can use these programme to make a model simulation for this variable analysis. This chapter can also tell how well the Vibration Analysis (VA) works based on the method and steps of the project. Next, to figure out how vibration works, you need to use a MATLAB programme to show how sound and vibration affect the parts you choose. These parts are usually inside a transportation component.



Figure 3.1 Project Flow Chart

# 3.2 Research Design

There are two types of gear used in this study: Spur Gear and Helical Gear. The vibration signals from both of these types of gear are compared in MATLAB software for vibration analysis. It will be compared to the ISO 13373:2017 standard (condition monitoring and diagnostic of machines vibration condition monitoring). Next, we have ISO 18431-2:2004. (Mechanical vibration and Shock-Signal Processing-Part 3: time domain windows for Fourier Transform Analysis). ISO 18431-3:2014 is also important (Mechanical vibration and shock-signal processing-part 3: methods of time frequency analysis).

## 3.3 Experimental Setup

The configuration utilises two distinct types of gears: Spur Gear and Helical Gear. Both pieces of equipment operate autonomously. A mix of defective and normal gears in two distinct sizes, Large Fault (Lf) and Small Normal (Sn), are used in this experiment. For all types of gear, other combinations include Large Normal (Ln) and Small Normal (Sn), Large Fault (Lf) and Small Fault (Sf), and Large Normal (Ln) and Small Fault (Sf).



Figure 3.2 Experimental Setup



Figure 3.3 Large Gear Used



Figure 3.4 Small Gear Used



Figure 3.5 Data Acquisition ( DAQ )

## 3.3.1 Signal Processing

The vibration signal is generated using a gear experimental setup that includes two different types of gears: Spur Gear and Helical Gear. Both pieces of equipment operate autonomously. A mix of defective and normal gears in two distinct sizes, Large Fault (Lf) and Small Normal (Sn), is used in this experiment. For all types of gear, other combinations include Large Normal (Ln) and Small Normal (Sn), Large Fault (Lf) and Small Fault (Sf), and Large Normal (Ln) and Small Fault (Sf). The accelerometer will then be linked to the closest equipment base or motor and to the DAQ in order to create the signal. The signal express is used in conjunction with a computer to produce Time Domain and Frequency Domain signals. There are two locations for sensors: Sensor 1 (S1) and Sensor 2 (S2).



Figure 3.6 Accelerometer sensor1 (S1) and sensor 2 (S2)

#### 3.3.2 Signal Analysis

The setup consists of a simulation of a gear fault's real vibration. To begin, a model is created in MATLAB to serve as the basis for the simulation. Then, using the output of the simulation, do a vibration signal analysis. If the procedure does not succeed the first time, repeat it until it does. Following that, gather data based on the accurate findings from the simulation of the vibration signal analysis; this is a critical stage in order to compare it later to results from statistical method approaches. The first step is to collect signal processing data in the Time Domain and Frequency Domain for a combination of faulty and normal gears from Spur Gears and Helical Gears. These gears are available in two different sizes: Large Fault (Lf) and Small Normal (Sn), and contribute to this experiment at speeds of 500 rpm, 1000 rpm, 1500 rpm, and 2000 rpm. After signal processing is complete, do a signal analysis utilising RMS, Z-freq Coeffiency, Standard Deviation, Skewness, and Kurtosis. It is carried out in Excel, which is used to compute and compare the gears and speed. Finally, draw a conclusion based on the comparison of the simulation to the data obtained throughout the process.

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## 3.4 Parameters

The parameters used in this experiment include the machine's rotating speed, the sample rate, and the duration of the data collection period. Its purpose is to determine the difference in vibration between normal and defective gears. The data is taken during a 5 second period at the speeds of 500 rpm, 1000 rpm, 1500 rpm, and 2000 rpm at which the machine must work. Spur Gear and Helical Gear are utilised in this experiment.

# Table 3.1 First test for a parameter that is used in simulations and to get data on how well it works

Components	Speed (500 rpm)	Speed (1000 rpm)	Speed (1500 rpm)	Speed (2000 rpm)
Normal Gear				
Faulty Gear				

After that, the experiment is done again for the second and third time to make sure that the results are accurate.

Table 3.2 Second test for a parameter	r that is used in simulations and to get	data on how
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	well it works	

Components	Speed (500 rpm)	Speed (1000 rpm)	Speed (1500 rpm)	Speed (2000 rpm)
Normal Gear	کل ملیسیا م	ي کند	اونيۇمرسىتى	
Faulty Gear	ERSITI TEKN	IIKAL MALAY	SIA MELAKA	

Table 3.3 Third test for a parameter that is used in simulations and to get data on how well it works

Components	Speed (500 rpm)	Speed (1000 rpm)	Speed (1500 rpm)	Speed (2000 rpm)
Normal Gear				
Faulty Gear				

There will then be an average of the data from all three tests to figure out how much data there is. To get the correct results, you need to do this step first. Finally, a graph of rotations per minute (rpm) vs. time (mins) between a normal gear and a faulty gear with three lines is shown. Each graph has three lines. Each line has 500 rpm, 1000 rpm, 1500 rpm, and 2000 rpm.

Table 3.4: An average of the parameters that were used in the simulation and the data that was gathered

Components	Average Speed (500 rpm)	Averange Speed (1000 rpm)	Average Speed (1500 rpm)	Average Speed (2000 rpm)
Normal Gear	ALAYSIA MEL			
Faulty Gear			<b>a</b> M	
1993 1997	Ann			
الأك	کے ملتشیا ما	-i-	اوىيۇم سىت	

3.5 Data Verification UNIVERSITI TEKNIKAL MALAYSIA MELAKA

This is a method that enhances the vibrational measurements gathered in order to gain a better comprehension of the data provided. The R-Squared values and the data distribution graph were maintained using Excel software. R2 had to be more than 0.9 in order for it to be considered dependable.

## **CHAPTER 4**

## **RESULTS AND DISCUSSION**

## 4.1 Introduction

Expected outcomes from this experiment will be discussed in this chapter, which is based on the technique that has been proposed. Once a model has been constructed, the results will be assessed using Vibration Signal Analysis (VSA) in MATLAB and the National Instrument Signal Express, with the parameters specified by the researcher. Furthermore, using the R-Squared approach, the results are compared and confirmed. Spur gears and Helical gears are the two types of gears that exist. It is possible to run both gears in parallel. Combining defective gear with non defective gear, which is available in two distinct sizes, namely Large Fault (Lf) and Small Normal (Sn), contributes to the success of this experiment. Other possible combinations include Large Normal (Ln) and Small Normal (Sn), Large Fault (Lf) and Small Fault (Sf), Large Normal (Ln) and Small Fault (Sf) for one type of gear and Small Fault (Sf). Next, the experiment is carried out at four different speeds: 500rpm, 1000rpm, 1500rpm, and 2000rpm. The results are presented in figures below. In order to verify accuracy, the run will be performed.

## 4.2 Calibration Result

As for the first phase prior to conducting the analysis. Calibration of the sensor is performed to guarantee that no error occurs during the procedure. The calibration process is carried out using a calibration sensor metre, namely the Calibration Exciter Type 4294, which operates at 159.15Hz and has a maximum amplitude of nearly 160 Hz. All sensors have been calibrated and consistently produce the same result. This step is critical to ensuring that the accelerometer sensor provides correct readings during the data collection procedure.

# 4.3 Spur Gear Monitoring

Spur Gear Monitoring of time domain, frequency domain, and Z-Freq coefficients for this experiment. This experiment makes use of two sensors: Sensor 1 (S1) and Sensor 2. (S2). However, the time domain, frequency domain, and Z-Freq plots displayed below are from Sensor 2(S2) data alone. The particular sensor was chosen to represent the average outcome of the particular job. This is because the values of the data gathered from the two sensors are identical.







Figure 4.1 Z-freq scattering for 500rpm, 1000rpm, 1500rpm, 2000rpm at Large Normal and Small Normal spur gears.

The time domain and frequency domain experimental results for four different speeds in the Large Normal and Small Normal spur gear situation are shown in Figure 4.1. The time waveform data demonstrate the increase in transient components as the Spur Gear speed increases. The signal is filtered in the frequency domain using the Butterworth filter. Low frequency components, particularly those related to the spur gear speed, are eliminated. The fluctuation at high frequencies is statistically more significant for Z-freq analysis. When a spur gear fails, it generates high frequency vibration components that can be exploited to detect the fault in the Z-freq. As the gear speed increases, the amplitudes below 1000Hz increase. The scattering of Z-freq coefficients for the Large Normal and Small Normal spur gears at 500 rpm, 1000 rpm, 1500 rpm, and 2000 rpm is shown in Figure 4.1, along with the time and frequency domains for each gear speed. As the gear speed increases, the red and yellow dots, in particular, expand over the affix frequency. Additionally, all of the dots can be seen to split from one another at a high affix frequency relative to the annex frequency.



## 4.3.2 Large Normal and Small Fault



Figure 4.2 Z-freq scattering for 500rpm, 1000rpm, 1500rpm, 2000rpm at Large Normal and Small Fault spur gears.

The time domain and frequency domain experimental results for four different speeds in the Large Normal and Small Fault spur gear situation are shown in Figure 4.2. The time waveform data demonstrate the increase in transient components as the Spur Gear speed increases. The signal is filtered in the frequency domain using the Butterworth filter. Low frequency components, particularly those related to the spur gear speed, are eliminated. The fluctuation at high frequencies is statistically more significant for Z-freq analysis. When a spur gear fails, it generates high frequency vibration components that can be exploited to detect the fault in the Z-freq. As the gear speed increases, the amplitudes below 1200 Hz increase. The scattering of Z-freq coefficients for the Large Normal and Small Fault spur gears at 500 rpm, 1000 rpm, 1500 rpm, and 2000 rpm is shown in Figure 4.2, along with the time and frequency domains for each gear speed. As the gear speed increases, the red and yellow dots, in particular, expand over the affix frequency. Additionally, all of the dots can be seen to split from one another at a high affix frequency relative to the annex frequency.



## 4.3.3 Large Fault and Small Normal



Figure 4.3 Z-freq scattering for 500rpm, 1000rpm, 1500rpm, 2000rpm at Large Fault and Small Normal spur gears.

The time domain and frequency domain experimental results for four different speeds in the Large Fault and Small Normal spur gear situation are shown in Figure 4.3. The time waveform data demonstrate the increase in transient components as the Spur Gear speed increases. The signal is filtered in the frequency domain using the Butterworth filter. Low frequency components, particularly those related to the spur gear speed, are eliminated. The fluctuation at high frequencies is statistically more significant for Z-freq analysis. When a spur gear fails, it generates high frequency vibration components that can be exploited to detect the fault in the Z-freq. As the gear speed increases, the amplitudes below 1400 Hz increase. The scattering of Z-freq coefficients for the Large Fault and Small Normal spur gears at 500 rpm, 1000 rpm, 1500 rpm, and 2000 rpm is shown in Figure 4.3, along with the time and frequency domains for each gear speed. As the gear speed increases, the red and yellow dots, in particular, expand over the affix frequency. Additionally, all of the dots can be seen to split from one another at a high affix frequency relative to the annex frequency.







Figure 4.4 Z-freq scattering for 500rpm, 1000rpm, 1500rpm, 2000rpm at Large Fault and Small Fault spur gears.

The time domain and frequency domain experimental results for four different speeds in the Large Fault and Small Fault spur gear situation are shown in Figure 4.4. The time waveform data demonstrate the increase in transient components as the Spur Gear speed increases. The signal is filtered in the frequency domain using the Butterworth filter. Low frequency components, particularly those related to the spur gear speed, are eliminated. The fluctuation at high frequencies is statistically more significant for Z-freq analysis. When a spur gear fails, it generates high frequency vibration components that can be exploited to detect the fault in the Z-freq. As the gear speed increases, the amplitudes below 1600 Hz increase. The scattering of Z-freq coefficients for the Large Fault and Small Fault spur gears at 500 rpm, 1000 rpm, 1500 rpm, and 2000 rpm is shown in Figure 4.4, along with the time and frequency domains for each gear speed. As the gear speed increases, the red and yellow dots, in particular, expand over the affix frequency. Additionally, all of the dots can be seen to split from one another at a high affix frequency relative to the annex frequency.

# 4.4 Helical Gear Monitoring

Helical Gear Monitoring of time domain, frequency domain, and Z-Freq coefficients for this experiment. This experiment makes use of two sensors: Sensor 1 (S1) and Sensor 2. (S2). However, the time domain, frequency domain, and Z-Freq plots displayed below are from Sensor 2(S2) data alone. The particular sensor was chosen to represent the average outcome of the particular job. This is because the values of the data gathered from the two sensors are identical.



## 4.4.1 Large Normal and Small Normal



Figure 4.5 Z-freq scattering for 500rpm, 1000rpm, 1500rpm, 2000rpm at Large Normal and Small Normal helical gears.

The time domain and frequency domain experimental results for four distinct speeds in the Large Normal and Small Normal helical gear condition are shown in Figure 4.5. The time waveform data demonstrate the rise in transient components as the Helical Gear speed increases, as demonstrated by the spikes. The signal is filtered in the frequency domain using the Butterworth filter. Low frequency components, particularly those linked to the Helical gear speed, are eliminated. The fluctuation at high frequencies is statistically more significant for Z-freq analysis. In the instance of a malfunctioning helical gear, the flaws induce high frequency vibration components, which can be used to detect the fault in the Zfreq. As the helical gear speed increases, the amplitudes below 1200 Hz increase. The scattering of Z-freq coefficients for the Large Normal and Small Normal helical gears at 500 rpm, 1000 rpm, 1500 rpm, and 2000 rpm is shown in Figure 4.5, along with the time and frequency domains for each gear speed. As the gear speed increases, the green and yellow dots, in particular, expand over the affix frequency. Additionally, all of the dots can be seen to split from one another at a high affix frequency relative to the annex frequency.



# 4.4.2 Large Normal and Small Fault



Figure 4.6 Z-freq scattering for 500rpm, 1000rpm, 1500rpm, 2000rpm at Large Normal and Small Fault helical gears.

The time domain and frequency domain experimental results for four distinct speeds in the Large Normal and Small Fault helical gear condition are shown in Figure 4.6. The time waveform data demonstrate the rise in transient components as the Helical Gear speed increases, as demonstrated by the spikes. The signal is filtered in the frequency domain using the Butterworth filter. Low frequency components, particularly those linked to the Helical gear speed, are eliminated. The fluctuation at high frequencies is statistically more significant for Z-freq analysis. In the instance of a malfunctioning helical gear, the flaws induce high frequency vibration components, which can be used to detect the fault in the Zfreq. As the helical gear speed increases, the amplitudes below 1600 Hz increase. The scattering of Z-freq coefficients for the Large Normal and Small Fault helical gears at 500 rpm, 1000 rpm, 1500 rpm, and 2000 rpm is shown in Figure 4.6, along with the time and frequency domains for each gear speed. As the gear speed increases, the green and yellow dots, in particular, expand over the affix frequency. Additionally, all of the dots can be seen to split from one another at a high affix frequency relative to the annex frequency.





Figure 4.7 Z-freq scattering for 500rpm, 1000rpm, 1500rpm, 2000rpm at Large Fault and Small Normal helical gears.

The time domain and frequency domain experimental results for four distinct speeds in the Large Fault and Small Normal helical gear condition are shown in Figure 4.7. The time waveform data demonstrate the rise in transient components as the Helical Gear speed increases, as demonstrated by the spikes. The signal is filtered in the frequency domain using the Butterworth filter. Low frequency components, particularly those linked to the Helical gear speed, are eliminated. The fluctuation at high frequencies is statistically more significant for Z-freq analysis. In the instance of a malfunctioning helical gear, the flaws induce high frequency vibration components, which can be used to detect the fault in the Zfreq. As the helical gear speed increases, the amplitudes below 1600 Hz increase. The scattering of Z-freq coefficients for the Large Fault and Small Normal helical gears at 500 rpm, 1000 rpm, 1500 rpm, and 2000 rpm is shown in Figure 4.7, along with the time and frequency domains for each gear speed. As the gear speed increases, the green and yellow dots, in particular, expand over the affix frequency. Additionally, all of the dots can be seen to split from one another at a high affix frequency relative to the annex frequency.







Figure 4.8 Z-freq scattering for 500rpm, 1000rpm, 1500rpm, 2000rpm at Large Fault and Small Fault helical gears.

The time domain and frequency domain experimental results for four distinct speeds in the Large Fault and Small Fault helical gear condition are shown in Figure 4.8. The time waveform data demonstrate the rise in transient components as the Helical Gear speed increases, as demonstrated by the spikes. The signal is filtered in the frequency domain using the Butterworth filter. Low frequency components, particularly those linked to the Helical gear speed, are eliminated. The fluctuation at high frequencies is statistically more significant for Z-freq analysis. In the instance of a malfunctioning helical gear, the flaws induce high frequency vibration components, which can be used to detect the fault in the Zfreq. As the helical gear speed increases, the amplitudes below 1600 Hz increase. The scattering of Z-freq coefficients for the Large Fault and Small Fault helical gears at 500 rpm, 1000 rpm, 1500 rpm, and 2000 rpm is shown in Figure 4.8, along with the time and frequency domains for each gear speed. As the gear speed increases, the green and yellow dots, in particular, expand over the affix frequency. Additionally, all of the dots can be seen to split from one another at a high affix frequency relative to the annex frequency.

# 4.5 Root Mean Square (RMS)

In terms of RMS, the figure below uses data from Sensor 2(S2) to represent the average of the collected data. This is because the values of all the data collected from both sensors are similar. As for the trend depicted on the image, it indicates that the greater the running speed, the greater the RMS value. As the speed increases, the RMS value of both types of gear increases. The graph plots (y-axis) against (x-axis), i.e. RMS vs Speed (rpm).





Figure 4.9 RMS of Spur Gear

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Table 4.1 RMS of Spur Gear

13	Inc			
Speed (rpm)	Large F / Small F	Large F / Small N	Large N / Small F	Large N / Small N
3Ne	2 Juni 6		Sun and	
500	0.3004	0.3492	0.2891	0.2454
			÷	
1000	ERSITI 0.6188	IKAL M0.6455	SIA ME 0.4422	0.2426
1500	1.1989	1.3376	0.5833	0.3617
2000	1.3664	1.2172	0.8624	0.4762



Figure 4.10 RMS of Helical Gear

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Table 4.2 RMS of Helical Gear

Speed (rpm)	Large F / Small F	Large F / Small N	Large N / Small F	Large N / Small N
	"AINO			
500	0.3256	0.2028	0.2282	0.2209
_	ی میسیا مارد	- in the	ويور سيى ا	
1000	0.3706	0.381	0.3488	0.2419
U	NIVERSITI TE	KNIKAL MALA	YSIA MELAKA	
1500	0.4536	0.508	0.4511	0.318
2000	0.6476	0.6608	0.5779	0.4338

## 4.6 Z-Freq

The Z-freq coefficient obtained is plotted in Figure 4.11 for each speed between 500 and 2000 rpm for spur gear condition. For speeds between 500 and 1000 rpm, the Z-freq coefficient is nearly constant across the all condition. The Z-freq fluctuation is illustrated for the Large F/Small F and Large F/Small N. This could be a result of the spur gear state being unstable. This is also suggested by the fact that the Z-freq coefficient increased significantly from 1000 to 2000 rpm.



Figure 4.11 Z-Freq of Spur Gear

Table 4.3 Z-Freq of Spur Gear

Speed (rpm)	Large F / Small F	Large F / Small N	Large N / Small F	Large N / Small N
500	0 2131	0 3682	0 2089	0 1745
1000	0.2131	0.3082	0.2085	0.1745
1000	0.9913	0.4487	0.5908	0.1856
1500	2.5972	0.919	0.991	0.509
2000	2.7006	3.9421	1.5494	0.7967
The Z-freq coefficient obtained is plotted in Figure 4.12 for each speed between 500 and 2000 rpm for Helical gear condition. For speeds between 500 and 1000 rpm, the Z-freq coefficient is nearly constant across the all condition. The Z-freq fluctuation is illustrated for the Large F/Small F only. This could be a result of the helical gear state being unstable. This is also suggested by the fact that the Z-freq coefficient increased significantly from 1000 to 2000 rpm.



Table 4.4 Z-Freq of Helical Gear

Speed (rpm)	Large F / Small F	Large F / Small N	Large N / Small F	Large N / Small N
500	0.1732	0.1175	0.117	0.1085
1000	0.2501	0.3858	0.2683	0.1633
1500	0.5981	0.7329	0.6065	0.2898
2000	1.5124	0.8611	0.735	0.499

# 4.7 R-Squared

R-squared is a statistical measure that indicates how near the data is to the fitted regression line. It is also known as the coefficient of determination or, in the case of multiple regression, the coefficient of multiple determination.



Figure 4.13 R-Squared of Spur Gear

Figure 4.13 shows that the data collected from each Speed (RPM) and Z-freq is used to make the comparison by predict the statistical method. The polynomial regression has an R-squared value of 0.999, which is higher on Large Normal (Ln) and Small fault (Sf) spur gear condition because speed increase significantly on constant gear vibration at Spur gear condition. Due to the fact that the R-Square value exceeds 0.9, the data collected and analysis performed can be considered reliable in terms of predicting the outcome of spur gear vibration.



Figure 4.14 R-Squared of Helical Gear

Figure 4.14 shows that the data collected from the each Speed (RPM) and Z-freq is used to make the comparison by predict the statistical method. The polynomial regression has an R-squared value of 0.999, which is higher on Large Normal (Ln) and Small Normal (Sn) helical gear condition because speed increase significantly on constant gear vibration. Due to the fact that the R-Squared value exceeds 0.9, the data collected and analysis performed can be considered reliable in terms of predicting the outcome of Helical gear vibration.

#### 4.8 Distribution

In terms of distribution, the distribution procedure compares the accuracy of data acquired from the RMS and Z-Freq coefficients. All of the data presented is from both Spur Gear and Helical Gear, which includes a variety of faulty gear and normal gear in two sizes, Large Fault (Lf) and Small Normal (Sn), which contribute to this experiment. Other combinations include Large Normal (Ln) and Small Normal (Sn), Large Fault (Lf) and Small Fault (Sf), Large Normal (Ln) and Small Fault (Sf) for both types of gear. The data is then processed at four separate speeds: 500rpm, 1000rpm, 1500rpm, and 2000rpm, in that order.



Based on the distribution result from figure 4.15, it can be seen that speeds of 500rpm and 1000rpm have the closest accuracy among the other types of spur gear speed, indicating an accurate distribution. The next speeds are 1500 rpm and 2000 rpm, which have a substantially lesser accuracy than the earlier distribution speeds.



Based on the distribution result from figure 4.16, it can be seen that speeds of 500rpm, 1000rpm and 1500rpm have the closest accuracy among the other types of helical gear speed, indicating an accurate distribution. The next speed are 2000 rpm, which have a substantially lesser accuracy than the earlier distribution speeds.

#### **CHAPTER 5**

#### **CONCLUSION AND RECOMMENDATION**

#### 5.1 Conclusion

For the sake of conclusion, it can be stated that the fault diagnosis of gears using condition monitoring techniques is one of the most significant studies or analyses in the subject of rotating equipment. When normal gears and faulty gears such as Spur Gears and Helical Gears are used in this experiment with multiple speeds and multiple combinations of faulty and normal gears that are carried out, and when the efficiency classification is used, this can aid in the ability to identify a variety of gear faults that can be used for further fault diagnosis and can be used for further fault diagnosis. As a result of the analysis performed using MATLAB software to obtain the results, it has been determined that the time domain is not suitable for fault prediction when compared to frequency domain because the graph difference between fault and good condition is similar to the graph shown in the frequency domain. Then, the signal analysis that has been utilised in this experiment, which is RMS and Z-freq coefficiency, is useful for assessing the validity of the data acquired, as it demonstrates in greater or greater detail the behaviour of the normal and faulty gears based on the graph data. Finally, the research is concluded with the application of R-Squared and scatter distribution for the verification of the vibration signal for both types of gears through the use of the statistical method to verify the vibration signal for each type of gear. The primary goal of this research has been achieved, and it can also aid in a better understanding of the verification process of vibration analysis through the use of statistical methods, as well as a better understanding of the approach Vibration Signal Analysis (VSA) in the experiment, which are both beneficial.

#### 5.2 Recommendation

For the recommendation on this study, other varieties of gear and many more combinations of faulty and normal gears can be employed to acquire a better understanding of Vibration Signal Analysis (VSA). For instance, it can make use of Bevel Gears, Worm Gears, or Rack Gears to aid in the analysis's comprehension. Then, the laboratory's equipment can be improved by utilising a more advanced sort of machine that collects data more quickly or a machine that collects data more accurately. This is to ensure that time is saved and data obtained is more accurate, which results in increased efficiency for the individual doing the experiment or conducting the research.



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# APPENDICES

#### LAYSIA Progress Weeks 4 10 12 13 2 3 5 6 8 9 11 14 15 7 1 Project briefing Project Title Selection & Report Preparation Chapter 1 Chapter 2 Chapter 3 Report Completion and Draft Submission Report Submission and Presentation Video Submission BDP Weekly Logbook HMI

### APPENDIX A PSM 1 Gantt Chart.

PROGRESS	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11	W12	W13	W14	W15
PROJECT BRIEFING	COMPLETED			19.00					COMPLETED						
EXPERIMENTAL SETUP	CIII.	COMP	LETED	PE											
DATA COLLECTION	TE)	0		COMP	LETED						1				
RESULT ANALYSIS	III						C	OMPLE	TED		1				
RESULT VERIFICATION	843A					1	/			COMP	LETED				
CONCLUSION & RECOMMENDATION		nn :										COMPLETED			
WEEKLY BDP REPORTING (LOGBOOK)	ملاك	h	m	0,	4	2	$\leq$	СОМ	PLETED	11 m	نىق	9			
PROJECT REPORTING	-	44	44						COMPLE	TED					
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PRESENTATION & SLIDES														COMP	LETED

# APPENDIX B PSM 2 Gantt Chart.

<pre>59 title ('Time (s)'); 14 ylabel ('Time (s)'); 50 ylabel ('Time (s)'); 51 set(gcf, 'color', 'white'); 52 set(gca, 'FontSire', 20); 53 figure (1); 54 a = fft(data_2(:,1))/2; 55 power = abs(a(1:b)); 56 power = abs(a(1:b)); 57 power = abs(a(1:b)); 58 nyd = 1/2; 59 figure (1) 50 power = abs(a(1:b)); 51 ylabel('Arequency (tri)); 52 ylabel('hequency Domain (Sensor)'); 53 xlim([0 16600]); 54 ylim([0 4600]); 55 title('Frequency Domain (Sensor)'); 56 xlabel('Frequency (tri)); 57 ylabel('Armultude (ms^2)'); 58 set(gca, 'fontSire', 20); 59 set(gca, 'fontSire', 20); 50 figure (1); 51 ylabel('Arequency (tri)); 52 set(gca, 'fontSire', 20); 53 set(gca, 'fontSire', 20); 54 figure (1); 55 title('Frequency (tri)); 56 set(gca, 'fontSire', 20); 57 set(gca, 'fontSire', 20); 58 set(gca, 'fontSire', 20); 59 set(gca, 'fontSire', 20); 50 figure (1); 51 set(gca, 'fontSire', 20); 52 set(gca, 'fontSire', 20); 53 set(gca, 'fontSire', 20); 54 set(gca, 'fontSire', 20); 55 title('Frequency (tri)); 56 set(gca, 'fontSire', 20); 57 set(gca, 'fontSire', 20); 58 set(gca, 'fontSire', 20); 59 set(gca, 'fontSire', 20); 50 set(gca, 'fontSire', 20); 51 set(gca, 'fontSire', 20); 52 set(gca, 'fontSire', 20); 53 set(gca, 'fontSire', 20); 54 set(gca, 'fontSire', 20); 55 set(gca, 'fontSire', 20); 56 set(gca, 'fontSire', 20); 57 set(gca, 'fontSire', 20); 58 set(gca, 'fontSire', 20); 59 set(gca, 'fontSire', 20); 50 set(gca, 'fontSire', 20); 50 set(gca, 'fontSire', 20); 51 set(gca, 'fontSire', 20); 52 set(gca, 'fontSire', 20); 53 set(gca, 'fontSire', 20); 54 set(gca, 'fontSire', 20); 55 set(gca, 'fontSire', 20); 56 set(gca, 'fontSire', 20); 57 set(gca, 'fontSire', 20); 58 set(gca, 'fontSire', 20); 59 set(gca, 'fontSire', 20); 50 set(gra, 'fontSire', 20); 50 set(gra, 'fontSire', 20); 50 set(gra, 'fontSire', 20); 50 set(gra, 'fontSire', 20); 51 set(gra, 'fontSire', 20); 52 set(gra, 'fontSire', 20); 53 set(gra, 'fontSire', 20); 54 set(gra, 'fontSire', 20); 55 set(gra, 'fontSire', 20); 56</pre>	58	ylim([-4 4])
<pre>60 xlabel ('Time (s)'); 51 ylabel ('Acceleration (m/s^2)'); 52 set(gca, 'FontSize',20); 63 a = fft(data_2(:,1)); 64 b = length(data_2(:,1)); 65 b = length(data_2(:,1)); 66 nyd = 1/2; 67 power = abs(a(1:b)); 68 nyd = 1/2; 69 freq = fs*(1:b)/b*nyq; 70 figure(1) 71 subplc(212) 72 plot(frea,power,'b'); 73 xlim([0 1600]) 74 ylim([0 400]) xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx</pre>	59	title ('Time Domain (Accelerometer)')
<pre>51 ylabel ('Acceleration (m/s^2)'); 52 set(gcf, 'color', 'white'); 53 set(gcs, 'fontSize', 20); 64 65 a = fft(data_2(:,1))/2; 66 b = length(data_2(:,1))/2; 67 power = abs(a(1:b)); 68 nyq = 1/2; 69 freq = Fs*(1:b)/b*nyq; 70 figure(1) 71 subplat(212) 72 plot(freq,power, 'b') 73 xlim([0 1600]) 74 ylim([0 400]) 75 title('Frequency Domain (Senson)') 76 xlabel('Frequency Comain (Senson)') 77 ylabel('Amplitude (m/s^2)'); 78 set(gcf, 'color', 'white'); 79 set(gc, 'fontSize', 20); 79 79 79 set(gc, 'fontSize', 20); 70 70 figure(1) 71 subplat('Amplitude (m/s^2)'); 72 set(gc, 'color', 'white'); 73 set(gc, 'fontSize', 20); 74 ylabel('Amplitude (m/s^2)'); 75 set(gc, 'fontSize', 20); 76 xlabel('Frequency (Hz)'); 77 ylabel('Amplitude (m/s^2)'); 78 set(gc, 'fontSize', 20); 79 set(gc, 'fontSize', 20); 70 figure(1) 71 subplat('Amplitude (m/s^2)'); 72 set(gc, 'fontSize', 20); 73 set(gc, 'fontSize', 20); 74 set(gc, 'fontSize', 20); 75 set(gc, 'fontSize', 20); 76 set(gc, 'fontSize', 20); 77 set(gc, 'fontSize', 20); 78 set(gc, 'fontSize', 20); 79 set(gc, 'fontSize', 20); 70 set(gc, 'fontSize', 20); 71 set(gc, 'fontSize', 20); 72 set(gc, 'fontSize', 20); 73 set(gc, 'fontSize', 20); 74 set(gc, 'fontSize', 20); 75 set(gc, 'fontSize', 20); 76 set(gc, 'fontSize', 20); 77 set(gc, 'fontSize', 20); 78 set(gc, 'fontSize', 20); 79 set(gc, 'fontSize', 20); 70 set(gc, 'fontSize', 20); 71 set(gc, 'fontSize', 20); 72 set(gc, 'fontSize', 20); 73 set(gc, 'fontSize', 20); 74 set(gc, 'fontSize', 20); 75 set(gc, 'fontSize', 20); 76 set(gc, 'fontSize', 20); 77 set(gc, 'fontSize', 20); 78 set(gc, 'fontSize', 20); 79 set(gc, 'fontSize', 20); 70 set(gc, 'fontSize', 20); 71 set(gc, 'fontSize', 20); 72 set(gc, 'fontSize', 20); 73 set(gc, 'fontSize', 20); 74 set(gc, 'fontSize', 20); 75 set(gc, 'fontSize', 20); 76 set(gc, 'fontSize', 20); 77 set(gc, 'fontSize', 20); 78 set(gc, 'fontSize', 20); 79 set(gc, 'fontSize', 20); 70 set(gc, 'fontSize', 20); 70 set(gc, 'fontSize', 20); 71 set(gc, 'fontSize', 20); 72 set(gc, 'fontSize', 20); 73 set(gc, 'fontSize', 2</pre>	60	<pre>xlabel ('Time (s)');</pre>
<pre>52 set(gcf,'cdor','white'); 53 set(gca,'fotSize',20); 54 65 66 67 79 power = abs(a(1:b)/b*nyd; 68 79 rigure(1) 71 subplot(212) 72 plot(freq.power,'b') 73 xlim([0 1600]) 74 75 title('frequency Domain (Sensor)') 75 xlite('Irrequency Dimain (Sensor)') 76 xlabel('Amplitude (m/s'2)'); 77 ylabel('Amplitude (m/s'2)'); 78 set(gcf,'color','white'); 79 set(gca,'FotSize',20); 80 71 82 83 fz = 0.5*Fmax; 84 85 85 87 86 85 87 86 85 87 86 86 86 86 86 86 86 86 86 86 86 86 86</pre>	61	ylabel ('Acceleration (m/s^2)');
<pre>63 63 64 65 65 66 66 66 66 67 67 67 67 67 67 67 67 67</pre>	62	<pre>set(gcf,'color','white');</pre>
<pre>64 65 66 67 68 69 69 69 69 69 69 69 69 69 69 69 69 69</pre>	63	<pre>set(gca, 'FontSize',20);</pre>
<pre>65 a = fft(data_2(:,i)); 66 b = length(data_2(:,1))/2; 67 power = abs(a(1:b)); 68 nyq = 1/2; 69 freq = Fs*(1:b)/b*nyq; 70 figure(1) 71 subplot(212) 72 plot(freq,power,'b') 73 xlim([0 400]) %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%</pre>	64	ALAYSIA
<pre>66 b = length(data_2(:,i))/2; 67 power = abs(a(1:b)); 68 nyq = 1/2; 69 freq = Fs*(1:b)/b*nyq; 70 figure(1) 71 subplct(212) 72 plot(freq.power,'b') 73 xlim([0 1600]) XXXXXXXXXX 75 title('Frequency Umain'(Sensor)') 74 ylim([0 400]) XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX</pre>	65	a = fft(data_2(:,i));
<pre>67  power = abs(a(1:b)); 68  nyq = 1/2; 69  freq = Fs*(1:b)/b*nyq; 70  figure(1) 71  subplot(212) 72  plot(freq, power, 'b') 73  xlim([0 400]) xxxxxxxxx 75  title('Frequency Domain (Sensor)') 74  xlabel('Frequency (Hz)'); 75  set(gcf, 'color', 'white'); 76  set(gcf, 'color', 'white'); 77  set(gca, 'FontSize', 20); 80 81  Fmax=0.5*Fs; 78  fk = 0.25*Fmax; 82  fk = 0.5*Fmax; 83  fz = 0.5*Fmax; 84 85  % ### 1-KAZ ### %</pre>	66	<pre>b = length(data_2(:,i))/2;</pre>
<pre>68 nyq = 1/2; 69 freq = Fs*(1:b)/b*nyq; 70 figure(1) 71 subplot(212) 72 plot(freq.power,'b') 73 xlim([0 1600]) ***********************************</pre>	67	power = abs(a(1:b));
<pre>69 freq = Fs*(1:b)/b*nyq; 70 figure(1) 71 subplct(212) 72 plot(freq.power,'b') 73 xlim([0 400]) %%%%%%%%% 75 title('Frequency Domain (Sensor)') 74 ylim([0 400]) %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%</pre>	68	nyq = 1/2;
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<pre>76 xlabel('Frequency (Hz)'); 77 ylabel('Amplitude (m/s^2)'); 78 set(gcf, 'color', 'white'); 79 set(gca, 'FontSize', 20); 80 81 Fmax=0.5*Fs; 82 fk = 0.25*Fmax; 83 fz = 0.5*Fmax; 84 85 % ### I-KAZ ### %</pre>	75	title('Frequency Domain (Sensor)')
<pre>77 ylabel('Amplitude (m/s^2)'); 78 set(gcf, 'color', 'white'); 79 set(gca, 'FontSize', 20); 80 81 Fmax=0.5*Fs; 82 fk = 0.25*Fmax; 83 fz = 0.5*Fmax; 84 85 % ### I-KAZ ### %</pre>	76	xlabel('Frequency (Hz)');
78       set(gcf, 'color', 'white');         79       set(gca, 'FontSize', 20);         80       81         81       Fmax=0.5*Fs;         82       fk = 0.25*Fmax;         83       fz = 0.5*Fmax;         84         85       % ### I-KAZ ### %	77	ylabel('Amplitude (m/s^2)');
79       set(gca, 'FontSize', 20);         80         81       Fmax=0.5*Fs;         82       fk = 0.25*Fmax;         83       fz = 0.5*Fmax;         84         85       % ### I-KAZ ### %	78	<pre>set(gcf,'color','white');</pre>
$F_{max=0.5*Fs;} = f_{k} = 0.25*F_{max;}; f_{z} = 0.5*F_{max;}; f_{z} = 0.5*F_{max;} = 0.5*F_{m$	79	set(gca, 'FontSize',20);
81       Fmax=0.5*Fs;         82       fk = 0.25*Fmax;         83       fz = 0.5*Fmax;         84         85       % #### I-KAZ #### %	80	
82 fk = 0.25*Fmax; 83 fz = 0.5*Fmax; 84 85 % ### I-KAZ ### %	81	Fmax=0.5*Fs;
83 fz = 0.5*Fmax; 84 85 % #### I-KAZ ### %	82	fk = 0.25*Fmax;
84 85 % #### I-KAZ #### %	83	fz = 0.5*Fmax;
85 % #### I-KAZ #### %	84	4 ⁸
	85	% #### I-KAZ #### %

APPENDIX C Coding used in MATLAB to obtain Time Domain and Frequency Domain.

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# UNIVERSITI TEKNIKAL MALAYSIA MELAKA

# BORANG PENGESAHAN STATUS LAPORAN PROJEK SARJANA

TAJUK: FAULTY GEAR VIBRATION DIAGNOSTIC AND MONITORING

SESI PENGAJIAN: 2021/22 Semester 1

Saya **RUTTIRAN A/L ANBUALAGAN** mengaku membenarkan Laporan PSM ini disimpan di Perpustakaan Universiti Teknikal Malaysia Melaka (UTeM) dengan syarat-syarat kegunaan seperti berikut:

- 1. Laporan PSM adalah hak milik Universiti Teknikal Malaysia Melaka dan penulis.
- 2. Perpustakaan Universiti Teknikal Malaysia Melaka dibenarkan membuat salinan untuk tujuan pengajian sahaja dengan izin penulis.
- 3. Perpustakaan dibenarkan membuat salinan tesis ini sebagai bahan pertukaran antara institusi pengajian tinggi.
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# FAKULTI TEKNOLOGI KEJURUTERAAN MEKANIKAL DAN PEMBUATAN

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