WIRELESS A/C COMPRESSOR VIBRATION DIAGNOSTICS USING MACHINE LEARNING-BASED SIGNAL ANALYSIS Z-FREQ 2D WITH REFRIGERANT AND OIL AS FAULTS

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MASTER OF SCIENCE IN MECHANICAL ENGINEERING

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MUHAMMAD YUSZAIRIE BIN YUSRI

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in partial fulfillment of the requirements for the degree of
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2024

DECLARATION

I declare that this thesis entitled "Wireless A/C Compressor Vibration Diagnostics Using Machine Learning-Based Signal Analysis Z-Freq 2D With Refrigerant And Oil As Faults" is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature :...

Name : Muhammad Yuszairie Bin Yusri

Date : ……….14 April 2025..................

APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality as a partial fulfillment of Master of Science in Mechanical Engineering

Signature	:...
Supervisor Name	: Ts. Dr. Nor Azazi Bin Ngatiman
Date	:……….14 April 2025.................

DEDICATION

This work of thesis I would like to dedicate my whole love to both beloved late parents Zaiton Binti Shamsudin and Yusri Bin Harun. Although both of them are no longer with us, their advice, wisdom, love, unwavering support, and encouragement patiently supported me through life's struggles, believing I could achieve great success both personally and academically. Undoubtedly, without their prayer, I will never be at where I am now. I wish both of you still with us, and the memories with you will always stay in my heart.

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ABSTRACT

Advanced diagnostic monitoring and fault detection in vehicle A/C systems are critical for the automotive and A/C industries to accurately identify system anomalies and enable early detection of mechanical failures, particularly in compressor health and performance. Key components of automotive A/C systems—compressor, condenser, evaporator, thermal expansion valve, and receiver drier—are essential for optimal functionality. A primary factor contributing to poor compressor performance is insufficient oil lubricant and refrigerant R134a. This study aims to develop the Z-Freq 2D coefficient as a novel statistical method for detecting faults in vehicle compressors by analyzing vibration data influenced by refrigerant and lubricant levels, using a wireless diagnostic approach and validating findings through machine learning, simulation, and experimental testing. Fault conditions were simulated by varying the speed of the compressor, refrigerant amounts, and lubricant volumes. Vibration data was collected using a Phantom Vibration Sensor attached to the compressor of a Myvi 1.5L X vehicle with a registered air conditioning system. Data analysis was performed using MATLAB, where the Z-Freq 2D coefficient was applied to generate graphical representations and validate results using machine learning models, specifically Support Vector Machine (SVM) and k-Nearest Neighbors (kNN). The experimental parameters included compressor speeds ranging from 750 to 2000 RPM, refrigerant levels from 280g to 360g, and lubricant volumes from 40ml to 120ml. Industry-recommended benchmark values were 320–330 g of refrigerant and 80–90 ml of lubricant. Results indicate that the Z-Freq 2D coefficient, combined with the Phantom Vibration Sensor, effectively identifies compressor faults. The SVM model outperformed kNN, achieving 87.1% accuracy and 98.6% sensitivity, compared to kNN's 82.9% accuracy and 88.6% sensitivity. Additionally, an increase in compressor RPM resulted in higher Z-Freq 2D data distribution, correlating with elevated vibration levels while excluding noise from the vehicle frame. The study also highlights a limitation in the wireless diagnostic method, which depends on stable network connectivity for transmitting data to cloud-based platforms such as DigivibeMX or EI Analytic. The findings demonstrate the reliability of the Z-Freq 2D coefficient as a diagnostic tool for fault detection in automotive compressors. This method, validated through experimentation and machine learning, offers significant potential for enhancing the accuracy of HVAC system diagnostics. The research underscores the importance of maintaining optimal refrigerant and lubricant levels to ensure compressor efficiency and overall system reliability.

ABSTRAK

Pemantauan diagnostik yang maju dan pengesanan kerosakan dalam sistem penyaman udara kenderaan adalah kritikal untuk industri automotif dan penyaman udara bagi mengenal pasti anomali sistem dengan tepat serta membolehkan pengesanan awal kegagalan mekanikal, terutamanya berkaitan kesihatan dan prestasi pemampat. Komponen utama sistem penyaman udara kenderaan—pemampat, kondensor, penyejat, injap pengembangan terma, dan penerima pengering—adalah penting untuk memastikan fungsi optimum. Faktor utama yang menyumbang kepada prestasi pemampat yang lemah ialah kekurangan pelincir minyak dan penyejuk R134a. Kajian ini bertujuan membangunkan pekali Z-Freq 2D sebagai kaedah statistik baharu untuk mengesan kerosakan pemampat kenderaan dengan menganalisis data getaran yang dipengaruhi oleh tahap penyejuk dan pelincir, menggunakan pendekatan diagnostik tanpa wayar serta mengesahkan dapatan melalui pembelajaran mesin, simulasi, dan ujian eksperimen. Keadaan kerosakan disimulasikan dengan memvariasikan kelajuan pemampat, jumlah penyejuk, dan isipadu pelincir. Data getaran dikumpul menggunakan Phantom Vibration Sensor yang dipasang pada pemampat kenderaan Myvi 1.5L X dengan sistem penyaman udara berdaftar. Analisis data dilakukan menggunakan MATLAB, di mana pekali Z-Freq 2D diaplikasikan untuk menghasilkan perwakilan grafik dan mengesahkan keputusan menggunakan model pembelajaran mesin, khususnya Support Vector Machine (SVM) dan k-Nearest Neighbors (kNN). Parameter eksperimen termasuk kelajuan pemampat antara 750 hingga 2000 RPM, tahap penyejuk dari 280 g hingga 360 g, dan isipadu pelincir dari 40 ml hingga 120 ml. Nilai penanda aras yang disyorkan oleh industri ialah 320–330 g penyejuk dan 80–90 ml pelincir. Keputusan menunjukkan bahawa pekali Z-Freq 2D, apabila digabungkan dengan Phantom Vibration Sensor, berkesan dalam mengenal pasti kerosakan pemampat. Model SVM mengatasi kNN, dengan ketepatan 87.1% dan sensitiviti 98.6%, berbanding kNN yang mencapai ketepatan 82.9% dan sensitiviti 88.6%. Tambahan pula, peningkatan RPM pemampat menghasilkan taburan data Z-Freq 2D yang lebih tinggi, yang berkorelasi dengan peningkatan tahap getaran sambil mengecualikan bunyi daripada kerangka kenderaan. Kajian ini juga menonjolkan had kaedah diagnostik tanpa wayar, yang bergantung kepada kekuatan isyarat rangkaian untuk menghantar data ke platform berasaskan awan seperti DigivibeMX atau EI Analytic. Penemuan ini membuktikan kebolehpercayaan pekali Z-Freq 2D sebagai alat diagnostik untuk pengesanan kerosakan pemampat automotif. Kaedah ini, yang disahkan melalui eksperimen dan pembelajaran mesin, menawarkan potensi besar dalam meningkatkan ketepatan diagnostik sistem penyaman udara. Kajian ini menekankan kepentingan mengekalkan tahap penyejuk dan pelincir yang optimum bagi memastikan kecekapan pemampat dan kebolehpercayaan keseluruhan sistem.

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LIST OF ABBREVIATIONS

UTeM	-	Universiti Teknikal Malaysia Melaka
A/C	-	Air Conditioning
HVAC	-	Heating, Ventilation, And Air Conditioning
RPM	-	Revolution Per Minute
i-Kaz	-	Integrated Kurtosis Algorithm
SVM	-	Support Vector Machines
k-NN	-	k-Nearest Neighbors
CFC	-	Chlorofluorocarbon
HCFC	-	Hydrochlorofluorocarbon
HFC	-	Hydrofluorocarbon
ML	-	Machine Learning
MATLAB	-	Matrix Laboratory
PVS	-	Phantom Vibration Sensor
HEV	-	Hybrid Electric Vehicle
PMSMs	-	Permanent Magnet Synchronous Motors
OCR	-	Oil Circulation Rate
GWP	-	Global Warming Potential
COP	-	Coefficient Of Performance
NMS	-	Network Management Systems
IoT	-	The Internet of Things
AUC	-	Area Under the Curve

LIST OF SYMBOLS

δ	-	Voltage angle
n	-	The number of sample
f	-	frequency
σ	-	The Square Standard deviation value
x	-	value of data point
μ	-	mean of the data
Z_2^f	-	z frequency 2D at second central moment

LIST OF APPENDICES

LIST OF PUBLICATIONS

The followings are the list of publications related to the work on this dissertation paper:

Muhammad Y., Azazi N., Shamsul A., Muhammad N.O. 2024. Wireless HVAC compressor diagnostics using machine learning-based signal analysis Z-Freq 2D. Journal of Physics: Conference Series, Volume 2688, 7th International Conference on Mechanical Engineering Research 2023 (ICMER 2023) 12-13 september 2023 Kuantan, Malaysia

CHAPTER 1

INTRODUCTION

1.1 Background

Diagnostic monitoring and fault detection in vehicle HVAC systems have become crucial for both the automotive and HVAC industries to detect faults and prevent mechanical failures or breakdowns (Zhan and Makis. 2006). The information obtained from the diagnostic performed, is capable of providing an early planning strategy when there are early warning signs of machine faults which preventing any further critical damage to the machine components in the future. Statistical diagnostics is an effective method for mechanical applications involving high vibration signals, which can lead to significant failures in machine performance, such as in wind turbines, aircraft motors, and building HVAC systems..

In many industrial applications, compressors are essential components because they supply the power required for a wide range of operations. Efficiency is essential for these systems to function optimally and have a long lifespan. However, preventive maintenance and the avoidance of costly downtime still rely on the early identification and diagnosis of potential problems, particularly those related to vibration. This work investigates the application of wireless diagnostics, with a focus on utilizing newly developed Z-freq 2D coefficients, to obtain unparalleled understanding of the vibration dynamics of compressors.

Since vibration analysis reflects wear, misalignment, and mechanical imbalances, it has long been acknowledged as a critical machinery health indicator. One of the drawbacks of traditional wired monitoring systems is their geographical and installation complexity. In addition to overcoming these obstacles, the use of wireless technologies creates opportunities for real-time diagnostics and monitoring, offering a more thorough grasp of compressor health.

The specific objective of this study is to introduce a new method for vibration analysis, known as Z-freq coefficients. According to Ngatiman N., et al (2021) Z-freq is a technology that uses vibration sensors to evaluate signals and convert auditory data into signal features. It is also used to monitor engines. The Integrated Kurtosis-based Algorithm (i-Kaz), which divides a time-domain signal into frequency ranges, is one of the simplified and effective statistical signal assessment approaches used in this method (Ngatiman N., et al. 2021). Our objective is to formulate a new statistical-based signal data analysis using Z-Freq 2D and to understand the distribution of compressor vibrations and their frequency components through this advanced statistical method. In addition, to examining and evaluating experimentation data in order to identify the relationship between vibration on the compressor and experimental parameters.

The following sections will cover our study's methodology, results from our Z-freq 2D coefficient analysis, and implications for the compressor health monitoring field. We will also examine the literature that has already been written on wireless diagnostics and vibration analysis. With potential applications spanning beyond compressors, the knowledge gathered from this study is expected to make a substantial contribution to the development of wireless diagnostics in industrial settings.

This study aims to rigorously assess the impact of different amount of refrigerants and the amount of oil on the performance and efficiency of vehicle air conditioning (A/C) systems. Employing Z-freq 2D statistical analysis alongside machine learning validation techniques, the research aims to explain the optimal refrigerant choices that enhance A/C functionality while ensuring environmental sustainability. This approach promises to contribute significantly to the field, offering a comprehensive evaluation of refrigerant efficacy within vehicular contexts.

1.2 Problem statement

It is crucial to assess and monitor the performance of the compressor in vehicle air conditioning (A/C) systems to ensure both the quality of the A/C and the comfort of the users. Wireless diagnostics using state-of-the-art machine learning-based signal analysis with Z-freq 2D is a method for monitoring the performance of vehicle compressors remotely, eliminating the need for close-up physical inspections to detect system faults.

In this research, the coefficients in the formula are derived from the standard notation of 2D Z-frequencies. In another words new formula based on a coefficient system for 2D Z-frequencies defined notation has been put forth. For two-dimensional digital signal processing applications, this method shows potential in streamlining calculations and analysis. Nonetheless, there is still much to learn about the formula's efficiency, especially with regard to how quickly and accurately the standard notation and coefficient representation may be converted.

Using a wireless diagnostic approach, vibrations from a car compressor were evaluated in an early exploratory experiment. But the study's concentration on a single issue or a small sample size meant that its breadth was constrained. With the goal of improving the wireless technique and proving its effectiveness for thorough compressor vibration analysis, this preliminary study lays the groundwork for future research.

This innovative study represents a paradigm shift in the identification of car compressor problems. It offers an innovative methodology that breaks from conventional practices and provides a new viewpoint on locating compressor problems. By gaining a greater understanding of defect causes and enabling more accurate and efficient identification, this novel technique has the potential to completely transform the field of compressor diagnostics. The study lays the groundwork for additional investigation and advancement, which may result in the development of cutting-edge diagnostic instruments for car compressors.

Hence, the three problem statement of this research can be stated as follow;

i) The current efficiency of the formula, derived from the standard notation of 2D Z-frequencies, is under investigation, highlighting the need for further optimization and validation,
ii) The existing evaluation of vehicle compressor vibration using a wireless diagnostic technique has been limited in scope, indicating the necessity for a more comprehensive and detailed study,
iii) This research proposes a novel and innovative approach to diagnosing vehicle compressor faults, offering a fresh perspective that addresses the limitations of current diagnostic methods.

1.3 Research question

The main aim of this research is to propose a new statistical diagnostic methodology focusing on the implementation of wireless HVAC compressor diagnostics using state-of-the-art machine learning-based signal analysis with Z-freq 2D. In this section of the proposal, there are several research questions that can be define. Specifically, the research question are as follows:

i) Is there enough foundation in the vibration sensitivity found in this study to create a fault detection system that can identify and isolate specific compressor faults?.

ii) Could the wireless Phantom Vibration Sensor (PVS) provide better defect detection performance than connected cable sensors, producing quantifiably separate data sets?.

iii) Is it possible to determine the accuracy level attained by using 2D Z-Frequency analysis as a trustworthy tool for identifying compressor faults?.

1.4 Research objective

The primary goal of this study is to develop new statistical diagnostic techniques that are more organized and efficient for accurately estimating the likelihood of malfunctions or defects in a car's HVAC system, thereby preventing further damage. Specifically, the objectives are as follows:

i) To formulate a new statistical - based signal data in Z-freq 2D for accurate wireless system fault diagnosis and improve the fault detection in the HVAC,

ii) To investigate and analyze experimentation data to recognize the connection of vibration on the compressor with a range of different experimental parameters,

iii) To validate the data gained through simulation, experimental and field testing using a machine learning method and Z-freq 2D.

1.5 Scope of research

This research aims to explore and understand the significance of wireless diagnostics by employing a wireless sensor to evaluate the impact of various parameters, which may function as flaws, in the A/C system on the high-frequency vibrations generated by vehicle components. The scope of this research are as follows:

- Discover the benefits of the new inspection techniques that initialize the Z-Freq 2D coefficient for the automotive sectors,
- Using a high-end sensor with many parameters including speed (RPM), refrigerant volume, and oil %, a number of tests will be conducted and assessed,
- The recorded data will be analyzed using state-of-the-art machine learning-based signal analysis with Z-Freq 2D,
- The data will be analyzed using MATLAB software, and the integrated kurtosis algorithm (i-Kaz) will be used to examine the frequency reported as i-Kaz can help to determine the dispersed of data scattered,
- The outcome of the diagnostics will be used to determine the kind of system malfunction.

1.6 Dissertation paper outline

Based on the objectives previously presented and on the approach proposed before, this dissertation paper is made up of five (5) chapters, which contents are summarized as follows:

- Chapter 1. Introduction. This chapter presents the background of the study, research problems, objectives, scope, contributions, and significance of the research.
- Chapter 2. Literature review. This chapter starts with brief overview of the important of a good air-conditioning system on the daily lives of human. Vehicle air conditioning is covered in detail in this chapter. It begins with regular compressor maintenance and investigates the effects of faults on compressor performance. The information on automotive HVAC systems, including heat and cold distribution, is then reviewed. Lastly, it explores other machine learning approaches for automotive diagnostics, concentrating on the particular approach employed in this study.
- Chapter 3. Materials and Methods. This chapter outlines the techniques developed to organize the study's execution. It describes the specific methods and procedures required to gather, examine, and evaluate data based on parameters such as speed (RPM), refrigerant amount, and oil percentage, to address the research questions.
- Chapter 4. Result and Discussion. In this chapter, the developed models have been tested and verified through the machine learning training in the MATLAB software and obtaining the k-NN and SVM data.

- Chapter 5. Conclusion and Recommendations. The primary findings and accomplishments of the research are outlined in this chapter, which also makes recommendations for future research directions.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The presence of air conditioning in our daily lives has provided numerous benefits and comfort. Our comfort, health, and general well-being are greatly enhanced by air conditioning, which is an essential part of our life. Our perception of comfort in indoor spaces has changed dramatically since the development of air conditioning. Air conditioning systems enhance our well-being and productivity by providing relief from intense summer heat and regulating the climate across various industries. Automotive air conditioning can be defined as a collection of parts that work together to cool the inside of an automobile, cooling the environment to make people more comfortable even when the summer heat is at its worst as it is their main purpose (Student Lesson. 2013). Central to these systems, the compressor and its oil are crucial for system efficiency, dictating the overall effectiveness of the A/C system. Recent advancements, such as the development of high-efficiency Permanent Magnet Synchronous Motors (PMSMs) for automotive electrical air conditioning compressors, underscore the importance of optimizing these components for reduced noise and improved performance, especially in electrified vehicles (Khanchoul et al., 2023). In addition, the two most frequent reasons for compressor failure, according to Don't Blame The Compressor (Kimberly Schwartz. 2016), are slugging and lubricant loss.

A consistent annual checkup for the vehicle compressor especially for HEV's compressor, is a must as it will help to prevent any problems rise for the driver such as car breakdown or poor driving condition while on the road. Improper diagnostic of the vehicle also will cause some faults in the vehicle to be overlooked. In the long term, would cause bad effects on both the vehicle and people in the cabin. For an examples a dangerous gaseous from the HVAC leaks into the vehicle. From an average human point of view it may be nothing to worry about, from a medical and hazard point of view it is a very concerning case and could lead to death. Originally the HVAC system should provide safe and fresh air into the cabin but, a bad diagnostic to find the leak which releases harmful gases such as Carbon Dioxide (CO2) will cause numerous effects from headache, and vomiting to death (Prabhu, S., et al. 2018).

The invention of air conditioning eventually have swept into automotive industry providing not only cools air in home but also in vehicle. Having an air conditioning definitely provide a comfortable lives to everyone not only able to control the room temperature but also helps in productivity and performance of individual. Besides that the quality of air produce by good air conditioning especially in vehicle, would enhance the comfortably of passenger during a long ride. A number of attempts have been made to establish a standardized test procedure for interior air quality in the automotive industry. Fractional air re-circulation is one potential solution to this problem, showing that a balance can be struck between the advantages of full re-circulation and its drawbacks (Russi L., et al. 2022).

Nowadays seeing the importance of having air conditioning to our daily lives, almost all automotive vehicle applying the air conditioning concept as part of their working mechanism. Therefore overall structure for automotive air conditioning to functions, the compressor, condenser, evaporator, thermal expansion valve, and receiver drier are the key parts of the air conditioning system. A vehicle's A/C system is built using these fundamental and common parts, with the compressor serving as the system's central component. (Ahmad Z.A, et al. 2016 and Lee G.H. et al. 2000). Recent studies, the heart of a good air conditioning of a vehicle is the the health of the air conditioning compressor according to Meena et al. (2023) which elucidate that the optimal balance of compressor oil volume as well as the refrigerants amount is crucial for maximizing the lifespan of the compressor while ensuring thermal efficiency. Excessive oil or refrigerant, however, can detrimentally affect the system's thermal performance, underscoring the importance of precise oil management for optimal A/C operation (Meena, et al. 2023). This signified that balancing refrigerant and oil quantities are in high priority in optimizing the cooling performance and system longevity.

Vehicle air-conditioning systems are pivotal in ensuring passenger comfort and safety, incorporating components like compressors and refrigerants for efficient thermal management. Recent advancements highlight the integration of vapor injection heat pump air conditioning for enhanced heating performance, crucial for electric vehicle range and battery safety under varying conditions (Yuan, Guo, & Zhang. 2024).

The significance of refrigerant type in vehicle A/C systems is paramount, affecting performance, efficiency, and environmental impact. As the automotive sector evolves towards electrification, the choice of refrigerants becomes crucial in optimizing thermal management strategies, directly influencing the efficiency and environmental sustainability of these systems (Bali et al. 2024). This underscores the need for ongoing research to identify refrigerants that strike an optimal balance between cooling efficiency and environmental sustainability.

Evaluating vehicle A/C system performance, particularly the dynamic responses of components like compressors, presents significant challenges. Recent studies, such as the one by Kim and Kang (2023), highlight the complexities of analyzing piston air compressors in railway vehicles through sensor data, underscoring the intricacies in monitoring operational states and performance characteristics. This dynamic analysis is crucial for enhancing safety, reliability, and maintenance practices, offering a glimpse into the broader challenges faced across vehicular A/C systems (Kim & Kang. 2023).

The motivation for investigating the effects of refrigerant and compressor oil volumes on air-conditioning performance is underscored by the quest for enhanced system efficiency and operational capabilities. Recent studies, such as that by Alahmer and Ghoniem (2023), highlight the potential of optimizing these variables through advanced lubrication technologies and modeling techniques, aiming to bridge gaps in current literature and achieve significant improvements in energy efficiency and performance metrics of air-conditioning systems (Alahmer, A., & Ghoniem, R. M. 2023).

Recent advancements in automotive air-conditioning systems have focused on optimizing the oil circulation rate (OCR) and exploring the impact of refrigerant types and oil volumes on system efficiency. Studies like those by Haider, Wang, and Elbel (2023) have highlighted the critical role of accurate OCR measurement for system optimization, particularly with the shift towards low-OCR compressors. Additionally, research into low-global warming potential (GWP) refrigerants, such as R1234yf and R1234ze(E), has shown promising reductions in exergy destruction and improvements in system performance compared to traditional refrigerants (Alhendal et al., 2020). This review builds upon these findings, aiming to contribute new knowledge on the synergistic effects of refrigerant types and oil volumes on the efficiency and environmental impact of automotive air-conditioning systems.

In this research studies, the Perodua Myvi is chosen as Myvi is automotive vehicle that have widespread use, demographic suitability, and the particular characteristics of its air-conditioning system that align with the research objectives. This example demonstrates how rigorous selection criteria and test rig evaluation are crucial in research, even though it's not directly related to the Perodua Myvi. For a precise introduction tailored to the Perodua Myvi, it would be beneficial to consult the most recent automotive and mechanical engineering literature that specifically addresses vehicle test rigs and their selection criteria.

We employed a comprehensive methodological framework leveraging wireless vibration accelerometer for precise measurement of compressor vibrations. This approach was meticulously calibrated to ensure measurement accuracy. We introduced the innovative Z-freq 2D statistical analysis for enhanced data interpretation. Crucially, machine learning algorithms, specifically Support Vector Machines (SVM) and K-Nearest Neighbors (k-NN), played a pivotal role in validating our findings, laying the groundwork for a detailed exploration in subsequent sections. This integration of advanced statistical techniques and machine learning validation represents a significant advancement in the field of compressor diagnostics and vibration analysis (Muhammad Y. et al., 2024).

The primary objective of this study is to investigate the impact of refrigerant and oil volume changes on the efficiency and performance of air conditioning systems. Recent research by Mohammed Dilawar and A. Qayoum (2023) evaluated the performance of novel refrigerant mixtures in air conditioning systems using Al2O3 nanolubricant, highlighting the significance of refrigerant composition and lubrication in optimizing system performance (Dilawar & Qayoum, 2023). This study hypothesizes that specific alterations in refrigerant and oil volumes can lead to measurable improvements in system efficiency and overall performance, contributing to the development of more sustainable and efficient cooling technologies.

2.2 Heating, ventilation, and air conditioning (HVAC) system

The HVAC (heating, ventilation, and air conditioning) system is a complicated combination of technology intended to control and enhance the interior climate of different types of buildings. With a foundation in science, HVAC systems seek to ensure the health and comfort of inhabitants by precisely controlling humidity, air quality, temperature, and ventilation. Initially, HVAC systems were only integrated into building compartments; however, in the late 19^{th} (nineteenth) century, an inventor decided to install HVAC systems in vehicles.

Vehicles were invented in the 19^{th} (nineteenth) century, with the earliest designs resembling horse-drawn carriages powered by internal combustion engines. In most of history books, both designer Gottlieb Daimler or Karl Benz are the designer of automobiles, but if we were in thorough research the earlier automobile design were invented by Nicolas Joseph Cugnot of France. Given that steam engines propelled the earliest self-powered road vehicles, Nicolas Joseph Cugnot of France constructed the first automobile in 1769, which is acknowledged as the first by the Automobile Club de France and the British

Royal Automobile Club and this is because the era of modern automobiles was ushered in by the extremely successful and useful gasoline-powered vehicles that Daimler and Benz both designed (Bellis, Mary. 2019). Through numerous design configuration and experimentation, designer such Karl Benz's Motorwagen (1886) and the Ford Quadricycle (1896) finally made a automobiles that worked and looked like the automobiles we used today.

Conduction and convection is the fundamental idea underlying how an HVAC system works. The concepts of thermodynamics must first be understood in order to comprehend how air conditioning operates. Refrigerator fluid, which is used in air conditioners, is a liquid that absorbs heat and turns into a gas (evaporate) as a result. The liquid cools as heat is absorbed from the surrounding region (Bhatia A. 2014).

Hence the compressor, condenser, evaporator, thermal expansion valve, and receiver drier are thus the essential components of the air conditioning system's overall structure and function. These basic and typical components make up the A/C system of a car, with the compressor functioning as its main component. (Ahmad Z.A, et al. 2016; Lee G.H, et al. 2000).

In spite of widely supported environmental issues like global warming and ozone depletion, for which this refrigerant is highly responsible, most of the refrigerant and air-conditioning industries are still using mechanical compressor-based refrigerant technology today due to its high COP and high refrigerant effect. The adsorption cooling system was neglected for several decades while the compression refrigeration technology was accelerated by technological innovations like CFC/HCFC/HFC refrigerants and compact mechanical compressors (Mohd Khanafiah M., et al. 2022). Due to this reason, this research is conducted in safe environment and inside a experiment laboratory with safety gears.

2.3 Understanding machine learning: Machine learning in automotives

When analyzing an A/C compressor malfunction, which may be related to factors such as a lack of refrigerant or oil in the system, machine learning offers a valuable mathematical and statistical methodology. This experiment analysis method involves calculating and identifying any data changes using the coefficient formula.

Machine learning (ML) is a subfield of artificial intelligence (AI) that uses algorithms and data to enable software programs to anticipate outcomes with accuracy. Additionally, machine learning algorithms can mimic how people learn by using past data as input to forecast new output values (Tarek B. et al., 2021). The ability of a machine to mimic intelligent human behavior is the general definition of machine learning. The Z-freq 2D coefficient will be validated using Machine Learning through the MATLAB software. MATLAB stands for Matrix Laboratory which is a high level programming language and computing environment that developed by company known as MathWorks. One example of invention using the machine learning is the usage of reasonably priced smart sensors, which allow users to record environmental conditions and upload them to the cloud (Wandy Y, et al. 2021). Numerous techniques exist for studying the vehicle refrigeration system. For instance, computational method simulation can be used to mimic the functioning of the HVAC system in three dimensions (Joudi, K. A., et al. 2003).

2.3.1 Machine learning: Matrix Laboratory (MATLAB)

The history of MATLAB dates back to the late 1970s, when it was created by computer scientist and mathematician Professor Cleve Moler, who is also a co-founder of MathWorks (Cleve M., Little J. 2020). The full version of MATLAB was released in 1980s. Machine learning is a technique that many researchers employ to process large amounts of data and identify malfunctions in machinery, such as the HVAC compressor in this car, whether the compressor is operating normally or abnormally (Mochammad S., et al. 2021).

The concept of machine learning can be traced back to the 1950s, known as "The Birth of Machine Learning", when Alan Turing proposed the Turing Test to explore machine intelligence. Then a year later in 1951, another pioneer Christopher Strachey successfully developed the first computer learning program. The invention of machine learning have becoming advancing through ages until in year 1990s, support vector machine (SVM) is introduced and became popular in year 2000s as the most useful and powerful classification algorithm.

The earliest known applications of k-NN can be detected in early 1950s and 1960s. Researchers who investigated the concept of using nearest neighbors for pattern categorization, like Evelyn Fix and Joseph Hodges, lay the groundwork for it. However the first algorithm that implemented for k-NN was introduced by Dasarathy in 1991 which the wider machine learning community began to take notice of k-NN. A machine learning method is used to classify an unlabeled testing set and a testing article by computing the distance between the article and all of the training articles. The algorithm reads a collection of labeled training sets (Ismail H., et al. 2007). Its appeal was influenced by its intuitiveness and capacity to manage difficult choice boundaries.

Through out the world history of machine learning both SVM and k-NN have remained the most reliable and fundamental algorithm for engineers and research pioneers in the field of machine learning especially due to their simplicity and ease of implementation. Increased availability and simplicity of implementation have resulted from the integration of k-NN and SVM into machine learning frameworks and tools. For both practical uses and educational ones, the algorithm is still a useful tool.

Utilizing a data measuring device for experimentation, machine learning was employed in this study to compute and diagnose the data. Through the measurement of the vibration data signal gathered at the compressor, the research introduces a novel statistical approach to air conditioning system diagnosis. In statistical comparison findings, the acquired data are examined and presented. In contrast to the conventional approach, which depends on the human senses, we demonstrate the effectiveness of utilizing machine learning to identify problems in automobile air conditioning.

2.3.2 Z-freq 2D Signal Analysis

The evaluation of how good the performance metrics are determined by the accuracy of the measurements and the measuring of a signal can reveal changes in energy, phase, amplitude, and frequency. There are currently two types of categories of collected signal data which are deterministic and non-deterministic. A deterministic signal can be define as a mathematical link between the time domain and frequency domain values.

Numerous signals in everyday applications are stochastic or non-deterministic, making it difficult to analyze them with signal processing techniques (Ngatiman and Nuawi.2018).

The collected data needs to be filtered to remove any unwanted noise produced during testing or by linked components, such as the entire HVAC system of the vehicle. There will be two primary categories will be created from filtered signal data: low frequency (called affix) and high frequency (called annex). These classifications are crucial for examining the trends in each condition under investigation. In order to gain a deeper understanding of the association between affix and annex frequency, the analytical approach is utilized in the second phase to calculate the Z-freq 2D coefficient and create a 2D representation graph. Hence a filtering coding was insert in the MATLAB software.

Z-freq 2D is a statistical method used to calculate and analyze measured signal data. From the measured signal, the statistical features were extracted using the statistical parameter which is an indicator of the air conditioning system's performance or the compressor's ability to operate is the statistical parameter utilized in research for signal classification. Therefore in this research, the Fast Fourier Transform (FFT) will be used as the collection of random data was first transformed into the frequency domain. According to Ngatiman N.A. et al. (2021), Z-freq is a statistical technique, was used to further examine the data set. Z-freq 2D was in fact an advancement form that derived from Z-freq. Z-freq 2D is a new statistical signal analysis method that analyse data signal from vibration sensor namely Phantom Vibration Sensor (PVS) which records three different axial data that based on frequency domain and have an output of acceleration (mm/s2) (Ngatiman N., et al. 2021).

2.3.3 Wireless diagnostics technologies

In today modern societies, we have achieved numerous success throughout all of humanity civilisation. The invention of thousands of technologies have create a great impact to our lifestyle. Providing comfort, stabilities and amusement to our daily life, either to help ease our life and/or to provide a futuristic development. One of the invention human ever achieved is wireless diagnostics. Wireless diagnostics is a variety of instruments and frameworks are included in the category, and their purpose is to keep monitoring, identify, diagnose, and control wireless networks and associated equipment. These technologies are necessary to provide connectivity, maintain network performance, and resolve problems. According to Marasovi´c I., et al. (2024), With applications including electric motor programming and control, remote system and environment monitoring, and industrial equipment fault diagnostics, wireless technologies are becoming a regular feature of modern industrial facilities (Marasovi´c I., et al. 2024)

Development of wireless diagnostics have been integrated and utilized into a wide range of industries such as automotives, medical, healthcare, manufacturing, public safety, energy and utilities, and et cetera. There are about 9 key aspects of wireless diagnostics technologies that can be identified which are Network Analyzer and Sniffers, Spectrum Analyzer, Performance Monitoring Tools, Remote Diagnostic Tools, Mobile Diagnostics Apps, IoT Device Diagnostics, Cloud-Based Diagnostic Platforms, Network Management Systems (NMS), and Artificial Intelligence and Machine Learning Tools. Each of these devices and techniques are necessary to keep wireless networks operating well, guarantee connectivity, and address problems as soon as they appear. The proliferation of information, ease of deployment, low installation costs for monitoring applications, and advancements in wireless communication technology have all contributed to the substantial benefits of monitoring technology systems (Kaidi H., et al. 2024).

2.3.4 Machine learning classification metrics

To validate the data analysis, Evaluation Metrics (EM) are employed. An Evalution Metrics (EM) is the method to quantify the performance of a machine learning which to assess the performance of a model, algorithm and even systems. In EM there severals types of evalution including Classification, Regression, and Clustering, which depends on the type of problem addressed in the situation.

In this research, Classification Metrics (CM) were used to evaluate performance metrics. Classification Metrics (CM) is the quantifiable measurements that are employed to assess a classification algorithm's performance. There are nine common of CM, which are Accuracy, Precision, Recall, F1 Score, Confusion Matrix, Receiver Operating Curve (ROC), Area Under the Curve (AUC), Specificity, and Matthew Correlation Coefficient (MCC). According to Jude C.O. (2023), any classification function can be used to generate a classification metric. This process involves building a classifier using a training set or a collection of labeled classes (Jude C.O. 2023). A near-zero ratio is the result of an effective prediction model while a poor model one that performs worse than a naive model will yield a ratio larger than one 100% (Vujovic Ž. 2021)

2.3.4.1 Accuracy

Accuracy can be defined as the proportion of correctly classified instances out of the total instances, which are the are the sum of true positive (TP) and true negative (TN) divided with total of true positive (TP), true negative (TN), false positives (FP), and false negatives (FN).

$$\text{Accuracy} = \frac{\text{True Positives (TP)} + \text{True Negative (TN)}}{\text{Total Instances}} \qquad (1)$$

2.3.4.2 Precision

Precision is the measurement of the proportion of true prositive predictions divided up with the total positive predictions.

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}} \qquad (2)$$

2.3.4.3 Recall/ Sensitivity

Recall which also known as sensitivity or True Positive Rate (TPR) can be defined as the the proportion of true positive predictions out of the total actual positives. Sensitivity possesses the capacity of a model to accurately pinpoint the genuine positive.

$$\text{Sensitivity} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}} \qquad (3)$$

2.3.4.4 Specificity

Specificity is employed to calculate the percentage of accurate negative forecasts among all real negative forecasts. According to Jude C.O. (2023), if FP is equals to 0 while the Specificity is equals to 1, and the model in question is a useful one.

$$\text{Specificity} = \frac{\text{True Negatives (TN)}}{\text{True Negatives (TN)} + \text{False Positives (FP)}} \tag{4}$$

2.3.4.5 Confusion Metrics

Confusion metrics is a table of η x η that shows the details on a classification model's predictions, the number of TP, TN, FP, and FN.

		Predicted Positives	**Predicted Negatives**
		P	**N**
Actual Positives	**P**	True Positives (TP)	False Negatives (FN)
Actual Negatives	**N**	False Positives (FP)	True Negatives (TN)

2.3.4.6 Receiver Operating Curve (ROC)

Receiver operating curve, ROC is a graph that displays the recall rate or sensitivity (true positive rate) vs the false positive rate at different threshold values. The false positive rate can be seen in equation (5).

$$\text{False Positive Rate (FPR)} = \frac{\text{False Positives (FP)}}{\text{False Positives (FP)} + \text{True Negatives (TN)}} \tag{5}$$

2.4 Previous research findings

These are the straightforward tables of earlier studies that are connected to these investigations. A thorough understanding of background research on wireless diagnostics utilizing Z-freq 2D can enhance research quality and benefit engineering practices. As a guide and resource for the newest generation of young scientists and engineers, it can be essential to finish this master's degree report in its entirety. A selection of the previously examined studies is presented in Table 2.1.

Table 2.1 Table of some previous research studies

No	Author	Title project	Case study/ Summary of research	Advantage	Disadvantage
1.	Jude Chukwura Obi	A Comparative Study of Several Classification Metrics and Their Performances on Data	The accuracy and area under the curve (AUC) are the two classification metrics that consistently provided results across the 20 different datasets used in the study, with accuracy appearing to be marginally better than	- Accuracy and AUC are the most consistent classification metrics across the datasets, with accuracy being slightly better overall. - Accuracy can yield high results even when sensitivity is zero, indicating a potential issue with	- Accuracy and error rate alone are not sufficient for evaluating classifier performance, and other metrics like ROC curve and AUC should also be considered. - Accuracy may not be a

			AUC, but caution should be applied in using accuracy as the preferred metric without also considering sensitivity and specificity.	relying solely on accuracy. - When both sensitivity and specificity are high, accuracy can be a reliable metric for classification performance.	reliable metric when sensitivity is zero, and the performance of classification metrics may depend on the characteristics of the dataset. - Before using accuracy as the primary metric, it is important to also consider sensitivity and specificity, as a model with high accuracy but low sensitivity may not be a good model.
2.	Željko Đ Vujović	Classification Model Evaluation Metrics	- The four standard classification models (BayesNet, NaiveBayes, MultilayerPerceptron, and J48) performed very poorly when applied to a specific set of hepatitis C virus data for Egyptian patients, with only 25.24% of instances correctly classified on	The summary of the discussion is that the standard classification models used negatively evaluated the classification of the hepatitis C virus data set for Egyptian patients, leading to the conclusion that the data set needs to be pre-processed before reliable classification can be achieved.	- The classification models used (BayesNet, NaiveBayes, MultilayerPerceptron, and J48) performed poorly on the dataset, with unsatisfactory results. - The number of attributes in the dataset may be too large, and it is unclear how many attributes are optimal for this

			average. - Detailed accuracy metrics for each class showed very poor results for all four models and all four classes, indicating that the models did not match the data marked as ground truth. - The confusion matrices and analysis of Type I and Type II errors further confirmed the poor performance of the classification models, with errors being relatively high compared to correctly predicted results.		classification task. - The data may need to be preprocessed in some way (e.g., discretization, purification, reduction) in order to be reliably classified by the models. - The authors suggest that a 5-class classification (inflammation, fibrosis, cirrhosis, end-stage disease, cancer) may be more appropriate than the 4-class classification used in the study.

3.	N A Ngatiman, M N B Othman, M Z Nuawi	Wireless Hybrid Vehicle Three-Phase Motor Diagnosis Using Z-Freq Due to Unbalance Fault	- The Z-freq statistical method can effectively detect and differentiate rotor unbalance faults, including static, coupled, and dynamic faults, based on the vibration signals. - The Z-freq method outperforms other traditional techniques, such as i-Kaz and RMS, in detecting and predicting rotor unbalance faults. - Wireless monitoring using a piezo-based sensor (wireless accelerometer) can be a promising approach for diagnosing and monitoring hybrid	The Z-freq statistical method can effectively detect and differentiate rotor unbalance faults, including static, coupled, and dynamic faults, across a range of rotor speeds, and that this wireless monitoring approach has potential for future mechanical machine fault diagnosis.	- The need for further development and improvement of analytical methods, including the Z-freq method, for rotor bearing condition monitoring and maintenance strategy - The need to fully validate the performance of the Z-freq method using additional metrics beyond accuracy, sensitivity, and specificity - The potential for the Z-freq method to have limitations or room for improvement compared to other analytical methods

			electric motor faults.		
4.	Muhammad Azim Mohd Khanafiah Nur Adilah Sahafudin Fauziah Jerai	Evaporator Performance for Water Refrigerant Adsorption Cooling System	The optimal water refrigerant height for maximizing the heat transfer coefficient, evaporation heat transfer rate, and specific cooling power of the evaporator in an adsorption cooling system is around the tube diameter level, and that higher chilled water temperatures lead to better system performance.	- The highest heat transfer coefficient and evaporation heat transfer rate are achieved when the water refrigerant level is set at the heat exchanger tube diameter level. - The maximum evaporation heat transfer rate or cooling generation by the system is around 25 W. - The highest Specific Cooling Power (SCP) is obtained when the outer surface area of the heat	- The study does not conclusively determine the optimal heat exchanger design for adsorption cooling systems. - The amount of adsorbent (silica gel) used was only 0.1 kg, which is a relatively small amount and limited the cooling capacity of the system. - The adsorbent uptake and amount of adsorbent in the

				exchanger tube is at least 80% immersed in the refrigerant.	adsorber bed could be further improved to increase the specific cooling power (SCP) of the system.
5.	Ismail Hmeidi, Bilal Hawashin, Eyas El-Qawasmeh	Performance of k-NN and SVM classifiers on full word Arabic articles	Both the k-NN and SVM classifiers performed well on Arabic text categorization, with SVM outperforming k-NN as the number of features increased, and SVM also having better prediction time.	- Both the k-NN and SVM classifiers performed well on Arabic text categorization, with SVM having better recall than k-NN when the number of features was small. - As the number of features increased, the SVM classifier outperformed the k-NN classifier, as the SVM was able to find a clearer optimal hyperplane. - Overall, the SVM classifier generally had better performance than the k-NN classifier, likely because the SVM uses offline learning to find an optimal hyperplane, while the k-NN is a	- Small sample size of training and testing data - Need to study stemmed features in addition to full word features - Need to further study the effect of Arabic language sparsity on classifier performance - Lack of a large publicly available Arabic corpus for text categorization research

				more statistics-based and comparison-dependent algorithm.	

2.5 Case studies and applications

2.5.1 Vehicle Air Conditioning Compressor

Nowadays in the field of vehicle air conditioning (A/C) systems, diagnostic methodologies range from conventional techniques to advanced approaches, yet the demand and needs for innovation and new methods is continue to exist due to inherent limitations. In order to achieving an optimal A/C performance, a compressor performance review is given top attention, given its critical role in system efficiency, despite challenges in achieving comprehensive diagnostic accuracy. Assessing the dynamic performance of key components, such as compressors itself, presents significant difficulties, as current diagnostics methods rely on manual inspections and basic performance metrics, which are often insufficient for detecting subtle inefficiencies. Additionally, external and internal variables introduce further complexity in system evaluation, as evidenced by prior studies, including those by Kim and Kang (2023), which will be able to overcome through this study research despite it is a novel diagnostic method, in address these challenges, with the objective of improving the safety, reliability, and maintenance of automotive AC systems.

Numerous researcher have conducted method in diagnostic and monitoring for number of possible of faults in reciprocating compressor however most of them pay more attention in diagnosis of broken valve as it is one of the most common fault in reciprocating compressor or a abnormal belting that indirectly affecting the compressor's performance. Compared to valves, fault detection and diagnosis in translational machinery present greater complexity due to their placement within sealed, airtight chambers. At present, the most prevalent and effective diagnostic methodologies for these components are grounded in vibration analysis techniques (Xiao S. et al., 2021).

As heart and critical unit in vehicle A/C system, the compressor is mounted near the engine or fitted to the body of the engine and consisted of multiple subassemblies and components, including the piston-shoe assembly, swash and shaft assembly, as well as the front and rear cylinder blocks and corresponding head covers, all of which work cohesively to ensure the efficient operation of the system (Avadhesh Meena. 2020). Figure 2.1 shows the schematic diagram of exploding view for the standard A/C compressor for conventional vehicle or in this research study, A/C compressor of Myvi 1.5L X.

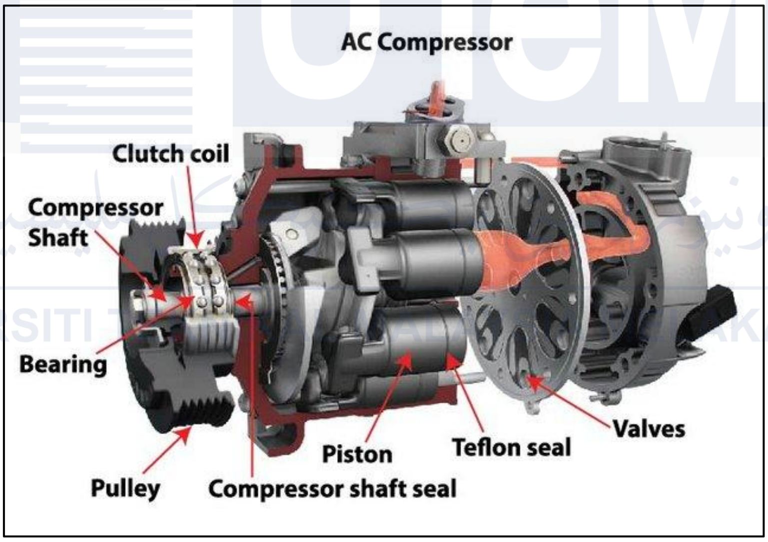


Figure 2.1 Exploding view of A/C compressor Denso 10PA15C

2.5.2 Vibration Phenomena: Causes, Failures, and Impacts on Vehicle A/C Compressors Performance

In world of mechanical vibration especially in vehicle A/C compressors, there are numerous types of vibration can occur or present in systems such as imbalances, misalignments, loose components, or external forces. Although certain vibration are considered normal behaviour to system function, however an excesive or unusual vibrations might be a sign of problems in the system either it be a faults, inefficiencies, or potential failures which requires us to do thorough a diagnosis and corrective action to be taken.

Nevertheless, what precisely constitutes vibration? According to general textbook about vibration, vibration is defined as an oscillatory motion of an object or a system in mechanical structure around the equilibrium which occurs when a force causing the object either to move back and forth or up and down in a repetitive motion. There are several types of vibration that can be classified includes free vibration, forced vibration, damped vibration and undamped vibration. According to Mohd Ghazali M.H. and Rahiman W. majority of machines have moving elements that produce undesired vibration and vibration analysis can be used to determine whether the machine can continue to run or has to be stopped and fixed (Mohd Ghazali M.H. and Rahiman W. 2021).

In vehicle air conditioning system which in this case the compressor itself, the failure of vibration usually refers to the occurrence of abnormal or excessive vibrations within the system structure which it can causing either mechanical issues, reduced efficiency, or complete failure of the component in the system. As mentioned several times earlier the causes of this failure are imbalance in rotating components, misalignment, worn bearings, refrigerant and oil issues, loose or damaged mounting, internal component failure, and contaminants or blockages in the system. This failure of vibration in vehicle A/C compressor usually can be identified in several categories including **Rotating Components** such as crankshaft and bearings or pulley and belt assembly, **Internal**

Moving Parts such as pistons and cylinder assembly or swash plate or wobble plate mechanism, **Mounting Points**, **Refrigerant And Oil Flow** such as valve plate and ports or oil circulation, **Structural Components** such as housing and casing or heat exchanger interfaces, and last but not least **External Connections** such as piping and hoses.

2.5.3 A/C compressor Denso 10PA15C

In Malaysia automotive industries, since early 1990s almost all conventional vehicle especially that from Japanese manufacturer, A/C compressor Denso 10PA15C are widely used and integrated making it the most common and popular compressor that can be found in vehicle A/C system. There are various vehicle models that utilized Denso 10PA15C as their A/C compressor, for an example Honda CR-V RD5 2.4L models that produced between 2001 and 2006 or Toyota vehicle such as Toyota Hilux KZN165 models from the year 2000, and of course Malaysian Perodua vehicle Myvi which owns by Perusahaan Otomobil Kedua Sendirian Berhad (Perodua). The main reason Denso 10PA15C is widely used in automotive air conditioning (A/C) system is due to its efficiency, reliability, and compact design. The name Denso 10PA15C is combination of compressor series 10PA and 15C is refers to the nominal displacement of 15 cc per revolution.

A/C compressor Denso 10PA15C is a reciprocating piston compressor type. It's a type of compressor where uses a set of pistons that moves forward and back to compress the refrigerant. This can be seen from Figure 2.1 at page 2.5.1 Vehicle Air Conditioning Compressor where is shows the exploding view of A/C compressor Denso 10PA15C. Using the power from the engine through the drive belt that is connected to crankshaft pulley, the compressor harnesting the power to operate the air conditioning system. Whenever the A/C system is activated by the vehicle user, the electromagnetic clutch is engaged, which instantly link the compressor shaft and drive pulley activating the system. Within the compressor structure, the piston that were driven by the swash plate mechanism which connected to the drive shaft will rotates and transform the motion into the linear movement for the piston in each of their respective cylinders. As the pistons move in linear motion, it compressed and moves the refrigerant within the air conditioning system in the vehicle. In suction port, during the suction stroke the refrigerant vapor will enter the compressor and flows into the cylinder. During the suction stroke, the refigerant are in 100% gaseous state with low temperature and low pressure. The piston then compress the refrigerant which reduce the volume inside the cylinder, and increase the temperature and pressure of the refrigerant. During this process, the refrigerant is in 100% gas state with temperature between 60 ℃ to 70 ℃ and high pressure. The refrigerant which in high temperature and pressure then discharged through the discharge port. The refrigerant then flows towards condensor where it will be cools down by the fan that blow cool air from the outside. The condenser is constructed in design with a parallel flow structure which comprises of a thin metal tubes and fins which helps to facilitate the heat in the system and usually located in the most front of the vehicle. As the refrigerant leaves the condenser, the refrigerant is in 100% liquid state with temperature high around 40℃ approximately and high pressure. Then the refrigerant will flows into the expansion valve which function in regulating the refrigerant flows and ensure the an efficient cooling system is taken effect. Basically expansion valve is like a switch, a thermal device that manages the transition of the refrigerant switching from the high pressure liquid to a low temperature and low pressure of refrigerant which consisted mixture of 70% gas and 30% liquid before the refrigerant flows into the evaporator. As the mixed gas - liquid refrigerant enters the evaporator (or the cooling coil), the blower directs the warm air through the unit which came from the warm cabin air. Within this process, heat exhanged is occur as the evaporator absorb the heat from the air and transferrs to the refrigerant which evaporates into gaseous state, then the cold air leaving the unit and recirculated into the cabin of the vehicle with a cold wind, lowering the temperature of the interior and creating a cozy and comfortable environtment. As the refrigerant left evaporator it will then flows back into the compressor in 100% gaseous state with low temperature and low pressure. In stis section the refrigerant is return to the suction port restart the process again as long the A/C system is continue to activate. The refrigerant flow can be refer to the figure 2.2 where is show an illustration of refrigerant flow in the system.

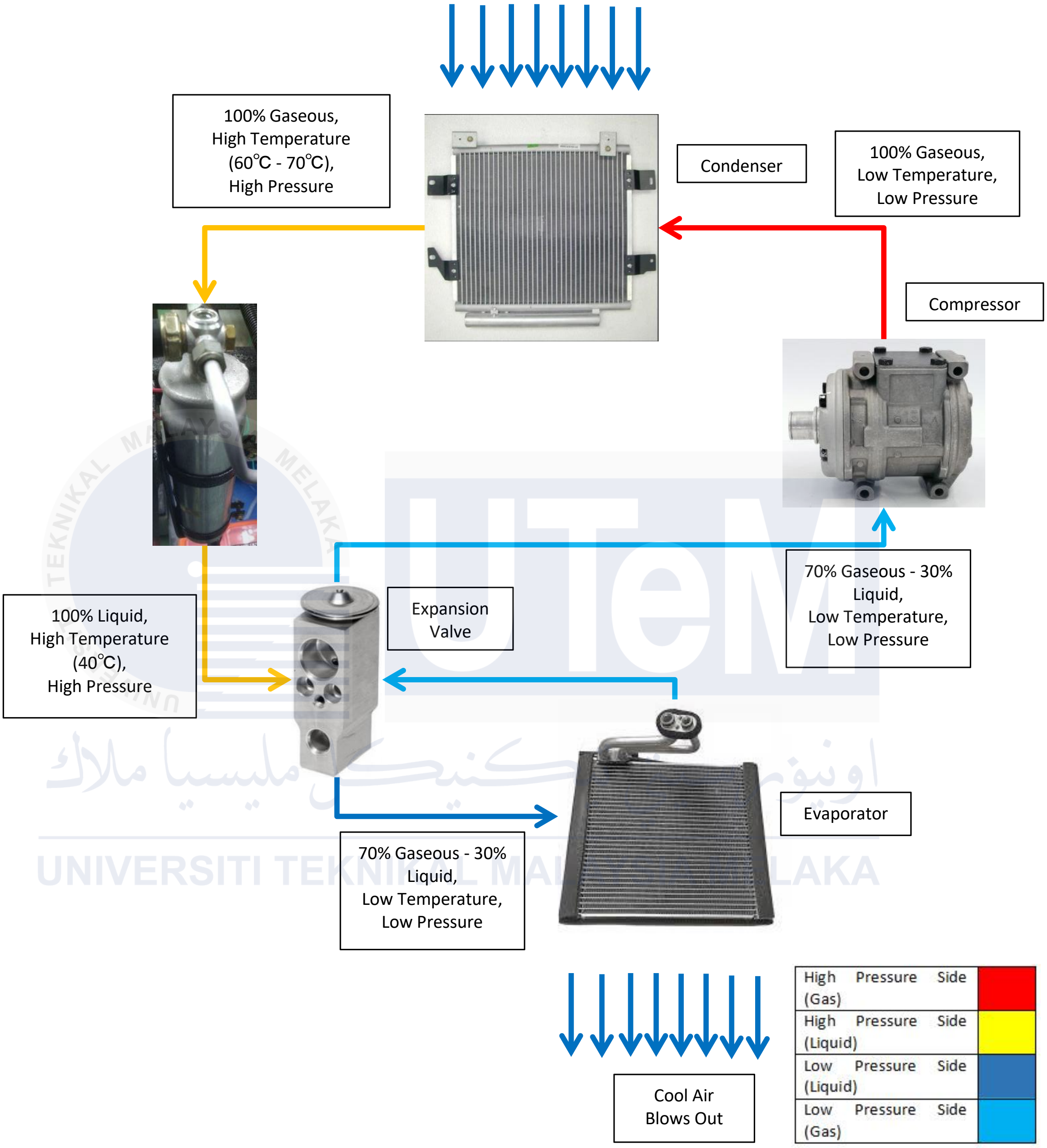


Figure 2.2 Illustration of refrigerant flow in A/C system

2.6 Summary

Given that wireless diagnostics employing cutting-edge machine learning has a significant impact on assessment and evaluation. Accurate data determination in vibration sensors is crucial for improving the efficiency and accuracy of fault detection related to HVAC compressor performance in vehicles. It is however, the problem to obtaining the accurate detail of the data requires a good signal network of the sensor and cloud system. Therefore some rigorous calculation effort is needed to analyze the data obtain. There is only one research literatures are able to determine the exact method to analyzes the wireless diagnostic method. This can be a initial benchmark model in estimating the "accurate" results of the wireless diagnostics method. Hence, determining the faulty in the HVAC system and the compressor performance can be approach more smoothly.

Therefore, further research is needed to investigate and integrate a more efficient methodology for wireless diagnostics based on the Z-freq 2D coefficient. This research aims towards a efficiency and accurate results. This is this dissertation paper's primary focus. The suggested wireless diagnostic model will be covered in full in the upcoming Chapter 3.

CHAPTER 3

MATERIALS AND METHODS

3.1 Introduction

In this research, simulations are necessary to monitor the performance of automobile air conditioning systems, which primarily consist of an evaporator, compressor, condenser, receiver drier, and expansion valve, as shown in Figure 2.2. These components are the basic and standard elements in constructing a functional vehicle A/C system, with the compressor serving as the heart of the system (Ahmad Z.A, et al. 2016; Lee G.H. 2000). Each of the component are connected by aluminium tubes which design to properly able the refrigerant to propagate in the system. There are several parameters that affects the performance of the air conditioning which are the amount of oil, volume of the refrigerant, the belting tension, temperature and humidity.

A key aspect of this research is utilizing the Z-freq 2D method to identify faults in the vehicle A/C system, with a specific focus on vibrations produced by the compressor. In this research, an experiment was conducted on the new car generation in Malaysia, Myvi 1.5L X. The experiment is set with two different kinds of parameter, one with different percentages of oil amount in vehicle A/C system and another is different amount refrigerant gas in the system. The standard amount for vehicle A/C system according to automotive industry specific for this type of car is about 320 g to 330 g of refrigerant and 80 ml to 90 ml of oil in compressor, which is the best amount to obtain the best performance result for the A/C system of the vehicle and also as benchmark for the baseline.

In general, the performance of the automotive's air conditioning will be monitored through the accuracy of the machine learning used in this experiment. The accuracy of the machine learning is indicated through the percentages of k-NN and SVM of the machine learning training results. The percentage is refers to how high the classifier percentage value which in this case the values of true positive rate (TPR) and false positive rate (FPR). In sense the higher the resources it require such as the computation effort and time, amount of data and cost, more accurate the result and the higher accuracy of faulty detection in HVAC system of the automotives. In this research conducted would be focusing on the amount of the oil and the volume of refrigerant in the A/C system of the vehicle to the performance of the air conditioning (A/C) with respect to the speed of the compressor.

Therefore, in an attempt to provide a compromised solution to experimentation, an integrated Z-freq 2D approach is presented in this dissertation paper. The general concept behind the proposed model is that it provides the user with the ability of accurate monitoring diagnostic through wireless method.

3.2 Research Design

This dissertation presents a new and integrated analytical approach using the Z-Freq 2D coefficient method, an advance coefficient that caculating from two different axis or dimension which derived from the previous Z-Freq coefficient by researcher Dr. Zaki Nuawi and Dr. Nor Azazi Ngatiman. The approach focuses on the concepts of True Positive Rate (TPR) and False Positive Rate (FPR). The selected approach is based on quantitative type, a set of collective data from different parameters that set up in the experiment which aims to develop analytical model to calculate and analyze using machine learning. The method (design) is experimental, which utilizes statistical approach. This research will be focusing on using the Z-Freq 2D coeffiient as the formula to identify the fault in the system which are created purposely to test the efficiency and effective of the formula. In addition, Phantom Vibration Sensor (PVS) will be the main vibration sensor that will detect and record the vibration produced by the compressor when the A/C system is put under different parameters of both oil and refrigerant.

The study starts with a thorough examination of the literature on vibration analysis, emphasizing earlier research to provide a theoretical framework. Initial trials are conducted to develop and refine the algorithm for the experiment. To guarantee a methodical approach, important experimental parameters are carefully identified. To gain a deeper understanding of the vehicle A/C system and validate parameter implementation, preliminary testing is conducted on a test rig that designed and constructed similar to actual vehicle A/C systems. The experimental setup is implemented on an actual vehicle. During the experiment, vibration data is obtained by using a vibration sensor, capturing the dynamic response of the compressor under different operating conditions.

To ensure the accuracy of the data collected, the collected data is filtered to isolated, eliminate any noise and undesired interference that existed during the data collection. After that, using Z-Freq 2D coefficient in the algorithmic coding to analyse the data in order to extract significant vibration features. The purpose of data characterization is to identify fault-related patterns and further isolate any remaining noise. Valid measurements are obtained by repeating the data collecting process if it is determined that the data is untrustworthy because of high noise or inconsistency.

Data that has been successfully analyzed is shown graphically in two dimensions, giving information on vibration patterns. Support Vector Machine (SVM) and k-Nearest Neighbors (kNN) are two machine learning models that use the processed data to validate and categorize fault conditions. The final validated results contribute to a comprehensive understanding of compressor vibration behavior. Subsequently, Figure 3.1 shows the research flowchart design of this dissertation.

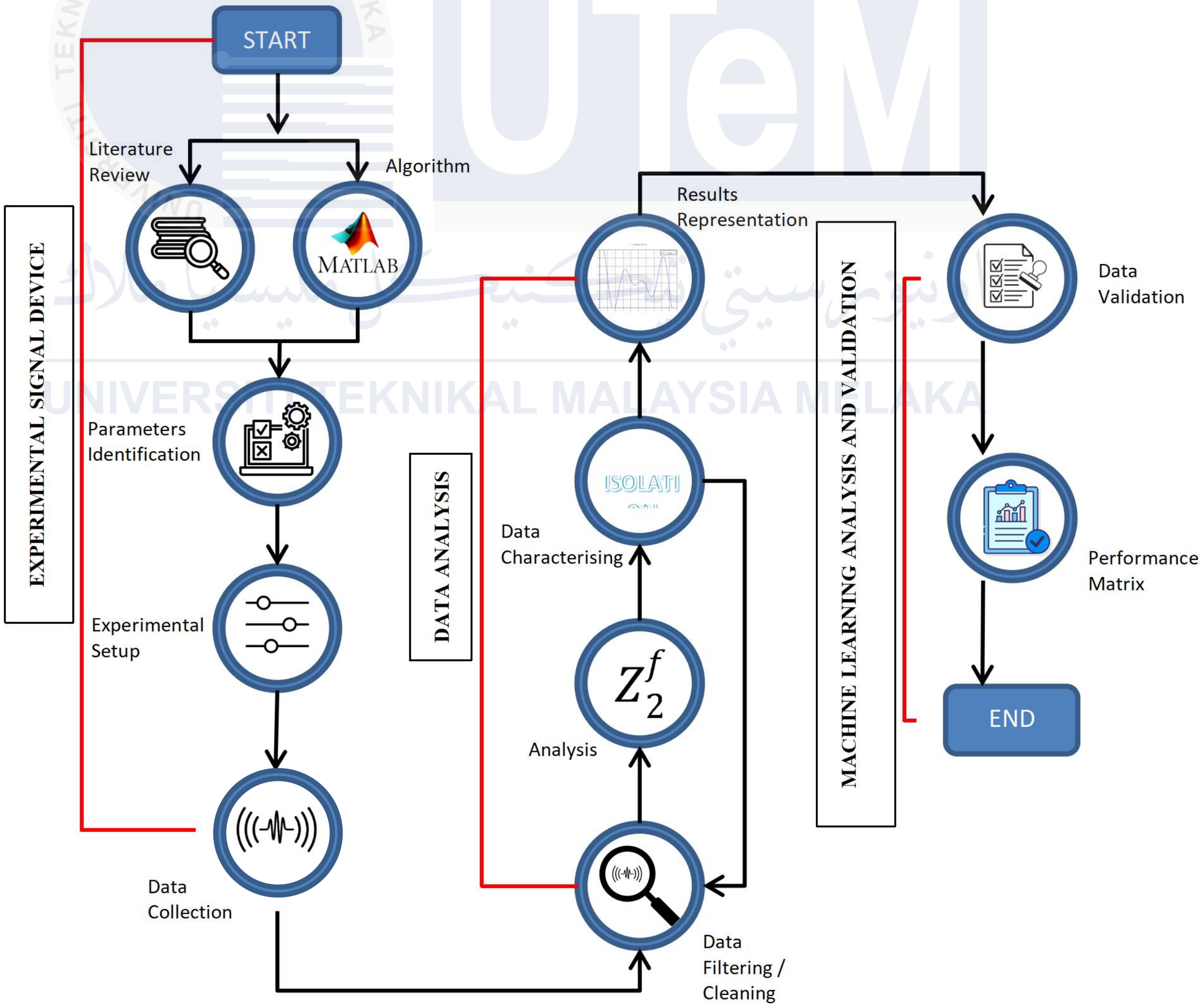


Figure 3.1 Reasearch flowchart design

3.2.1 Proposed Methodology

The experiment was conducted using two test subjects: a test rig as practice unit and a real vehicle as for the actual experimentation. The experiment is conducted on actual vehicle, Perodua Myvi 1.5L X a brand new model of automotive from Perodua. The test rig involved varying belting tension as the primary parameter, while the real vehicle was tested with different volumes of oil and refrigerant (R134a), ranging from the lowest to the highest levels. Each of the manipulative parameters is then tested with different speed (RPM) of compressor from 750, 900, 1000, 1250, 1500, 1750, and 2000 RPM in 5 second time recorded for the real vehicle while for test rig the speed of the compressor from 1000, 1100, 1200, 1300, 1400, and 1500 RPM. The vibration data is then captured by vibration sensor called as Phantom Vibration Sensor (PVS) as shown in Figure 3.4 and then the data is calculated using Z - Freq 2D coefficient in the coding. The sensor is set up to produce 16, 384 samples per channel at a sampling rate of 3.2 kHz and a resolution of 6400 lines throughout the course of around 5 seconds of recording. To evaluate the compressor performance as for the analysis, the vibration signal are categories into several types of vibration which are Forced vibration, Torsion Vibration and Fluid-Induced Vibration with acceleration (mm/s2) as its unit.

3.2.2 Experimental Setup

Machine learning is an important aspect of this research, utilizing the Z-Freq 2D coefficient to identify potential faults in the system. To utilizing the formula, a proper experimental setup is prepared for the research. Figure 3.2 show the schematic experimental flow of the experimental setup. By refering to Figure 3.2, the Phantom Vibration Sensor (PVS) is positioned exactly perpendicularly to the side of the compressor which the compressor are mounted beneath the Myvi near to the engine compartment. The sensor's orientation is meticulously adjusted according to its axis nodes to ensure a precise and accurate vibration data acquisition is obtain. Once the engine is running, the compressor receives power, and upon activation of the A/C system, it initiates operation to regulate the refrigerant flow within the vehicle's air conditioning system. The position of the PVS can also be refers to Figure 3.4 which shows the clear view of the PVS position.

As the compressor run, the PVS will start recording the data of the vibration once the record button from the software is click on. The data is obtain only when the compressor run its mechanism which can be heard clearly from the buzzing sound. The data is collected starting from the low amount of oil - low amount of refrigerant to medium oil - medium refrigerant to the highest oil amount - the highest refrigerant amount respectively which can be refer to both Figure 3.5 and Figure 3.6. Each amount of oil and refrigerant are being tested with different kind of speed of the compressor. To ensure the data are accurate, the data during compressor running which in this dissertion is labelled as Compressor On is compared with the data obtained during compressor not running which labelled as Compressor Off. This is to identify the exact vibration produced by the compressor during the data acquistion process to isolate the vibration from other source which considered as noise such as vibration from the engine.

The experiment began by starting from the idle speed of the compressor, which was 750 RPM when the compressor was off and 900 RPM when it was on. This both speed are considered as default speed or idle speed due its system already setup by the automotive developer. As the acceleration of the vehicle is activated, the speed instantly jumped to 1000 RPM which will the first point of the manipulated speed, RPM of the compressor. The data collection is then continue by increment of 250 RPM from the first speed which is 1000 RPM, then increment to 1250 RPM, 1500 RPM, 1750 RPM and lastly 2000 RPM.

In each of the speed of the compressor, the compressor is will be tested with different volume of oil and refrigerant. The refrigerant amount from 280g, 300g, 320g, 340g, and 360g while the oil volumes are 40ml, 60ml, 80ml, 100ml and 120ml. With the automotive industries standard of optimum oil volume and refrigerant for this particular vehicle which is around 80 ml to 90 ml of oil and 320 g to 330g of refrigerant, will be use as our benchmark of the experimentation. In this experiment, the optimum or benchmark of both oil and refrigerant are 80 ml for the oil while 320 g for the refrigerant. Then in each of these volume of oil and refrigerant will be tested with different speed of the compressor. As for example at 40 ml of oil with 320 g of refrigerant will then tested from 750 RPM to 2000 RPM, speed of the compressor. Then the experiment shall continue with 60 ml of oil with 320 g of refrigerant. This cycle is continue until reach highest amount of oil which is 120 ml and then change with different amount of refrigerant with standard volume of oil, which started from 280 g of refrigerant with 80 ml of oil and tested with different speed of compressor from low tp highest speed.

The vibration data signal is detected and recorded by vibration sensor, Phantom Vibration Sensor (PVS) which then sent the recorded data signal to the cloud system. As the experiment data is recorded by the PVS and taken with 3 times of test in each parameters to ensure the data taken are accurate, the data signal of the vibration is sent to the cloud system which then will be downloaded and store in secured data folder. Each of the data sample is then inserted into the MATLAB for the analysis process by using the Z - Freq 2D coeffient in the coding. Using a butterworth coding system, the unwanted data will be isolated within analysis process, providing the actual data result. As the actual data is obtained, all the collected vibration data is further processed and trained using machine learning algorithms which in this research are SVM and kNN, to enhance the fault detection accuracy and presented in performance matrix result table. This findings would be able to finds the correlation between the vibration behavior and the compressor performance which provide us some insights on the optimal refrigerant and oil volumes for efficient A/C system operation. Figure 3.2 shows the schematic of the experimentation flow while Figure 3.3 shows the experimental vehicle used for the research studies.

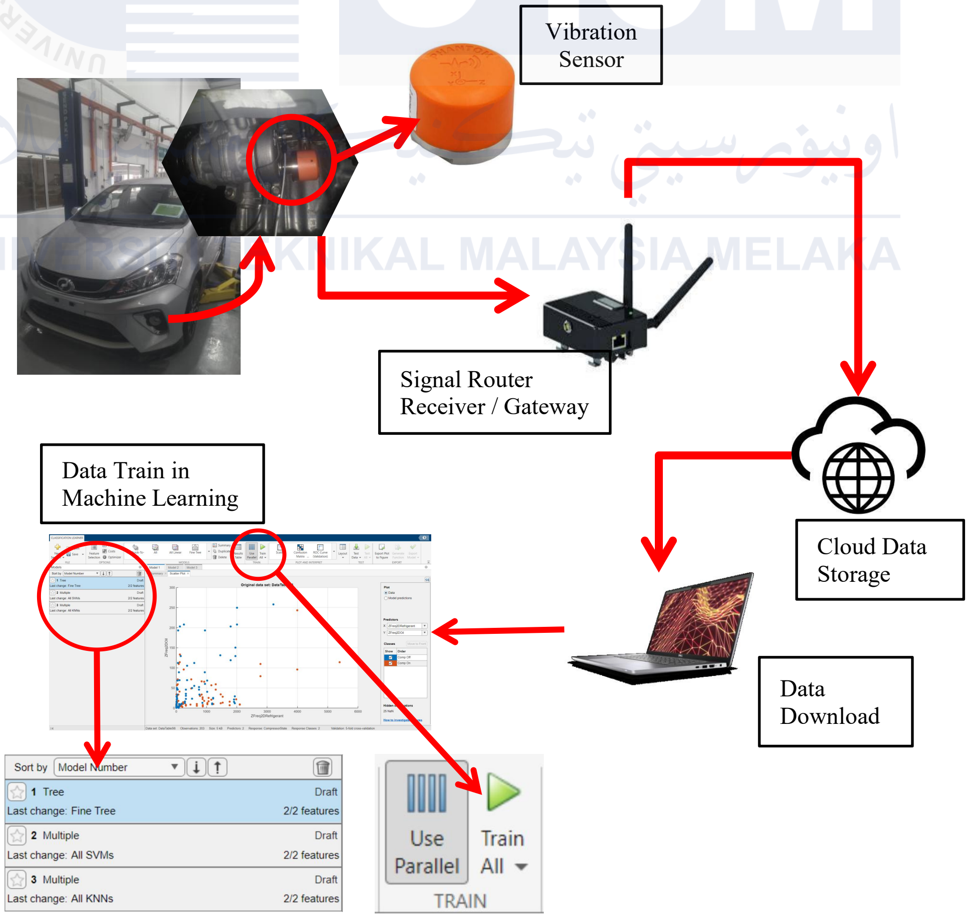


Figure 3.2 Schematic experimentation flow

Figure 3.3 Experimental research vehicle

Figure 3.4 shows the location of the Phantom Vibration Sensor (PVS), is placed under the experiment vehicle for the vibration data signal capture.

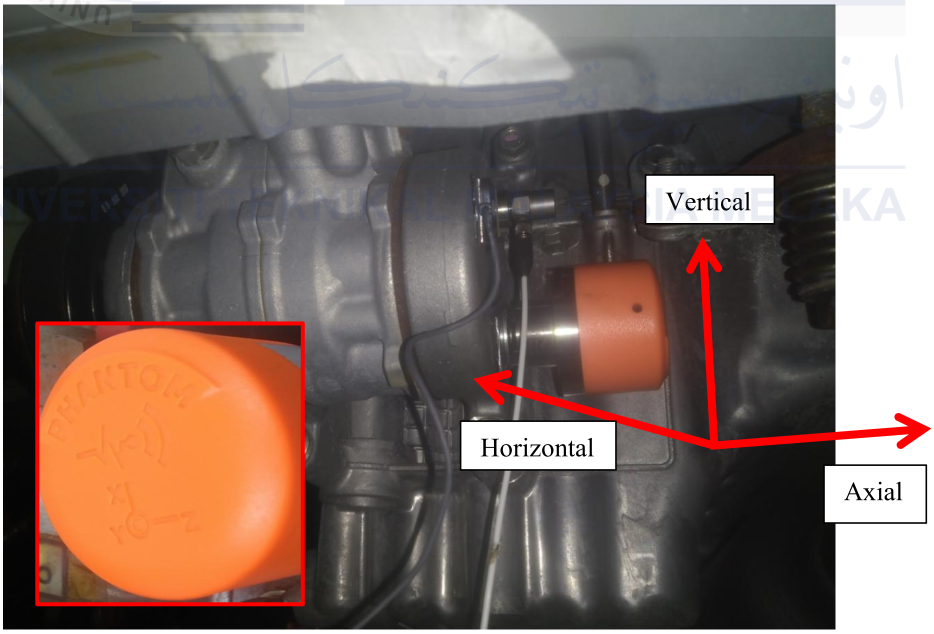


Figure 3.4 The location of Phantom Vibration Sensor (PVS) at the vehicle compressor

3.2.3 Research Mathematical Formula

The Integrated Kurtosis Algorithm (i-Kaz) is primarily used to measure the obtained data in relation to the dynamic signal analysis data centroid and to detect any changes in the experiment's data signal. The analysis of the data using the i-Kaz algorithm produces a three-dimensional graphic representation with a separate magnitude distribution for each axis, where each axis indicates the frequency range of the data distribution (Nuawi M.Z., et al. 2008). The Integrated Kurtosis-based Algorithm Z-filter (i-Kaz) has made it simple to determine how dispersed the data is in relation to the data centroid when performing a dynamic signal analysis (Muhammad Hanafi, et al,. 2019).

$$i\text{-}Kaz = \left(\frac{1}{N}\left(M_4^L\right) + \frac{1}{N}\left(M_4^H\right) + \frac{1}{N}\left(M_4^V\right)\right)^{\frac{1}{2}} \tag{6}$$

Where,

N = number of data

M4 = 4th order moment of signal in LF, HF and VF range respectively

Statistical parameters are commonly calculated using the following formulas: mean, standard deviation, root mean square (RMS), skewness, and kurtosis (Cain M.K., et al 2017). The statistical moment for kurtosis, denoted as K in global signal statistics, is contingent upon the degree of data spikiness. The kurtosis value in equation is written like this:

$$K = \frac{1}{n\sigma^4}\sum_{i=1}^{n}(f_i - \bar{f})^4 \tag{7}$$

Where,

K: Kurtosis,

n: The number of sample,

f: frequency,

σ: The Square Standard deviation value

Approximately 3.0 is the kurtosis value for a Gaussian distribution. Higher kurtosis values suggest the occurrence of extreme values in a Gaussian distribution (Nuawi M.Z., et al., 2008). Using the following formula, one may find the standard deviation value s for a signal with n data points, as shown in equation (8):

$$s = \left(\frac{1}{n}\sum_{i=1}^{n}(x_1 - \mu)^2\right)^{\frac{1}{2}} \tag{8}$$

Where,

x: value of data point,

μ: mean of the data,

n: number of sample

Equation (4) defines the Z-freq 2D coefficient using the previous equation as a basis. To find the Z frequency, two data frequency points are used: the x- and y-axes positions, which stand for x and y, respectively. Hence the formula is as respectively:

$$Z_{2D}^{f} = \frac{1}{n}\sqrt{K_x S_x^4 + K_y S_y^4} \tag{9}$$

Where,:

Z_{2D}^{f}*: z frequency 2D at second central moment,*

n: number of sample,

K: kurtosis values,

S: standard deviation,

x: x-axis location,

y: y-axis location.

3.2.4 Parameters

The overall experiment parameters can be seen in Figure 3.5 and Figure 3.6. Each of the amount of the refrigerant and oil is tested with different speed of compressor, from the lowest speed to the highest. The lowest will be the idle speed value where the speed is in default mode. Table 3.1 shows the variation of parameters that been set up in the experimentation.

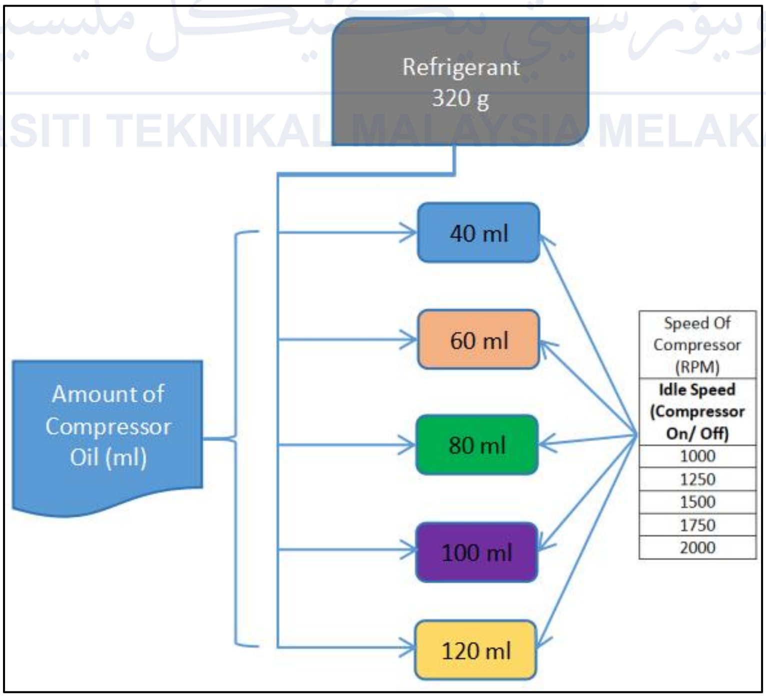


Figure 3.5 llustration of manipulative oil in the research experiment

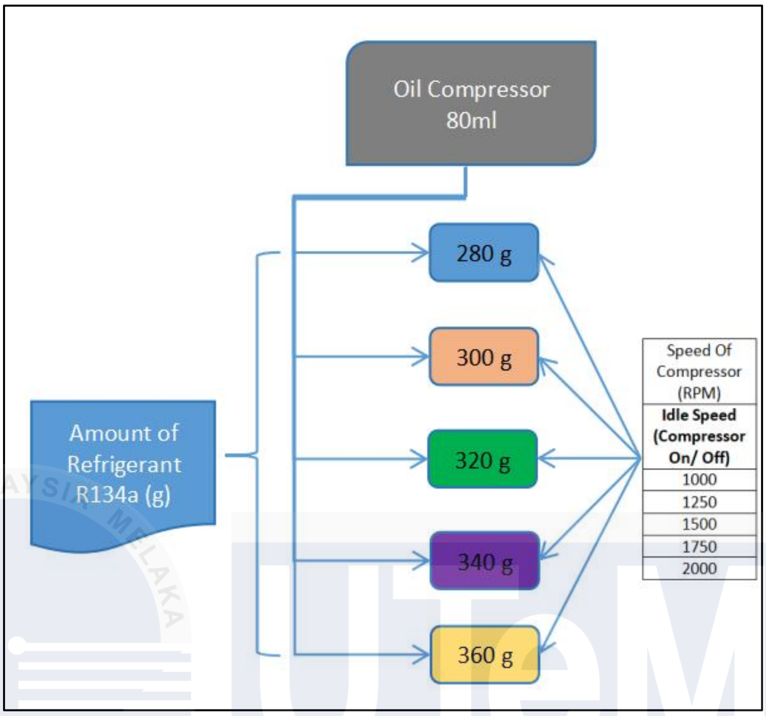


Figure 3.6 Illustration of manipulative refrigerant in the research experiment

Table 3.1 The variation of parameters set up in the experiment respectively of Refrigerant, Oil and Speed

<table>
<tr><th>The Speed of Compressor

(RPM)</th><th>The Amount of Refrigerant

(gram)</th><th>The Volume of Oil

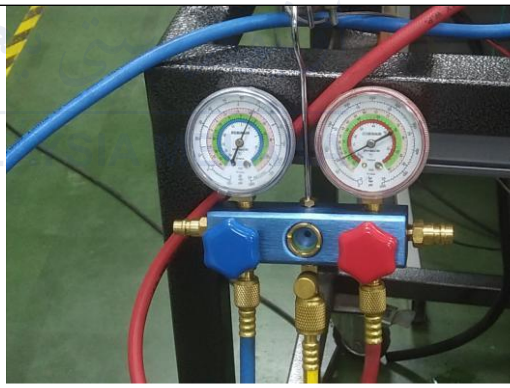
(mL)</th></tr>
<tr><td>Idle Speed</td><td>280</td><td>40</td></tr>
<tr><td>1000</td><td>300</td><td>60</td></tr>
<tr><td>1250</td><td>320</td><td>80</td></tr>
<tr><td>1500</td><td>340</td><td>100</td></tr>
<tr><td>1750</td><td rowspan="2">360</td><td rowspan="2">120</td></tr>
<tr><td>2000</td></tr>
</table>

3.2.5 Equipment

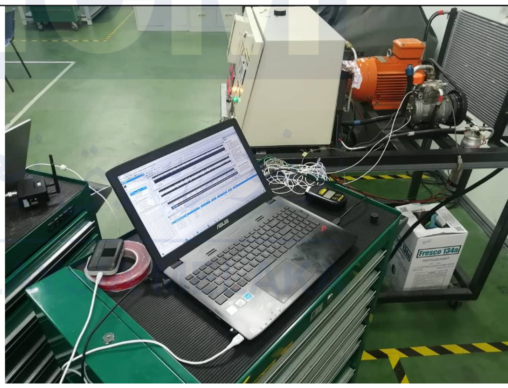
This section presents the list of equipment used during the experimental procedure to methodically test the research hypotheses.

Table 3.2 List Of Equipment

TOOLS AND EQUIPMENT	DETAILS	FIGURE
Myvi 1.5L X	Experimental vehicle testing for data	
Robinair Recovery Unit with oil separator	To recharge and recover refrigerant from the vehicle A/C systems.	
Phantom Vibration Sensor	To obtaining the vibration data from the compressor unit	

Robinair Recovery Machine Automatic	To recover and recharge the refrigerant and oil into the A/C system of the vehicle automatically	
Refrigerant R134A	Refrigerant gases for the vehicle A/C system	
A/C pressure hose	To monitor the pressure of the A/C during recharging and recovery of the refrigerant.	

Compressor oil 9 R134 3.5l - ASMO	To provide a lubricant for the compressor to work effectively	
Robinair TIF9055 Programmable Charging/Recovery Meter	To monitor the weight of the refrigerant tank during recharging process	
Vacuum pump	To extract gas particles from a sealed space and create a partial vacuum inside the chamber.	

EEBC500 Computer smart charging machine	To charge the batteries of the vehicle whenever the batteries runs out	
Computer	To extract data from DigivibeMX and conduct analysis of the data obtained using MATLAB	
CENTER-309 Protable digital thermometer	To monitor the level of temperature produced from the blower	

3.2.6 Field Testing Procedure and Machine Learning Techniques

The experiment was conducted on the Myvi 1.5L X, a compact car of 1.5cc with registered air conditioning system, model number XI447260-9990. The experiment started with low to high refrigerant volumes while maintaining a constant oil lubricant volume. Then, it was switched from low to high oil volumes with a constant refrigerant volume, all tested at different compressor speeds.

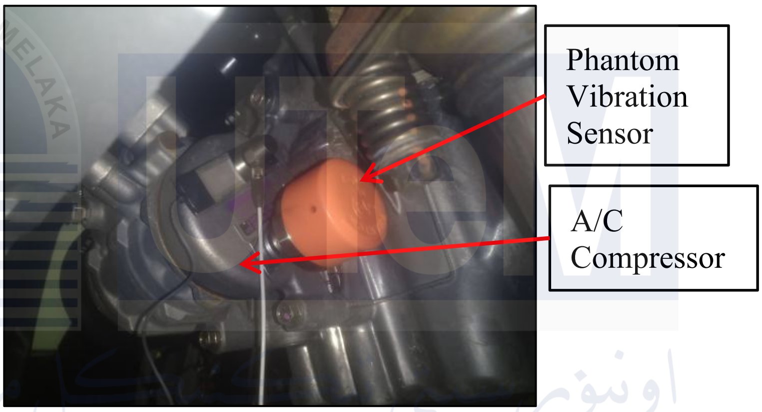


Figure 3.7 Research experiment set up

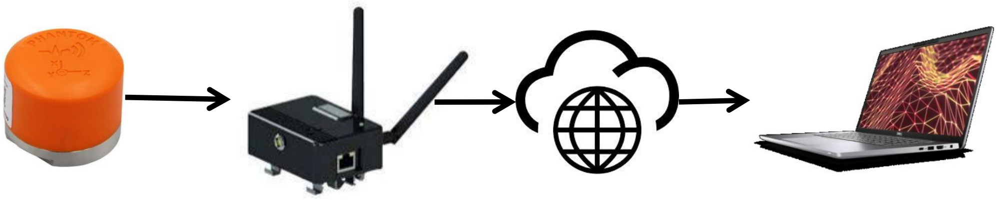


Figure 3.8 Illustration of research experiment set up

Table 3.3 The schematic set of experiments test

Set of experiments	Oil lubricant volume (ml)	Refrigerant R134a volume (g)	Speed of compressor		Number of test
			Compressor Off	Compressor On	
A	80	280	750	900	3
		300	1000	1000	3
		320	1500	1500	3
		340	1750	1750	3
		360	2000	2000	3
B	40	320	750	900	3
	60		1000	1000	3
	80		1500	1500	3
	100		1750	1750	3
	120		2000	2000	3

The acceleration (mm/s2) of the data signal is recorded through the PVS attached by using magnet on the compressor as shown in Figure 3.7. The data is then collected using the DigiVibe MX software which downloading the signal data that sent by the PVS through cloud system, or in another meaning internet access. Each of the parameters that set up in the experiment can be refer to table 3.3, shows the complete schematics of the experiments. The experiment is conducted in safe environment in workshop with some supervise from lecturer and UTeM staffs.

The PVS provide three different axial vibration signal data which included x-axis, y-axis and z-axis and saved as in excel sheet. Each set of parameters is conducted in three times test to ensure the value data are accurately. Figure 3.9 shows the data recorded in excel file. Around 16, 384 samples were recorded per channel at a sampling rate of 3.2 kHz and a resolution of 6400 lines within 5 seconds.

2	COMPRESSOR OFF NORMAL											
3												
4	750 RPM		1000 RPM		1250 RPM		1500 RPM		1750 RPM		2000 RPM	
5	TIME	NORMAL	TIME	NORMAL	TIME	NORMAL	TIME	NORMAL	TIME	NORMAL	TIME	NORMAL
6	0	2757.224	0	-306.4112033	0	2987.939	0	-1938.785267	0	-3348.007801	0	-11597.29911
7	0.000311	2649.448	0.000310945	-114.8096408	0.000310945	2556.836	0.000311042	-2573.465443	0.000311624	-2789.968251	0.000311915	-12665.47782
8	0.000622	1370.507	0.000621891	-953.0664767	0.000621891	2269.433	0.000622084	-403.5777479	0.000623247	-1173.330067	0.00062383	-14964.69657
9	0.000933	568.1758	0.000932836	-447.7173556	0.000932836	2528.095	0.000933126	695.7362169	0.000934871	-3946.762684	0.000935745	-17199.2498
10	0.001243	984.9092	0.001243781	-533.9380588	0.001243781	2995.124	0.001244168	-566.4390761	0.001246494	-4121.59911	0.001247661	-16581.33476
11	0.001554	702.2969	0.001554726	-603.3936252	0.001554726	3320.847	0.00155521	-159.2857558	0.001558118	-4387.446278	0.001559576	-14298.88114
12	0.001865	1408.828	0.001865672	1374.892508	0.001865672	2393.974	0.001866252	1110.074596	0.001869741	-5493.945301	0.001871491	-16622.05009
13	0.002176	1827.956	0.002176617	1897.006765	0.002176617	964.1477	0.002177294	1921.986217	0.002181365	-4420.976551	0.002183406	-15299.99931
14	0.002487	1157.351	0.002487562	2119.743582	0.002487562	-252.522	0.002488336	2848.858775	0.002492988	-4186.264637	0.002495321	-11563.76884
15	0.002798	970.5391	0.002798507	615.6713162	0.002798507	-2257.15	0.002799378	4084.688854	0.002804612	-3767.136219	0.002807236	-7923.339152
16	0.003108	261.6133	0.003109453	1188.080984	0.003109453	-1732.64	0.00311042	3438.03358	0.003116236	-5273.603505	0.003119152	-6021.693644
17	0.003419	98.75202	0.003420398	285.1586209	0.003420398	99.54563	0.003421462	2139.932994	0.003427859	-6887.846669	0.003431067	-4354.76005
18	0.00373	659.1866	0.003731343	962.9491483	0.003731343	657.5852	0.003732504	2573.431529	0.003739483	-6499.853505	0.003742982	-1044.843058
19	0.004041	601.7061	0.004042289	3398.684012	0.004042289	535.4392	0.004043546	2599.776744	0.004051106	-5412.514637	0.004054897	-977.7825111
20	0.004352	189.7628	0.004353234	3029.851004	0.004353234	-283.657	0.004354588	2453.680553	0.00436273	-5508.315419	0.004366812	1422.027059
21	0.004663	984.9092	0.004664179	2443.071219	0.004664179	-113.611	0.00466563	4290.660533	0.004674353	-4025.798329	0.004678727	4425.381551
22	0.004974	316.6988	0.004975124	2522.106863	0.004975124	-1517.09	0.004976672	4134.984264	0.004985977	-5419.699696	0.004990643	4894.80538
23	0.005284	-1.8388	0.00528607	2404.750906	0.00528607	-949.473	0.005287714	3660.770397	0.0052976	-5180.197743	0.005302558	6312.656942
24	0.005595	84.3819	0.005597015	2225.124441	0.005597015	597.7097	0.005598756	3790.101451	0.005609224	-3412.673329	0.005614473	5670.791708
25	0.005906	-167.095	0.00590796	1446.743094	0.00590796	1285.08	0.005909798	2286.029186	0.005920848	-3005.520009	0.005926388	5076.826864
26	0.006217	776.5425	0.006218905	1269.511648	0.006218905	2619.106	0.00622084	1248.985729	0.006232471	-2509.750966	0.006238303	4387.061239
27	0.006528	458.0049	0.006529851	1518.59368	0.006529851	1905.39	0.006531882	1311.256236	0.006544095	-1108.66454	0.006550218	4470.886922
28	0.006839	673.5567	0.006840796	574.9559842	0.006840796	1876.65	0.006842924	3071.595592	0.006855718	-644.0307507	0.006862133	6022.859579

Figure 3.9 Sample of vibration data over time

In this research only two axial were chosen to do a calculation by using Z-freq 2D coefficient formula which can be refer to equation (4). Figure 3.10 shows the coding in MATLAB to calculate the FFT, i-Kaz, standard deviation and Z-freq 2D.

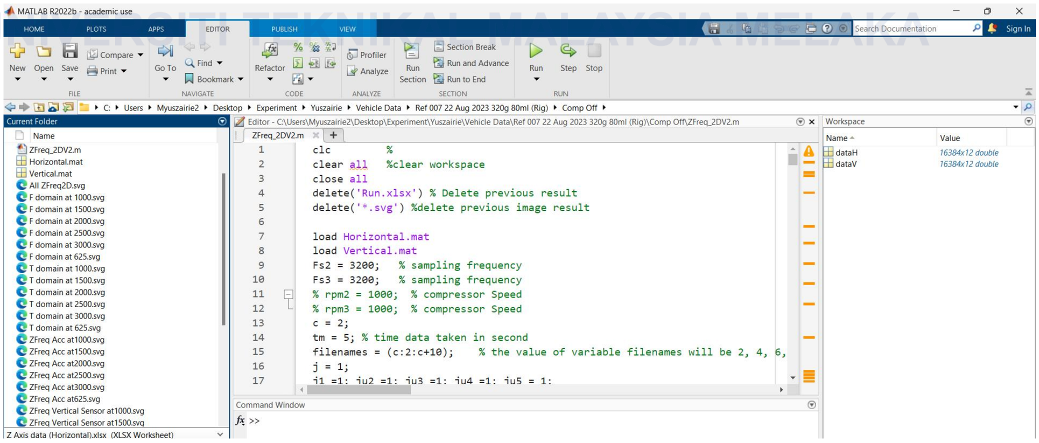


Figure 3.10 Algorithm to calculate Z - Freq 2D for vibration signal data

The calculation using MATLAB willl provide the data results of Z-Freq 2D values which to analyze the graph of the vibration signal that obtain from the experiment. The graph shows which parameters that have unstable and stabilized graph line,the unstable graph line indicated that the present of faulty in compressor performance while a smooth stable graph line indicated that the compressor able to perform well and received a proper amount of lubricant and refrigerant in the systems. This coding also shows the results of time domain and frequency domain of the data signal as can be refer from Figure 4.1 to figure 4.4.

By using all the data of Z-freq 2D values, the collected data is then compiled in one excel sheet to be analyzed using Classification Learner (CL). Table 3.4 is the example of compiled Z-freq 2D values.

Table 3.4 Sample of compiled Z-freq 2D values

Engine Speed (RPM)	Z - Freq 2D Refrigerant	Z - Freq 2D Oil	Compressor State
750	NaN	NaN	Comp On
900	4.8985	5.5666	Comp On
1000	5.4297	10.1666	Comp On
1250	12.4789	9.6443	Comp On
1500	22.3982	26.9344	Comp On
1750	46.1496	59.016	Comp On
2000	79.3594	109.6384	Comp On
750	3.208	1.0259	Comp Off
900	7.2176	5.9024	Comp Off

1000	11.2272	10.7789	Comp Off
1250	15.5354	21.3911	Comp Off
1500	23.4066	49.994	Comp Off
1750	55.0821	112.1121	Comp Off
2000	150.7322	129.4334	Comp Off

The compiled data of Z-freq 2D values is then run and train in CL to fine the best values of performance metrics and to validatet the data. k-NN and SVM data is obtained form the training in CL. Figure 3.11 shows the set of train sample in classification learner.

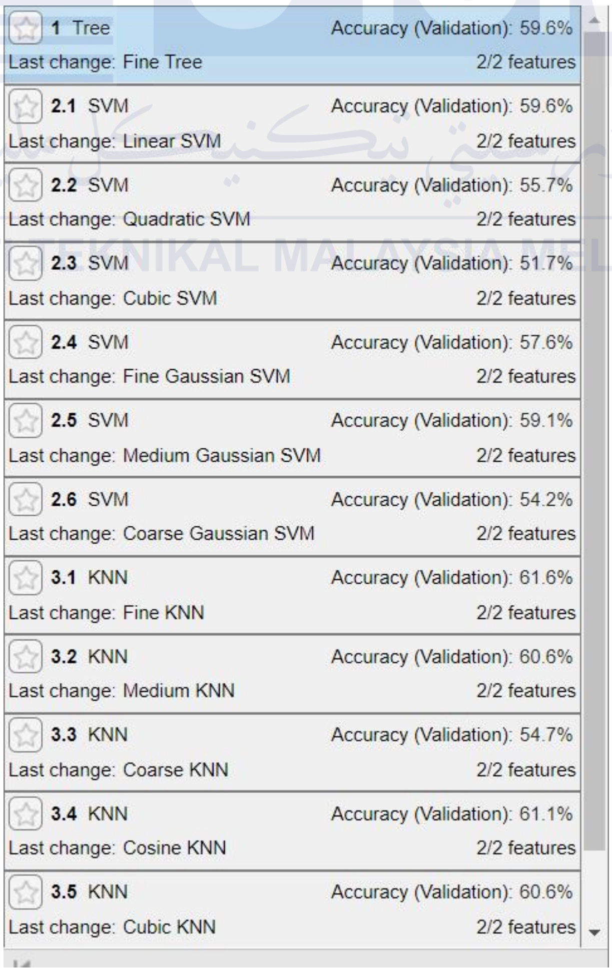


Figure 3.11 Set of training in Classification Learner (CL)

Each training of the Z-freq 2D value will provide the scatter diagram of the coefficients and the confusion matrix as can be refer to Figure 4.10 to Figure 4.13.

3.2.7 Limitation of Proposed Methodology

The wireless diagnostic system is a tool for locating and resolving issues using wireless networks, specifically Wi-Fi, in this experiment. These techniques are appealing since they don't need physically changing or unplugging any equipment, making them non-invasive. However despite how convenient this method was, it is not excluded from some limitations. To begin with, the wireless diagnosis data would be sometimes difficult to obtain due to the signal strength and network traffic data. Phantom Vibration Sensor (PVS) relies on the wifi to transfer the vibration data produce by the compressor to the cloud which then need to be downloaded through application system DigivibeMX. This procedure clearly need a good network signal for it to perform perfectly. Furthermore, distinguishing between internal equipment issues and external variables, such as vibration interference from other vehicle units, can be challenging and may skew the diagnostic results. It is greatly important for researcher to separate the data of vibration that produced by vehicle internal unit with compressor vibration to ensure the analysis are accurate. For an addition, the test also need to monitor and aware of the timestamp of each signal received as wrong time reading when the signal transfer to the cloud system, could lead to fail analysis.

3.3 Summary

This chapter presents the proposed methodology for developing a new, effective, and integrated statistical approach to identify faults in the vehicle's A/C compressor using the Z-Freq 2D coefficient in a wireless diagnostic method. The suggested methodology aims to efficiently perform a basic diagnosis of the car HVAC systems without significantly compromising the accuracy of the results, so saving a considerable amount of time that would otherwise be spent diagnosing errors. This method is intended not only for advanced automotive industries but also for average vehicle workshops. The wireless HVAC compressor diagnostics, utilizing state-of-the-art machine learning-based signal analysis with Z-Freq 2D, can greatly improve compressor performance and streamline the detection of faults in the vehicle's A/C system.

Generally, the concept of wireless diagnostics in this proposed methodoly is analysed using machine learning systems which providing a k-Nearest Neighbors algorithm (k-NN) and Support Vector Machine (SVM) data to show the efficiency of the data analysis. The result is expected to show the best values of true positive rate (TPR) and false positive rate (FPR) of the machine learning based on the coefficient of Z-freq 2D data. The next chapter will showcase multiple case studies aimed at illustrating, confirming, and enhancing the suggested techniques discussed in this chapter.

CHAPTER 4

RESULT AND DISCUSSION

4.1 Introduction

This chapter presents the results and analysis of the vehicle compressor's performance by manipulating the amount of refrigerant (R134a) and lubricant oil under various parameters. Data was then obtained using a wireless diagnostic device known as the Phantom Vibration Sensor (PVS), which detected vibrations produced by the compressor during engine operation. The results of the calibration process for the sensor are presented. The process of the calibration is important as it provide a significant criteria in accurate measurement of the frequency. It involving the standardization of reference materials, measurement and the isntruments. Calibration helps and necessary to assess the performance characteristics of the reference materials, measurement methods and equipment used. Case studies were conducted to monitor the vibration data signals and analyze them using a machine learning system to determine the k-NN and SVM values based on the Z-freq 2D coefficient.

Throughout the calibration process, it is essential to identify key parameters for each sensor, including the calibration factor, sensitivity, amplitude, and frequency range. In this study, calibration was carried out using a vibration exciter to evaluate both the input and output signal responses of the sensors. Each sensor was affixed to the vibration exciter, which was configured to operate at a precise frequency of 159.2 Hz with a minimal deviation of ±0.02 Hz.

The case study is based on a real vehicle performance rather than theoretical analysis. It is important to note that, these case study aims at the statistical proposed methodology. The experimental analysis results are presented in graphical form, including scattered data and machine learning performance matrices, showing the Z-Freq 2D coefficients for both refrigerant and oil.

4.2 Experimental Result and Analysis

The research study utilized a new statistical analysis by implementing the kurtosis coefficient in both the time and frequency domains of the converted data signal. Several parameters were set up for the experimental tests. Each test lasted approximately 5 seconds, during which 16,384 samples were recorded per channel at a sampling rate of 3.2 kHz and a resolution of 6400 lines.

In the first phase, which focused on testing sensor sensitivity, vibration data from the piezo-film sensor, micro-fiber sensor, and accelerometer were recorded. A vibration calibrator, as illustrated in Figure 4.0, was used to provide a constant input vibration at a frequency of 159.15 Hz with a tolerance of ±0.02%, and the output from each sensor was monitored. In the second phase, building on the successful development of the I-kaz™ statistical analysis method by Nuawi in the time domain, a new statistical analysis method called Z-freq was introduced. This method leverages the frequency domain to analyze output patterns, as it offers insights not available in the time domain.

Figure 4.0 A vibration calibrator

4.2.1 Analysis of vibration data

Figure 4 shows the gathered signal, which was displayed and transformed into frequency and time domain graphs. Figure 4.1 illustrates the vibration data signals produced during compressor not running which range from 750 RPM to 2000 RPM during a 5-second recording. The data shows that during the first stage of speed, the highest vibration detected almost reach 1 m/s^2 while during 2000 RPM the vibration reach around 3 m/s^2 for horizontal sensor, however for veritical its value way over 5 m/s^2. According to ISO 10816 & ISO 20816 Standards, the acceptable vibration for rotating machinery are around 1 – 5 m/s^2 while at around 5 – 20 m/s^2, indicated that of increased wearwhich leads to potential faults developing. By refers to the frquency graph, it is clear that, when the speed of compressor is increased, the value of vibration is also increased. Since at vertical sensor the data shows over 10 m/s^2 compared to horizontal sensor which only at 3 m/s^2, this shows that at low oil volume even with standard refrigerant volume at 320 g, it could cause some serious damage to the compressor health in long term even though if the compressor are not running.

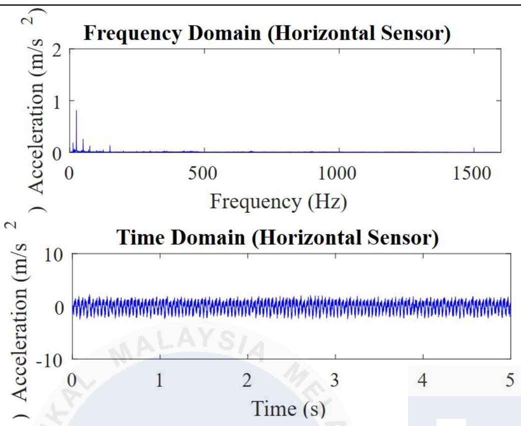


Figure 4.1a: 750 RPM Refrigerant (R134a) 320g Oil 40ml

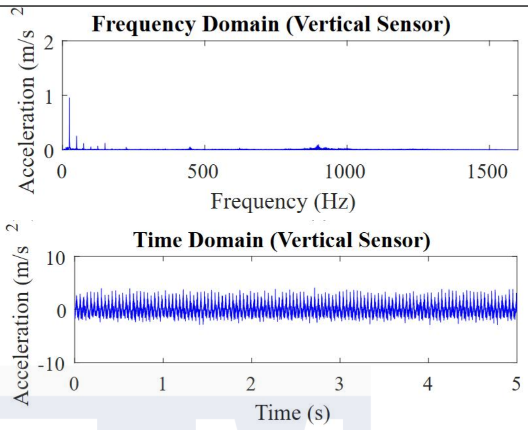


Figure 4.1b: 750 RPM Refrigerant (R134a) 320g Oil 40ml

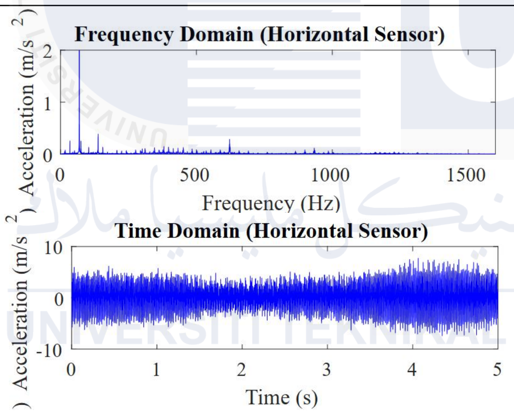


Figure 4.1c: 2000 RPM Refrigerant (R134a) 320g Oil 40ml

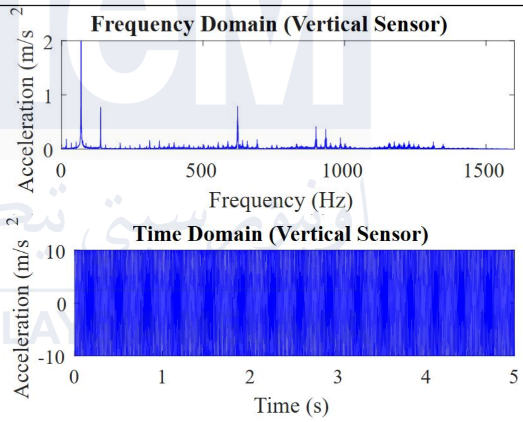


Figure 4.1d: 2000 RPM Refrigerant (R134a) 320g Oil 40ml

Figure 4.1 Illustrates the vibration data signals at 750 RPM and 2000 RPM for oil 40ml

From the figure 4.1 at parameters of 320g of refrigerant and oil volume at 40ml, shows a significant time domain vibration and frequency domain at two different speed of the compressor at two different axial. At high speed RPM at lowest oil volume, the data shows that axial vertical received a high vibration signal compared at horizontal graph which due to the structure of the compressor. Refers to Figure 2.1 and Figure 3.4, since the rotation of the pulley inside the compressor rotates at high speed it causing the force goes out from the inner to outer, creating a high vibration signal. Figure 4.2 illustrates how a compressor running at 900 RPM and 2000 RPM produce a vibration data signal within 5 seconds signal recorded respectively at parameter of 320g of refrigerant and 40ml of oil lubricant. When the air conditioning switched on, the compressor start to run. At 900 RPM, the highest vibration values almost reached 2 m/s² for both sensor. However at 2000 RPM, at horizontal sensor the value sligthly reach 4 m/s² while at vertical sensor over past 10 m/s². This condition is even worse for the compressor compared during the compressor are not switched on. This could increase the speed of the compressor to damage over time, when the air conditioning system have lacks of oil lubricant.

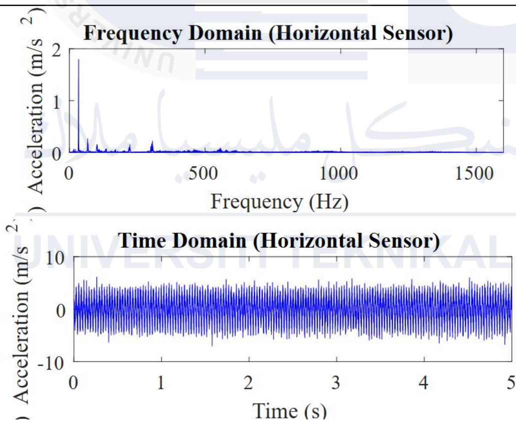


Figure 4.2a: 900 RPM Refrigerant (R134a) 320g Oil 40ml

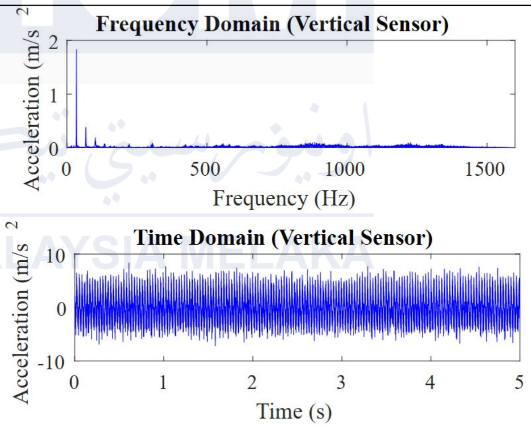


Figure 4.2b: 900 RPM Refrigerant (R134a) 320g Oil 40ml

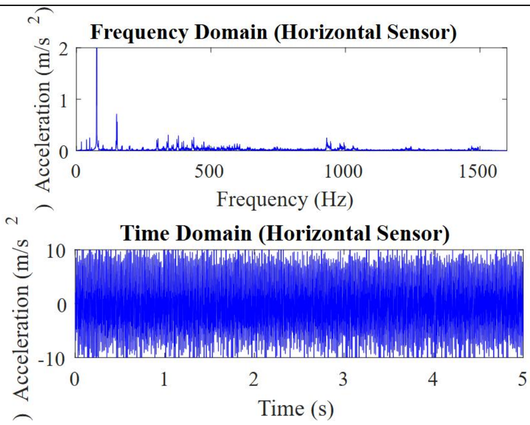


Figure 4.2c: 2000 RPM Refrigerant (R134a)

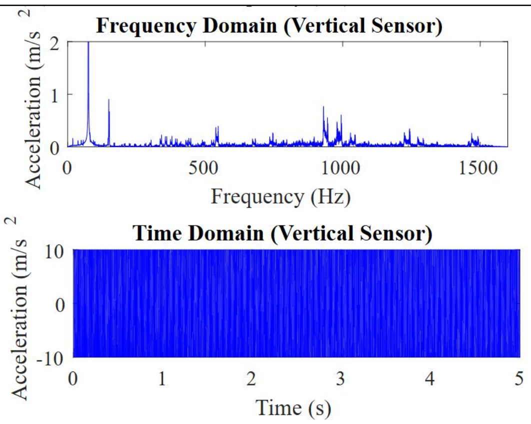


Figure 4.2d: 2000 RPM Refrigerant (R134a)

320g Oil 40ml	320g Oil 40ml

Figure 4.2 Illustrates the vibration data signals at 900 RPM and 2000 RPM for oil 40ml

Figure 4.2 is the vibration data signal collected during the compressor is running at 320g of refrigerant and 40ml of oil volume. The representation data of frequency and time domain from Figure 4.1 and 4.2 is then compared to the Figure 4.3 and Figure 4.4 for both state of compressor, which the signal data of optimal refrigerant and oil in the HVAC system which according to the standard of automotive industry specific for this type of car which around 320 g to 330 g of refrigerant and 80 ml to 90 ml of oil.

Figure 4.3 shows the vibration data that was taken for parameters of 320g of refrigerant and 80ml of oil volume in the compressor of the A/C in the vehicle HVAC during the compressor is not running. This is the standard amount of both refrigerant and oil volume in the respective vehicle according to the automotive standard. At the idle speed of the compressor which 750 RPM, the data recorded almost reached 1 m/s^2 both sensor. However during 2000 RPM the vibaration reach 10 m/s^2 for both side. Which this may from the noise which can be detected when compared with data during compressor is running. Figure 4.4 shows the vibration data during compressor is running and the peak data in 2000 RPM slightly over 5 m/s^2. This indicated that compressor are able to perform well when both refrigerant and oil are fill correctly to volume needed which in this case around 320g - 330g of refirgerant and 80ml-90ml of oil in the air conditioning system of the vehicle which is the optimum refrigerant and oil volume in the compressor systema as been standardize by the automotive industry and this Z Freq 2D coefficient are able to identify and diagnosed the data perfectly. This is the benchmark for experimentation.

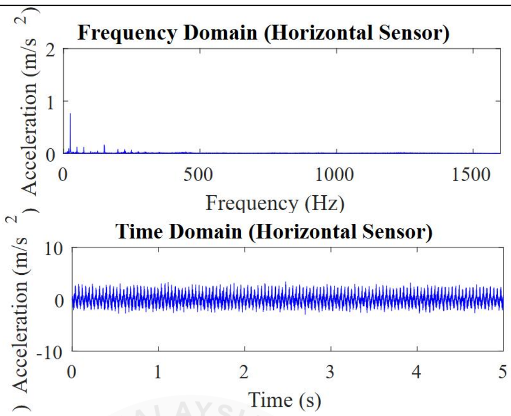


Figure 4.3a: 750 RPM Refrigerant (R134a) 320g Oil 80ml

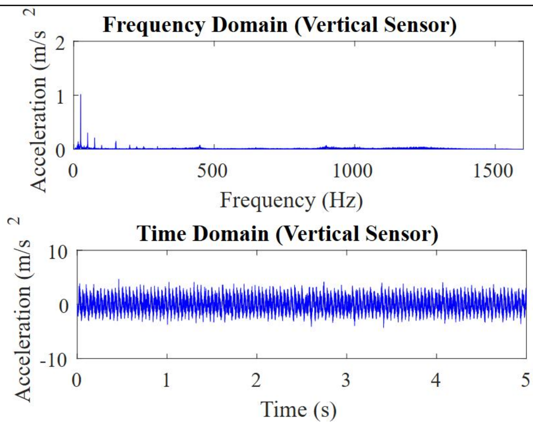


Figure 4.3b: 750 RPM Refrigerant (R134a) 320g Oil 80ml

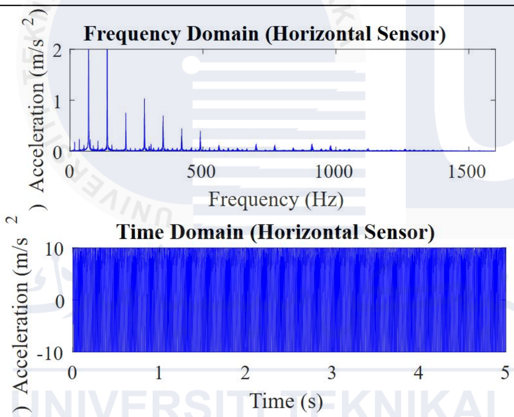


Figure 4.3c: 2000 RPM Refrigerant (R134a) 320g Oil 80ml

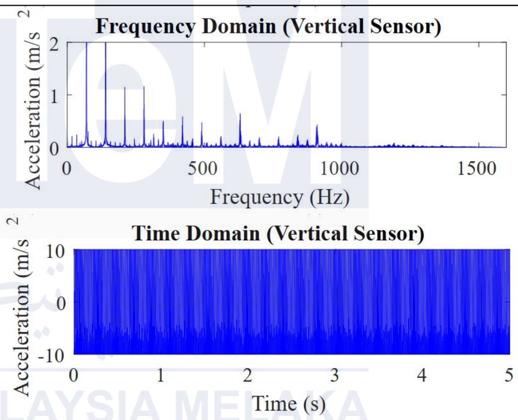


Figure 4.3d: 2000 RPM Refrigerant (R134a) 320g Oil 80ml

Figure 4.3 Illustrates the vibration data signals at 750 RPM and 2000 RPM for oil 80ml

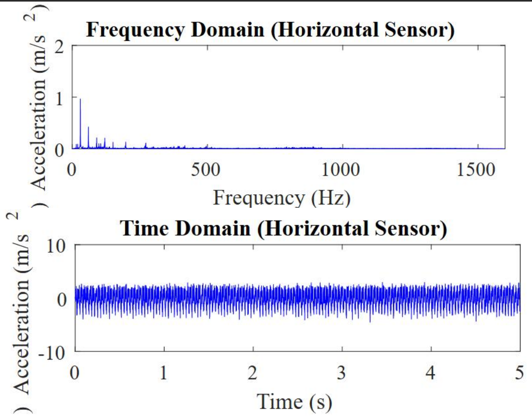


Figure 4.4a: 900 RPM Refrigerant (R134a) 320g Oil 80ml

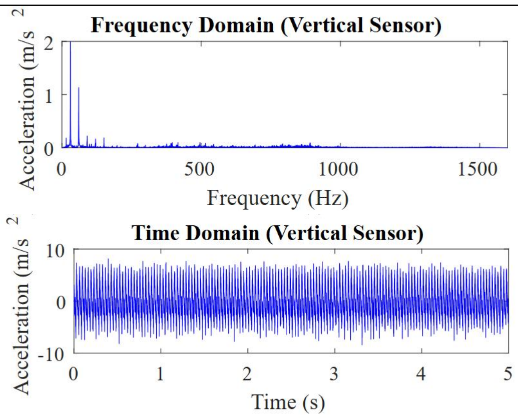


Figure 4.4b: 900 RPM Refrigerant (R134a) 320g Oil 80ml

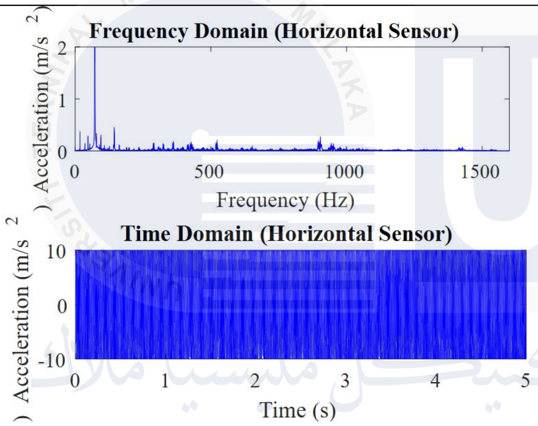


Figure 4.4c: 2000 RPM Refrigerant (R134a) 320g Oil 80ml

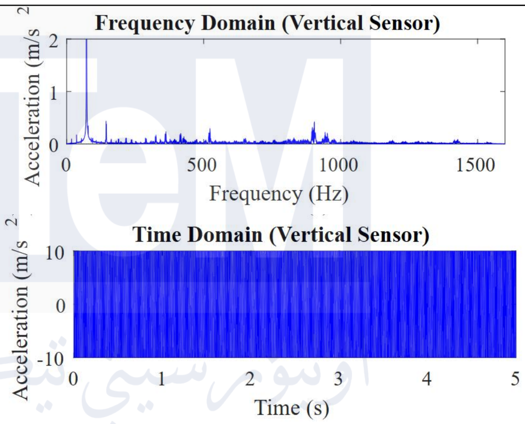


Figure 4.4d: 2000 RPM Refrigerant (R134a) 320g Oil 80ml

Figure 4.4 Illustrates the vibration data signals at 900 RPM and 2000 RPM for oil 80ml

Figure 4.5 shows the data results for the time domain and frequency domain for parameters of highest amount of oil in the compressor system which around 120ml for both during compressor not running and during compressor running. At compressor not running, at the idle speed of 750 RPM the signal barely reach 1m/s² while at 2000 RPM it reached over 10 m/s². During compressor is running, at 900 RPM the the frequency detected reached 2 m/s² while at 2000 RPM only 5 m/s². Even if the frquency is low and at acceptable frequency for most rotating machinery, the flaw is the air conditioning unable to cool the cabin area during the experimentation. This is assumed that a slugging may happened and blocking the refrigerant from cooling the system and unable do its work perfectly.

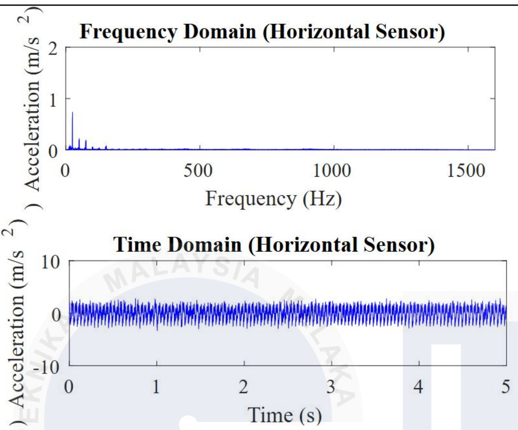


Figure 4.5a: 750 RPM Refrigerant (R134a) 320g Oil 120ml

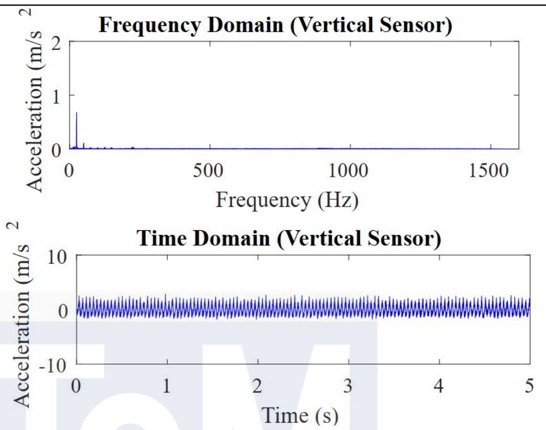


Figure 4.5b: 750 RPM Refrigerant (R134a) 320g Oil 120ml

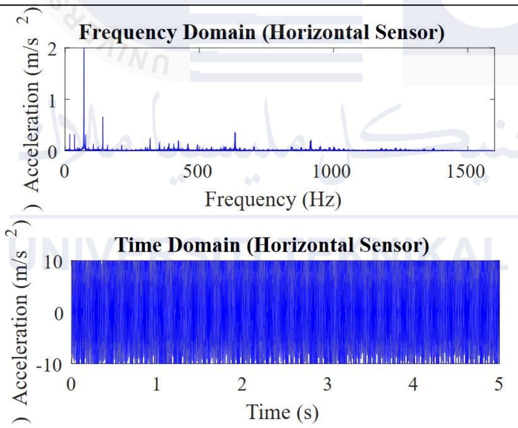


Figure 4.5c: 2000 RPM Refrigerant (R134a) 320g Oil 120ml

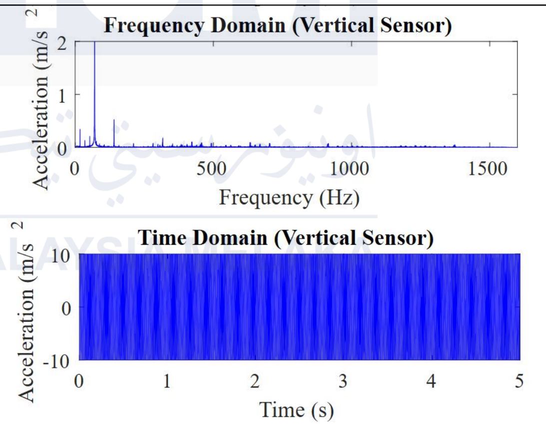


Figure 4.5d: 2000 RPM Refrigerant (R134a) 320g Oil 120ml

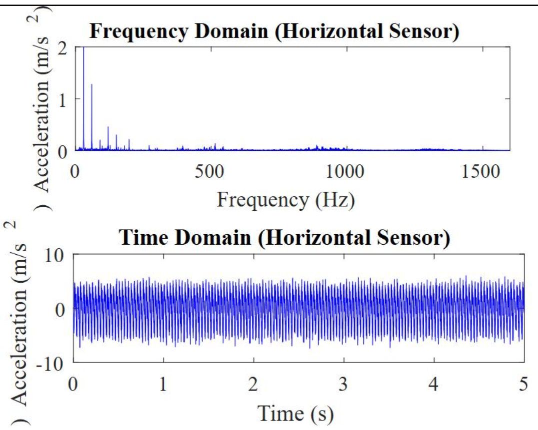


Figure 4.5e: 900 RPM Refrigerant (R134a) 320g Oil 120ml

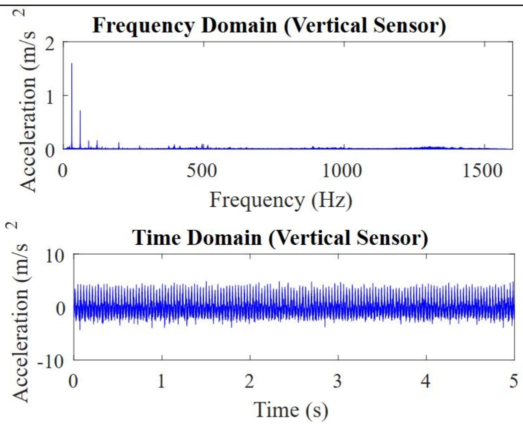


Figure 4.5f: 900 RPM Refrigerant (R134a) 320g Oil 120ml

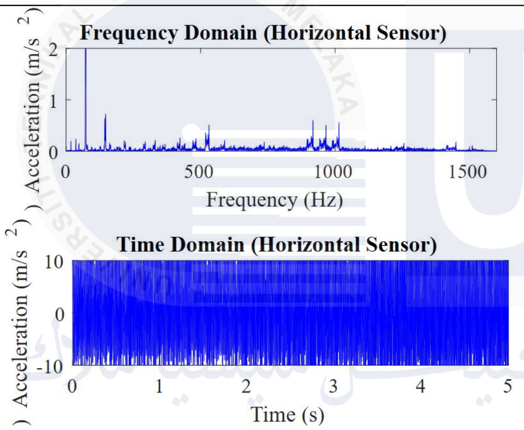


Figure 4.5g: 2000 RPM Refrigerant (R134a) 320g Oil 120ml

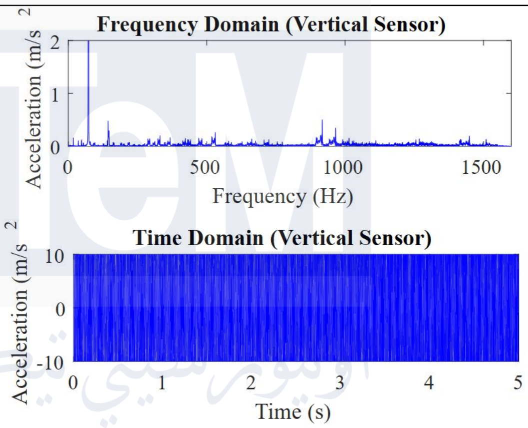


Figure 4.5h: 2000 RPM Refrigerant (R134a) 320g Oil 120ml

Figure 4.5 Illustrates the vibration data signals for 320g refrigerant - oil 120ml

Figure 4.6 shows the data results of both time and frequency domain for compressor off and compressor on for refrigerant 280g and 80ml of oil which at the lowest refrigerant volume in the A/C HVAC system.. At idle speed 750 RPM for compressor not running the frequency recored around 0 m/s² to 2 m/s² while at 2000 RPM the frequency is about 2 m/s² for horizontal sensor but for vertical sensor the frquency detected over 10 m/s². During the compressor is running at idle speed of 900 RPM the average frequency is around 1 m/s² to 2 m/s², while at 2000 RPM the frequency easily reached over 10 m/s² for vertical sensor while horizontal only at 1 m/s². From the data obtained it is can be seen that at idle speed during both compressor not running and running, the frequency of both state are not significantly difference compared at speed of 2000 RPM where during compressor running the value are higher than that during compressor not running. This is a sign that the A/C system may overheating causing some disturbance in the compressor.

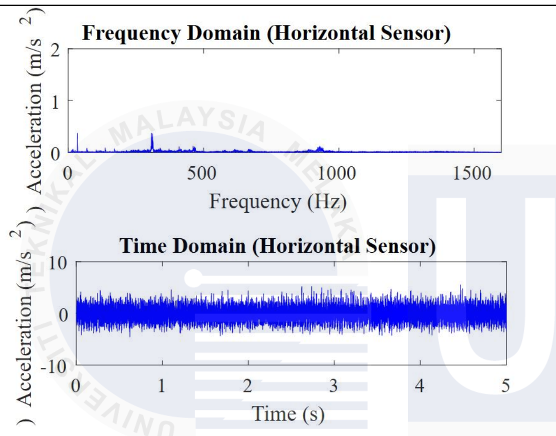


Figure 4.6a: 750 RPM Refrigerant (R134a) 280g Oil 80ml

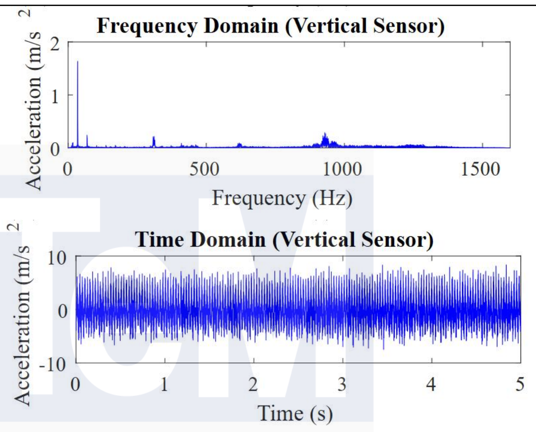


Figure 4.6b: 750 RPM Refrigerant (R134a) 280g Oil 80ml

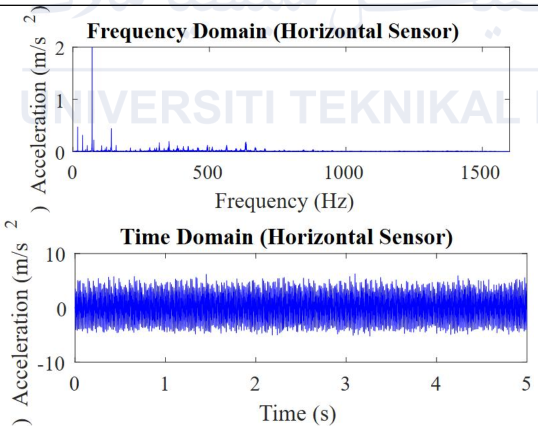


Figure 4.6c: 2000 RPM Refrigerant (R134a) 280g Oil 80ml

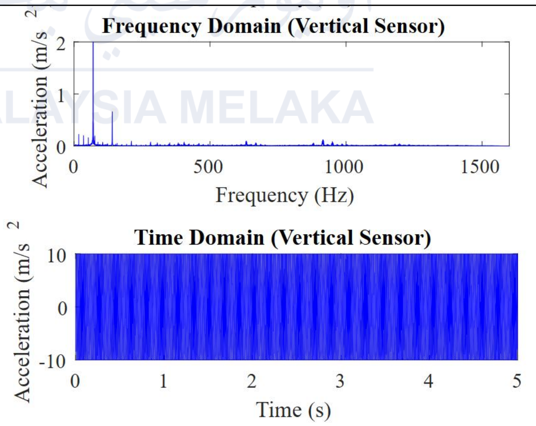


Figure 4.6d: 2000 RPM Refrigerant (R134a) 280g Oil 80ml

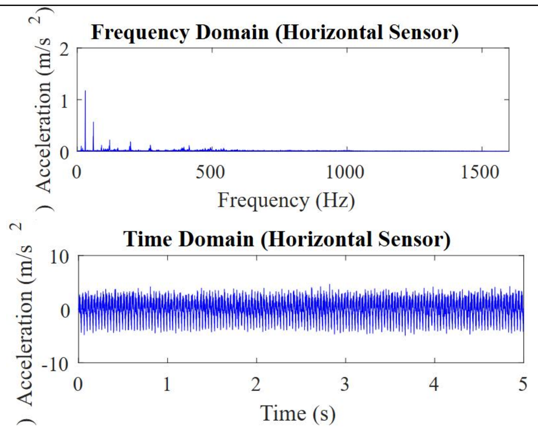
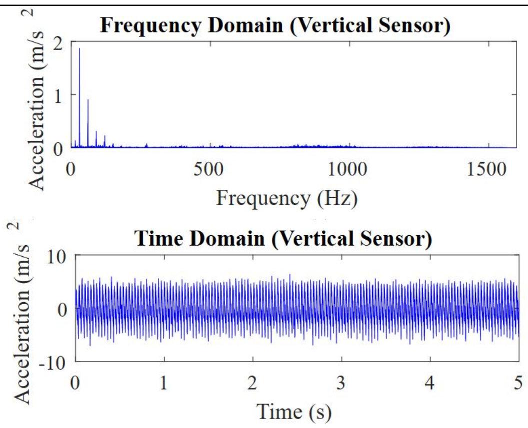
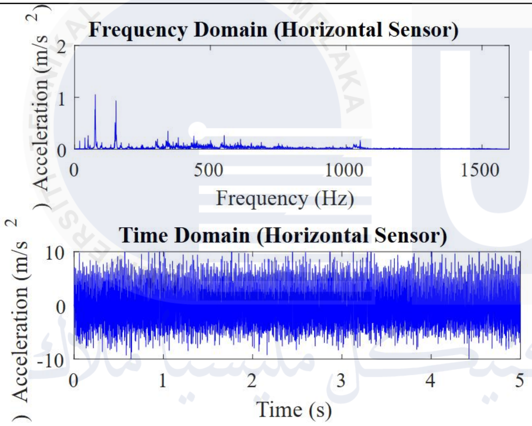
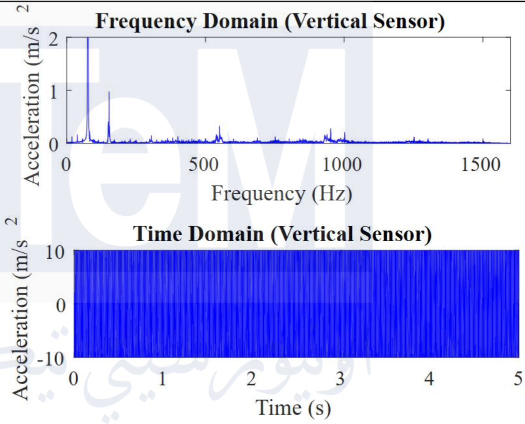
 Figure 4.6e: 900 RPM Refrigerant (R134a) 280g Oil 80ml	 Figure 4.6f: 900 RPM Refrigerant (R134a) 280g Oil 80ml
 Figure 4.6g: 2000 RPM Refrigerant (R134a) 280g Oil 80ml	 Figure 4.6h: 2000 RPM Refrigerant (R134a) 280g Oil 80ml

Figure 4.6 Illustrates the vibration data signals for 280g refrigerant - oil 80ml

Figure 4.7 shows the data results of both time and frequency domain for compressor off and compressor on for experiment for the highest amount of refrigerant and optimum amount of oil in the HVAC of the vehicle which is refrigerant 360g and 80ml of oil. At idle speed (750 RPM) of compressor not running the frequency recorded is about 1 m/s² for horizontal and 1.5 m/s² for vertical sensor while during compressor running (900 RPM) is 0.8 m/s² for horizontal and 1.5 m/s² for vertical. However at 2000 RPM, during compressor not running the frequency value is barely reach 5 m/s² for horizontal and 5 m/s² for vertical. However at compressor running the frequency recorded for horizontal is 5 m/s² but for vertical it easily past over 20 m/s². This shows that there are probably slugging phonemenon is occur where the overflow of refrigerant in the systsem causing the mechanical parts in the compressor froze and the build up of pressure which creates high vibration.

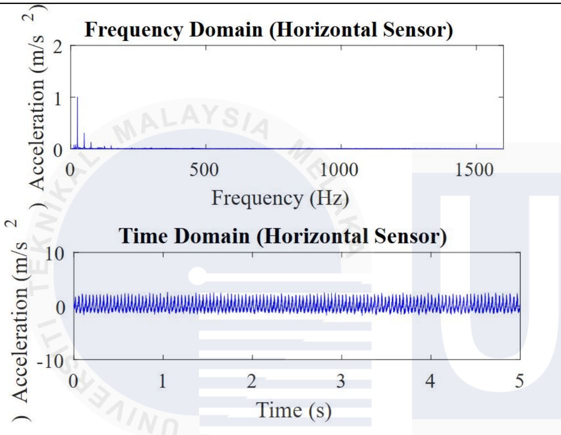


Figure 4.7a: 750 RPM Refrigerant (R134a) 360g Oil 80ml

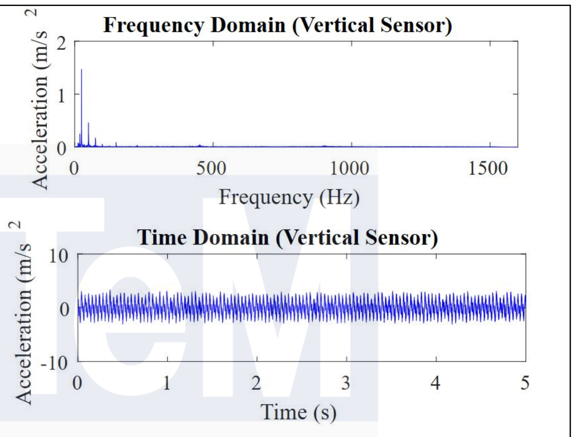


Figure 4.7b: 750 RPM Refrigerant (R134a) 360g Oil 80ml

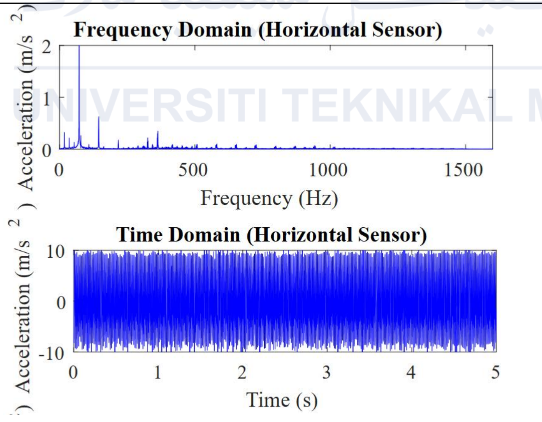


Figure 4.7c: 2000 RPM Refrigerant (R134a) 360g Oil 80ml

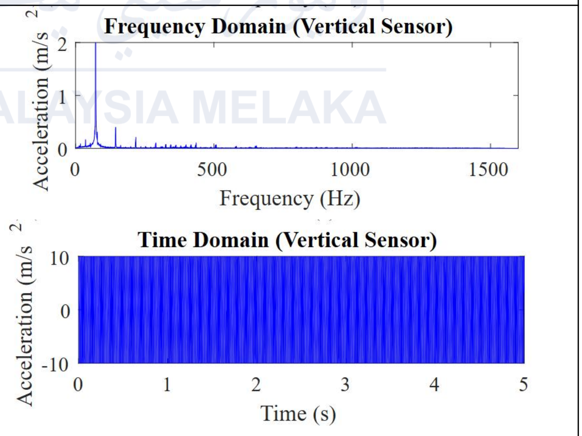
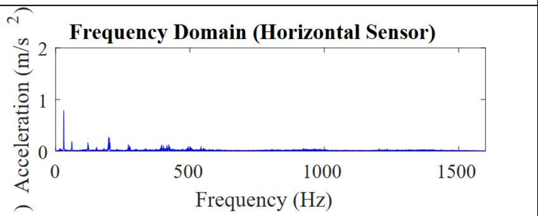
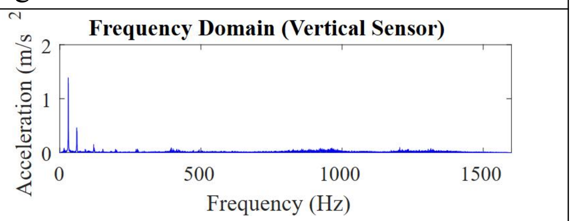


Figure 4.7d: 2000 RPM Refrigerant (R134a) 360g Oil 80ml





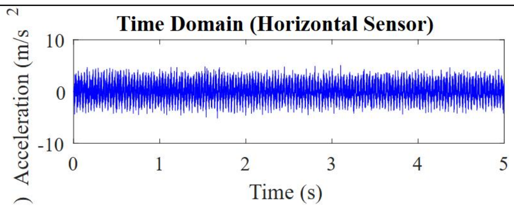


Figure 4.7e: 900 RPM Refrigerant (R134a) 360g Oil 80ml

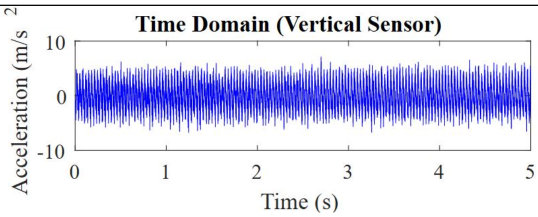


Figure 4.7f: 900 RPM Refrigerant (R134a) 360g Oil 80ml

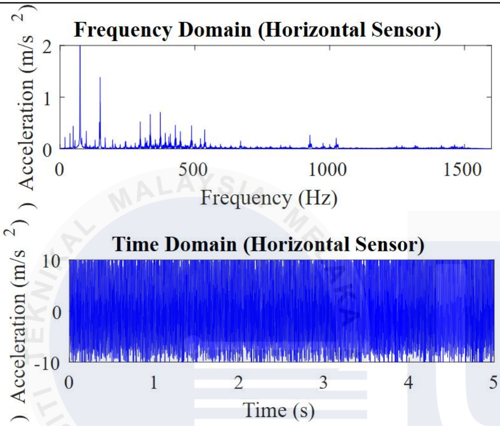


Figure 4.7g: 2000 RPM Refrigerant (R134a) 360g Oil 80ml

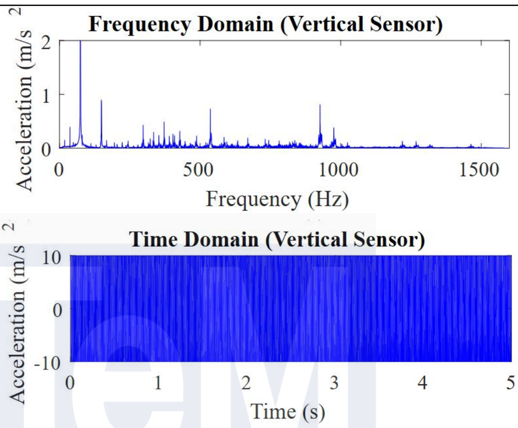


Figure 4.7h: 2000 RPM Refrigerant (R134a) 360g Oil 80ml

Figure 4.7 Illustrates the vibration data signals for 360g refrigerant - oil 80ml

By referring the data result from figure 4.1 to figure 4.7 it is clearly shows that the amount of either refrigerant or oil in the HVAC system of the vehicle potentially affecting the compressor performance. Figure 4.1 and figure 4.2 is the data result of time domain for lowest amount of oil in the system while figure 4.5 is the data results for the highest amount of oil in the system. By comparing the data, as the compressor running during low amount of oil, no significant frequency values compare to 80ml of oil in the system. However at high amount of oil in the system the average frequency value are spiking. This is due to overexcessive amount of oil in the system which this is known a slug. Slug is the phenomena of liquid entering a reciprocating compressor's cylinder as it fills with liquid.

This can lead to crankshaft breaks and con rod breakages as a result of hydraulic lock in the cylinder.

As for figure 4.6 is the data of time domain for low amount of refrigerant while figure 4.7 is the data for highest amount of refrigerant. From the data comparison, it is clearly shown a significant vibration produced as the amount of refrigerant in increased. As the amount of refrigerant increased in the system, the compressor are not be able to transition correctly between the gaseous and liquid states; a greater proportion of it will stay in the liquid state. It will cause ice buildup by freezing the machinery which highly dangerous for the compressor health and performance which eventually harm the compressor. Same as from overexcessive amount of oil, this phenomenon also known as slugging. Pressure imbalances in the system caused by high or low refrigerant levels interfered with the compressor's function and, as a result, impair the cabin's ability to cool.

Based on the representation displayed in the frequency domain random graph pattern, it can be simplified that as the compressor speed grew, a significant magnitude of frequency data is produced. Z-freq value is also influenced by the fact that the magnitude of frequency power at high frequency grew gradually as speed increased. From the data of time and frequency domain, the value of Z-freq 2D is calculated using MATLAB coding and displayed as line graph in figure 4.8 and figure 4.9 which shows the smooth graph line for the lowest parameters for both of the experiment respectively.

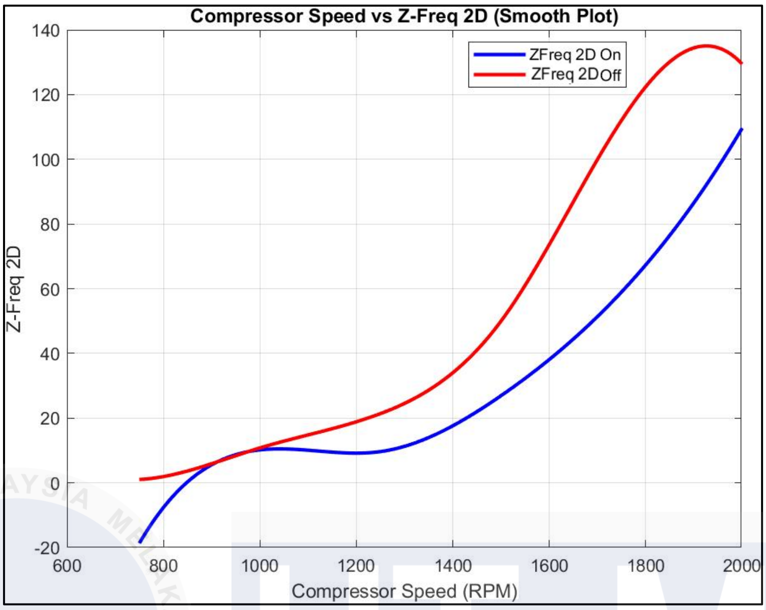


Figure 4.8 Parameter of Refrigerant (R134a) 320g Oil 40ml

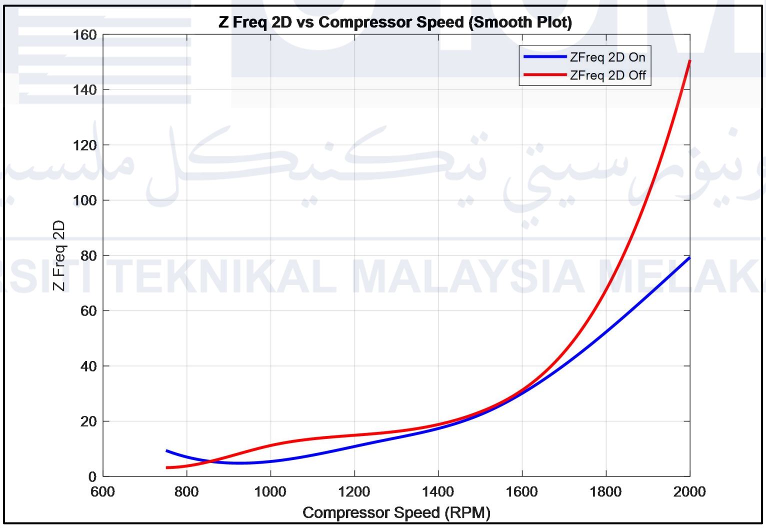


Figure 4.9 Parameter of Refrigerant (R134a) 280g Oil 80ml

It can be seen from the figure 4.8 and figure 4.9, the graph line are not entirely smooth. As the speed of the compressor increasing, the Z - Freq 2D also increasing. As mentioned in time domain and frequency domain analysis, a low amount of either refrigerant or oil in the compressor, would affect the compressor performance in compressing the refrigerant gas which causing the compressor producing a unstable vibration in the system. As the vibration are not stable, Z -Freq 2D coefficient able to capture the vibration as shown in both graph. The line are not in straight line as it shows the fluctuation in the vibration, indicating the unit inside the compressor are not functioning well in performing. There are several factors can considered in this situation, but main factor is the internal damage is being occurs in the compressor unit. Low oil causing the internal components such as the pistons, valve, or bearing are having wearness as the surface friction is increasing while low refrigerant making the internal of the compressor are excessively high in temperature which causing the compressor overheating and eventually burn-out the motor inside the compressor.

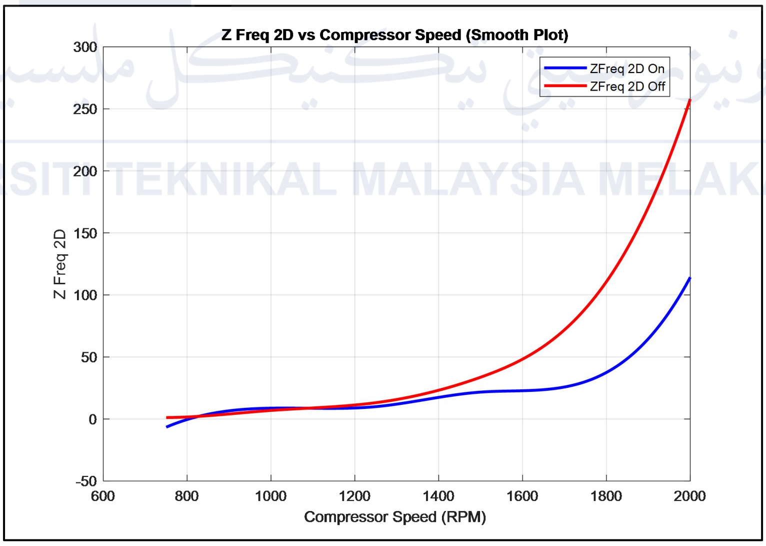


Figure 4.10 Parameter of Refrigerant (R134a) 320g Oil 80ml

Figure 4.10 shows the Z - Freq 2D coefficient value over speed of the compressor for the parameter of 320g refrigerant and 80ml oil. Compared to the previous graph, figure 4.10 graph line show a significant graph line trend which much more smooth. This defined that the Z - Freq 2D coefficient for parameter 320g and 80ml oil would produce a smooth vibration indicating it a stable vibration which perfect condition for the compressor performance. This can be further confirmed when compared with the highest parameter graph line result which shows the vibration are not completely stable even though the graph increase consistently. Figure 4.11 and figure 4.12 shows the result of graph line for highest parameters value for refrigerant and oil volume respectively.

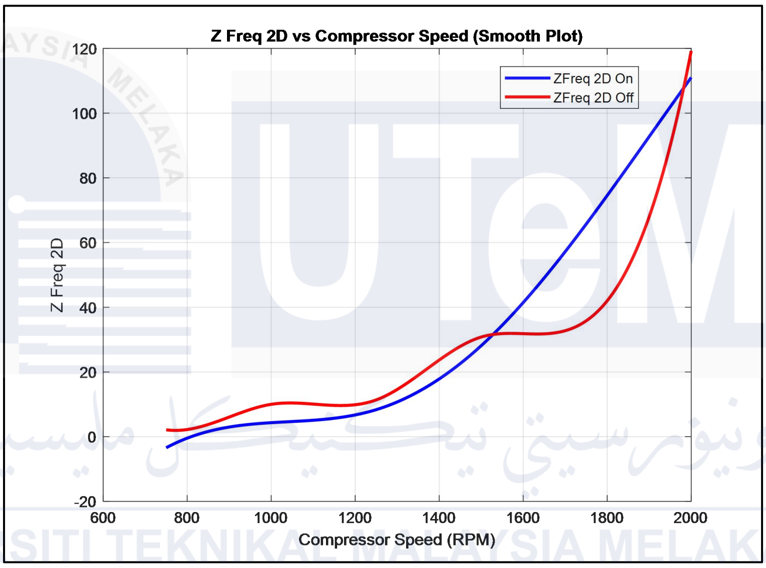


Figure 4.11 Parameter of Refrigerant (R134a) 360g Oil 80ml

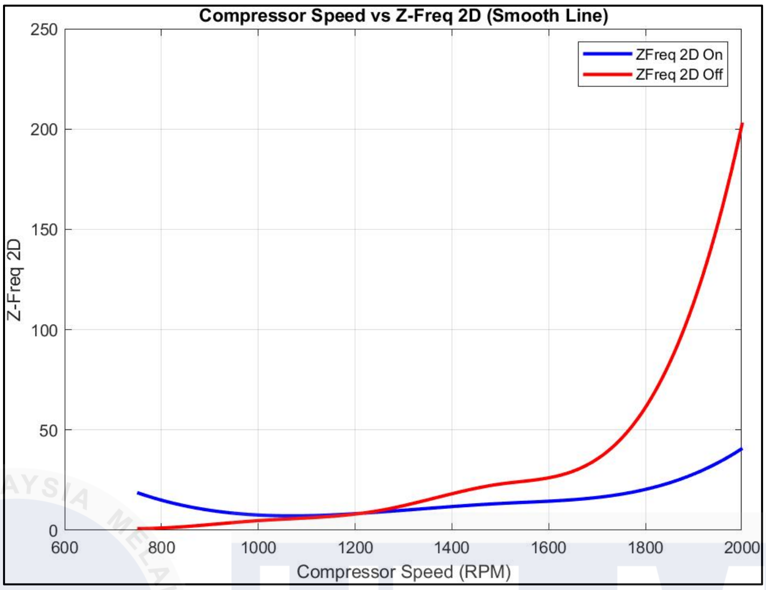


Figure 4.12 Parameter of Refrigerant (R134a) 320g Oil 120ml

By referring to the analysis of the time and frequency domain, as the volume of the refrigerant and oil is overexcessive poured into the system, a phenomena of slugging is triggered. As the overfilling of either the oil amount or refrigerant volume in the HVAC system, compressor will unable to perform well. As oil is important for lubricating the compressor, excessive amount of oil can cause several problem such as increase the internal pressure which eventually leading to friction. As shown in figure 4.12, as the compressor running, the Z - Freq 2D values drop into the baseline indicating the compressor are not perform perfectly as it should be. This can be seen as the compressor are not working even though the A/C button are activated. As for figure 4.11, the graph shows a significant vibration produced in the system. Z - Freq 2D able to recorded the data and shows that as refrigerant are overfilling in the HVAC system, it creates excessive pressure, which straining the compressor and cause premature wear and tear. The internal of the compressor unit probably mostly frozen from the overexcessive refrigerant in the system, which causing the graph line become erratic as shown in the figure. Based from the analysis of the time domain and frequency domain of each parameters in the experiments, it is can be summarised that key parameters affecting compressor performance which in this case is the lack or overfilling of both oil lubricant in the compressor and the refrigerant can affect the performance of the compressor leading it to create a faulty in the systems. The systematic identification of key parameters influencing compressor performance has provided crucial insights into optimizing operational efficiency and enhancing reliability. Any amount of oil or refrigerant lower or higher than 320g - 330g of refrigerant and 80ml to 90ml, is considered a faulty for the system of HVAC of the vehicle which perfectly detected by Z -Freq 2D coefficient.

4.2.2 Machine learning model performance

The overall results of the vibration data signals for Z-Freq 2D are presented in Tables 4.1 to 4.4, showing the relationship between refrigerant and oil volumes versus compressor speed. From the table presented, as the speed of the compressor increase, the Z - Freq 2D coefficient also increase.

Table 4.1 Z - Freq 2D coefficient of each speed for oil parameters (Compressor Off)

Compressor Speed (RPM)	**Volume of compressor oil (ml)**				
	Compressor Off				
	40	60	80	100	120
750	1.0259	1.1521	1.1632	1.6151	0.8431
900	5.9024	4.1215	4.02435	8.9132	2.8148
1000	10.7789	7.0909	6.8855	16.2113	4.7865
1250	21.3911	25.3994	13.1373	29.3503	9.795
1500	49.994	46.0733	33.6734	68.4771	23.0466
1750	112.1121	69.3886	89.0213	193.3409	45.7369
2000	129.4334	207.7664	257.9428	649.0413	203.2455

Table 4.2 show the result Z - Freq 2D data during the experimentation when the compressor is running. At the idle speed, which mean without pushing the accelerator, the compressor gave intinial speed of 900 RPM compared to during compressor is not running which started from 750 RPM. This condition are due to when the air conditioning is turn on, the compressor will started to run which causing the RPM to rises as the compressor started to spinning, this situation is also the same as shown in Table 4.4.

Table 4.2 Z - Freq 2D coefficient of each speed for oil parameters (Compressor On)

Compressor Speed (RPM)	**Volume of compressor oil (ml)**				
	Compressor On				
	40	60	80	100	120
750	N/A	N/A	N/A	N/A	N/A
900	5.5666	4.6627	6.588	7.5481	9.9491
1000	10.1666	6.1164	8.7301	14.6203	7.586
1250	9.6443	7.3622	9.9513	33.9365	9.0565
1500	26.9344	16.7978	21.6684	56.9152	13.3429
1750	49.016	33.6629	30.1304	71.6514	17.9986
2000	109.6384	96.0181	114.2458	133.169	40.8457

Table 4.3 Z - Freq 2D coefficient of each speed for refrigerant parameters (Compressor Off)

Compressor Speed (RPM)	**Volume of refrigerant (g)**				
	Compressor Off				
	280	300	320	340	360
750	3.208	1.0094	1.1632	1.8439	2.1253
900	7.2176	4.9974	4.02435	7.2088	6.06155
1000	11.2272	8.9854	6.8855	12.5737	9.9978
1250	15.5354	24.0503	13.1373	12.2645	11.3669
1500	23.4066	52.3992	33.6734	40.7285	30.7894
1750	55.0821	105.2142	89.0213	60.0934	35.8062

2000	150.7322	249.4896	257.9428	131.2716	119.2416

Table 4.4 Z - Freq 2D coefficient of each speed for refrigerant parameters (Compressor On)

Compressor Speed (RPM)	**Volume of refrigerant (g)**				
	Compressor On				
	280	300	320	340	360
750	N/A	N/A	N/A	N/A	N/A
900	4.8985	5.8947	6.588	6.9805	2.9715
1000	5.4297	7.8866	8.7301	10.4746	4.32
1250	12.4789	16.0457	9.9513	12.1862	8.3489
1500	22.3982	25.1654	21.6684	20.8209	28.1222
1750	46.1496	66.6291	30.1304	48.8787	65.713
2000	79.3594	243.2376	114.2458	124.5542	111.015

Figure 4.13 show the result of data scattered of Z - Freq 2D coefficient as the compressor vibration pattern can be described beside from graph line. The x axis represented the distribution of data from Z Freq 2D of refrigerant R134a and y axis represented as Z - Freq 2D coefficient of Oil volume. It is clearly shown from the scattered graph, the Z - Freq 2D coefficient data are scattering as the frequency magnitude be more wider as the speed of the compressor increases for compressor on and compressor off.

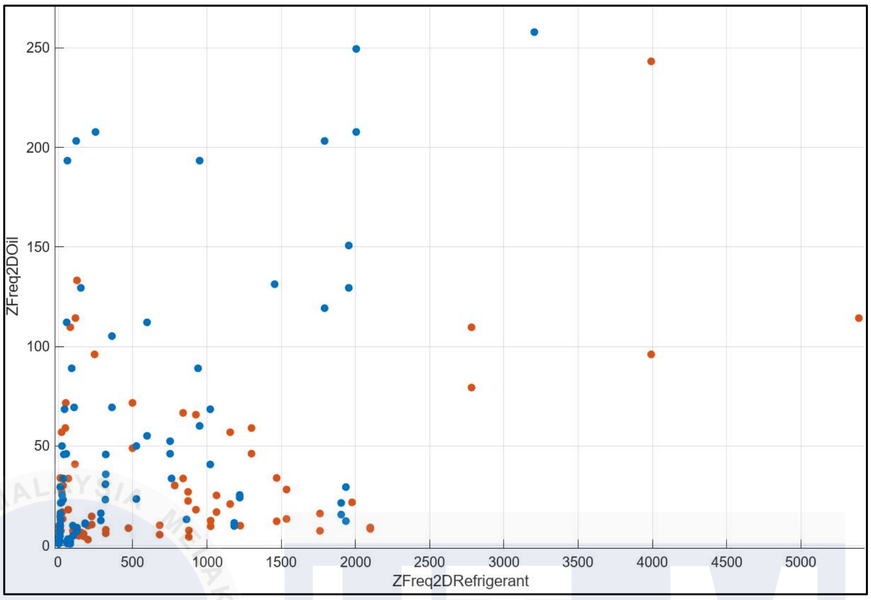


Figure 4.13 Overall data scattered of Z Freq 2D of Refrigerant - Oil parameters

Due to the frequency domain, the distribution of frequency data is increase significantly in frequency magnitude. The scatter data of each Z-freq 2D can be seen in Figure 4.14 for horizontal and Figure 4.15 for vertical axis, respectively for parameters of 320g refrigerant R134a with 80ml oil lubricant.

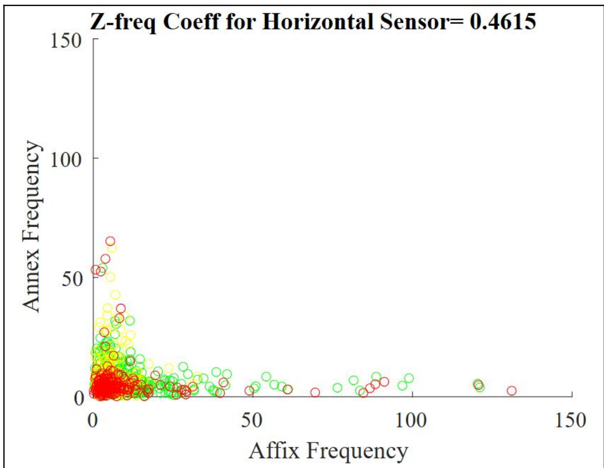


Figure 4.14a 46.2 Z Freq 2D of Refrigerant - Oil (750 RPM)

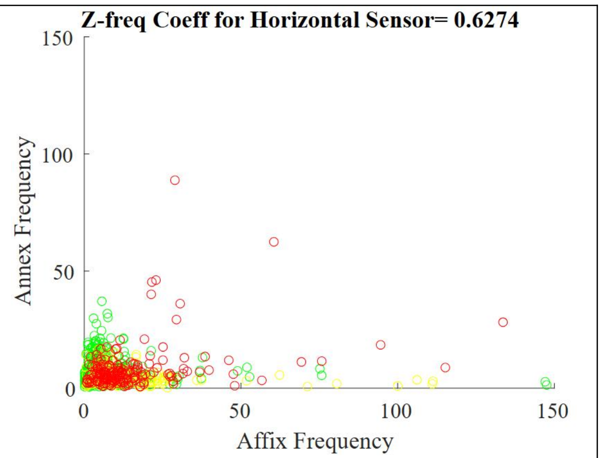


Figure 4.14b 62.7 Z Freq 2D of Refrigerant - Oil (1000 RPM)

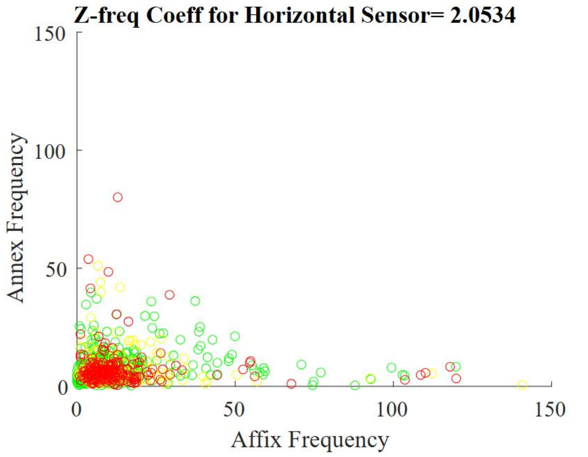


Figure 4.14c 205.3 Z Freq 2D of Refrigerant - Oil (1250 RPM)

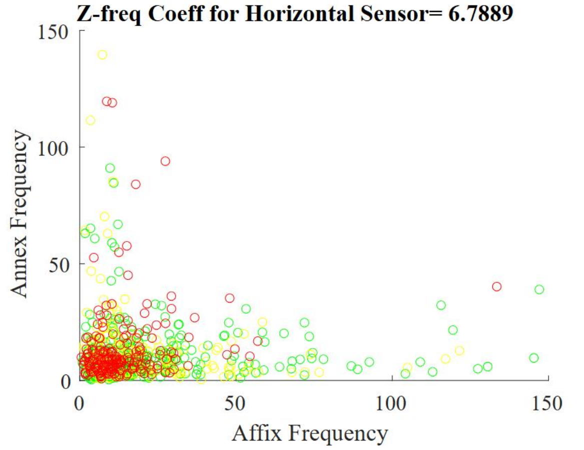


Figure 4.14d 678.9 Z Freq 2D of Refrigerant - Oil (1500 RPM)

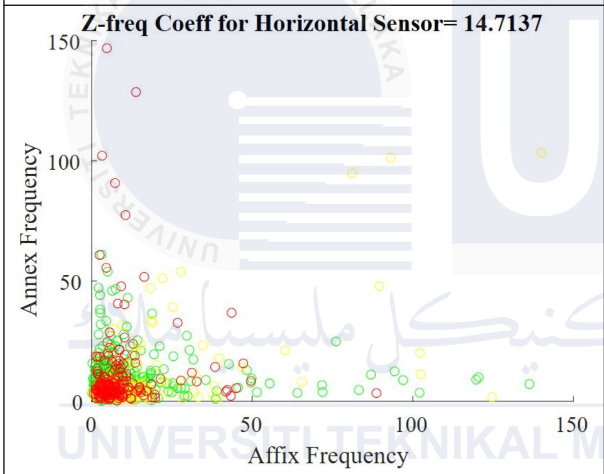


Figure 4.14e 1471.3 Z Freq 2D of Refrigerant - Oil (1750 RPM)

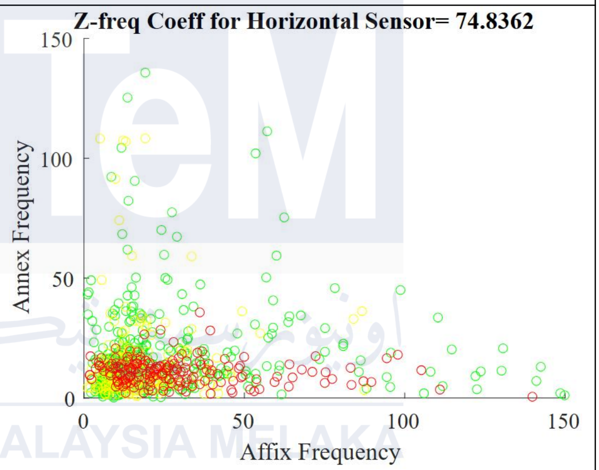


Figure 4.14f 7483.6 Z Freq 2D of Refrigerant - Oil (2000 RPM)

Figure 4.14 The scatter data of each Z-freq 2D for Horizontal when compressor off

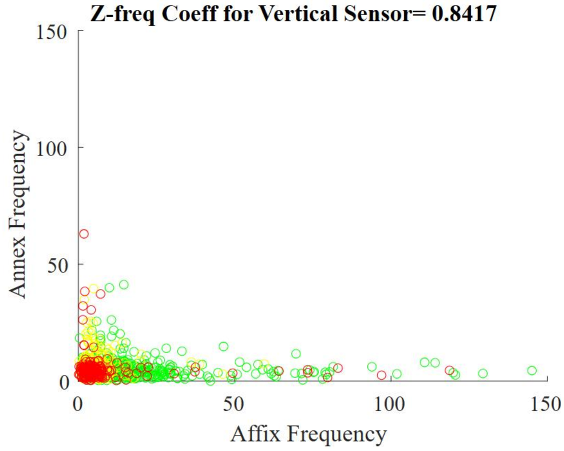


Figure 4.15a 84.2 Z Freq 2D of Refrigerant - Oil (750 RPM)

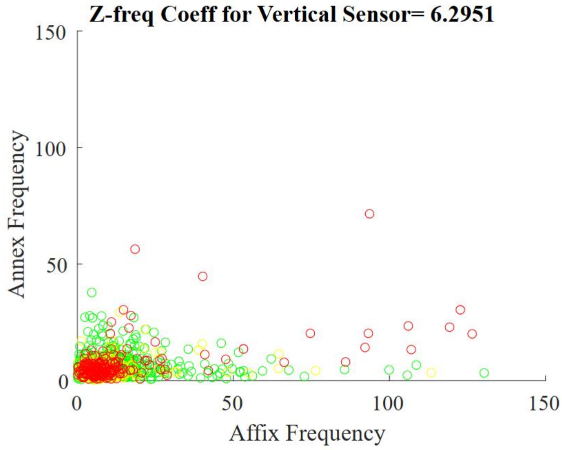


Figure 4.15b 629.5 Z Freq 2D of Refrigerant - Oil (1000 RPM)

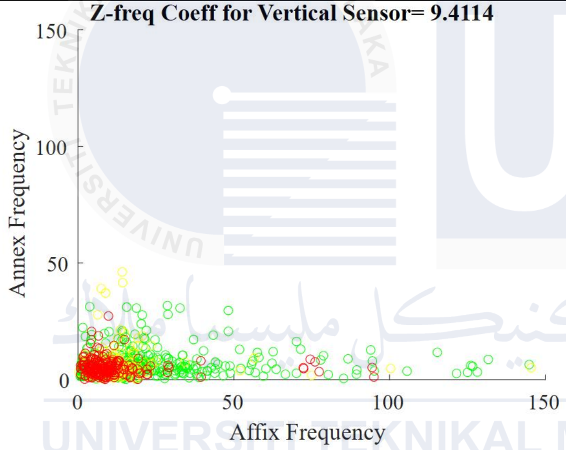


Figure 4.15c 941.1 Z Freq 2D of Refrigerant - Oil (1250 RPM)

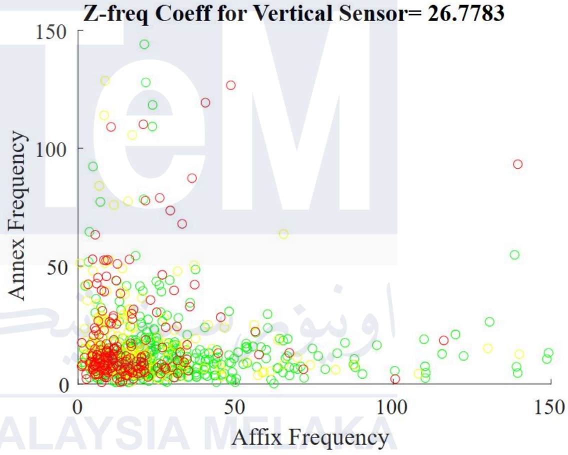


Figure 4.15d 2677.8 Z Freq 2D of Refrigerant - Oil (1500 RPM)

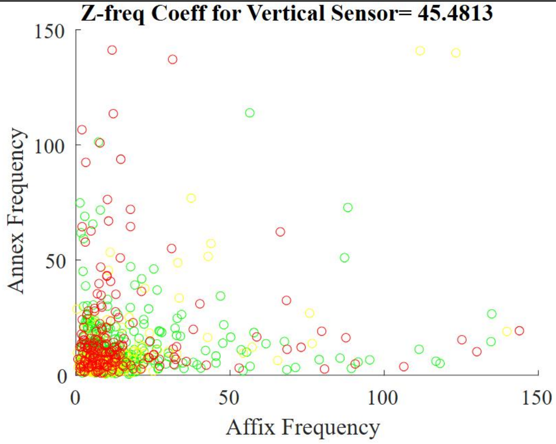


Figure 4.15e 4548.1 Z Freq 2D of Refrigerant - Oil (1750 RPM)

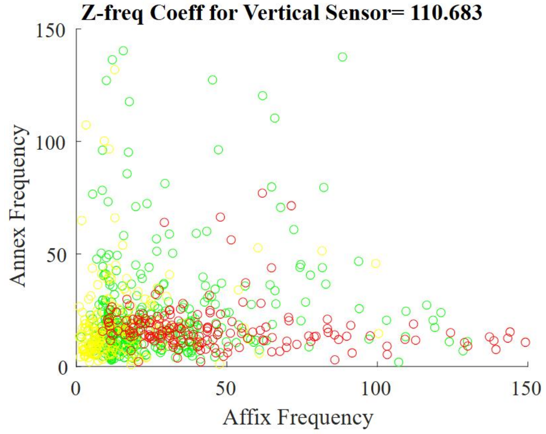


Figure 4.15f 11068.3 Z Freq 2D of Refrigerant - Oil (2000 RPM)

Figure 4.15 The scatter data of each Z-freq 2D for Vertical when compressor off

As seen in Figure 4.14 and figure 4.15, the current study discovered that the Z-freq 2D values grow greatly with compressor speed and that the value is same for each speed at a certain average. However in the experiment, it is indeed detects a significant effect as when the parameters are changes from low to high volume at specific speed of the compressor.

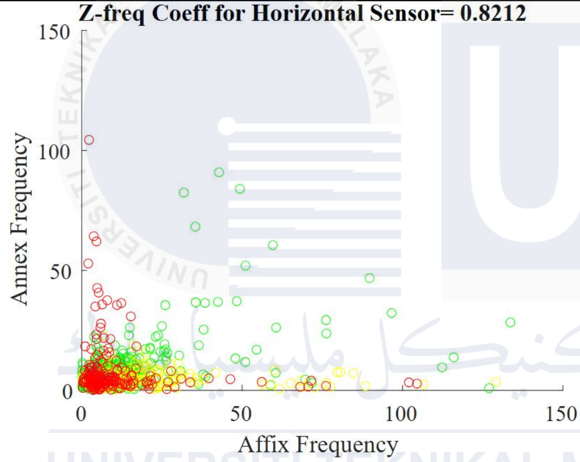


Figure 4.16a 82.12 Z Freq 2D of Refrigerant - Oil (900 RPM)

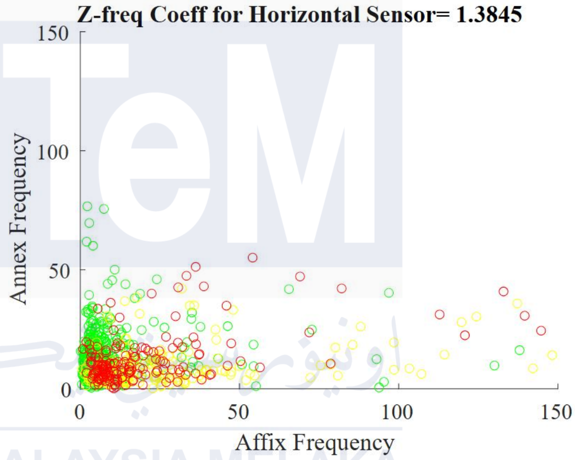


Figure 4.16b 138.45 Z Freq 2D of Refrigerant - Oil (1000 RPM)

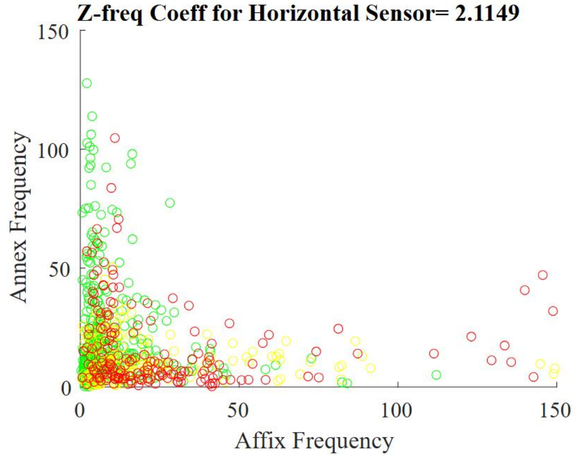


Figure 4.16c 211.49 Z Freq 2D of Refrigerant - Oil (1250 RPM)

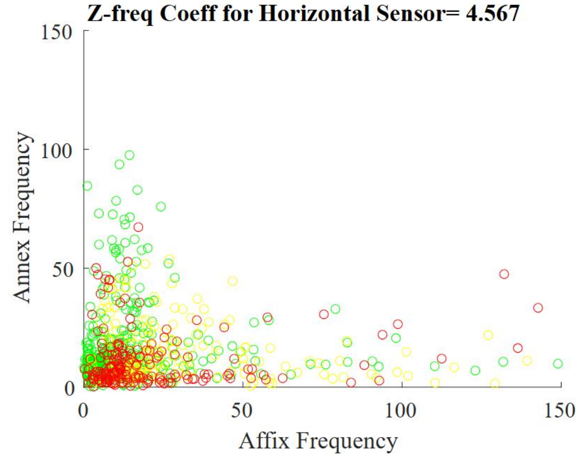


Figure 4.16d 456.7 Z Freq 2D of Refrigerant - Oil (1500 RPM)

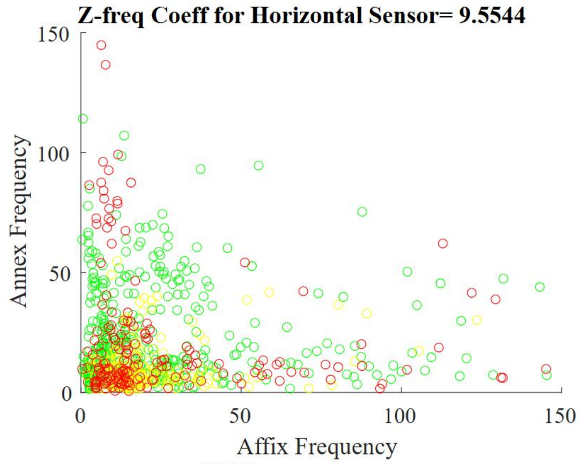


Figure 4.16e 955.44 Z Freq 2D of Refrigerant - Oil (1750 RPM)

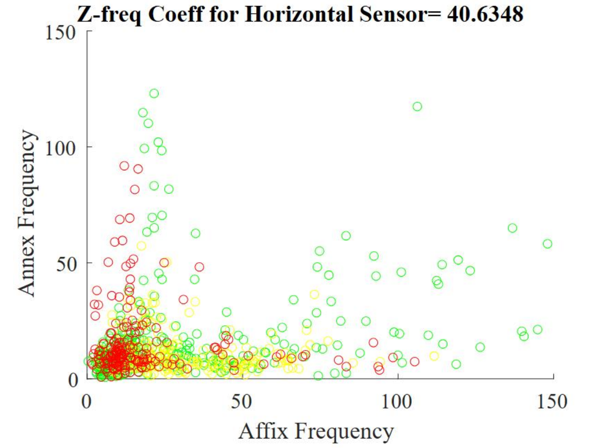


Figure 4.16f 4063.48 Z Freq 2D of Refrigerant - Oil (2000 RPM)

Figure 4.16 The scatter data of each Z-freq 2D for Horizontal when compressor on

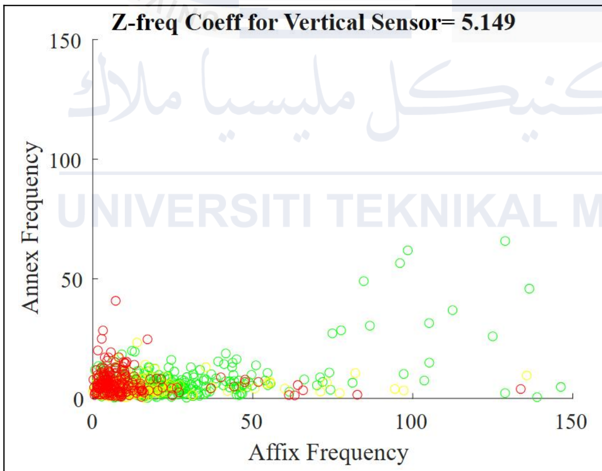


Figure 4.17a 514.9 Z Freq 2D of Refrigerant - Oil (900 RPM)

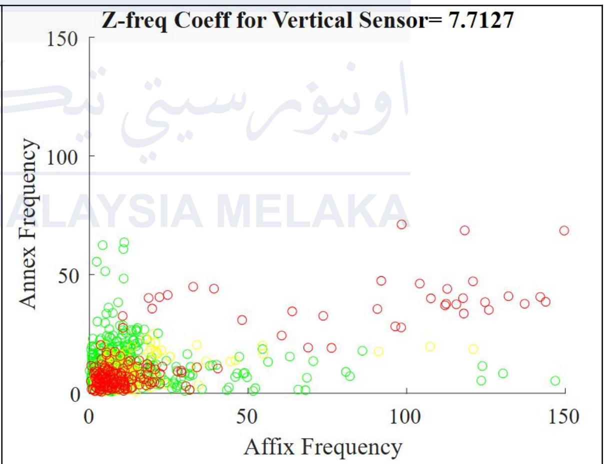


Figure 4.17b 771.27 Z Freq 2D of Refrigerant - Oil (1000 RPM)

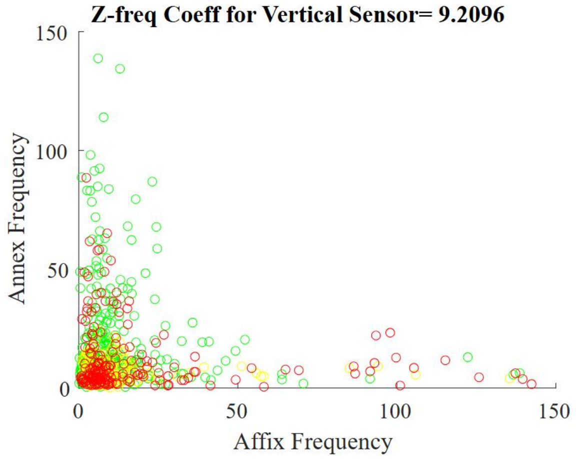


Figure 4.17c 920.96 Z Freq 2D of Refrigerant - Oil (1250 RPM)

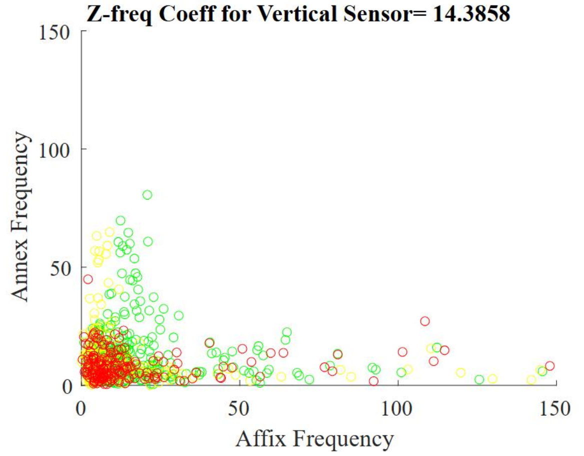


Figure 4.17d 1438.58 Z Freq 2D of Refrigerant - Oil (1500 RPM)

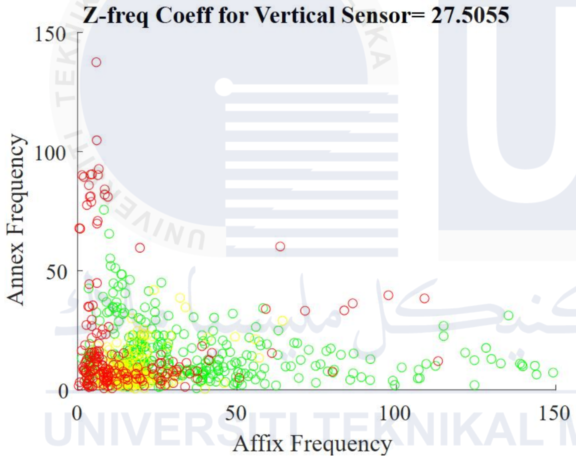


Figure 4.17e 2750.55 Z Freq 2D of Refrigerant - Oil (1750 RPM)

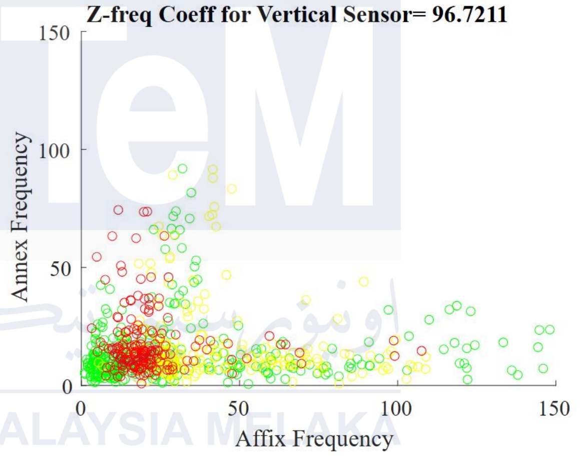


Figure 4.17f 9672.11 Z Freq 2D of Refrigerant - Oil (2000 RPM)

Figure 4.17 The scatter data of each Z-freq 2D for Vertical when compressor on

All the Z-freq 2D data from both horizontal and vertical values is then combined to produce a confusion matrix which is as summarized in the Figure 4.18. It shows the result of Z - Freq 2D classifier for SVM method of refrigerant parameter out of 70 Z - Freq 2D coefficients for all speed of compressor.

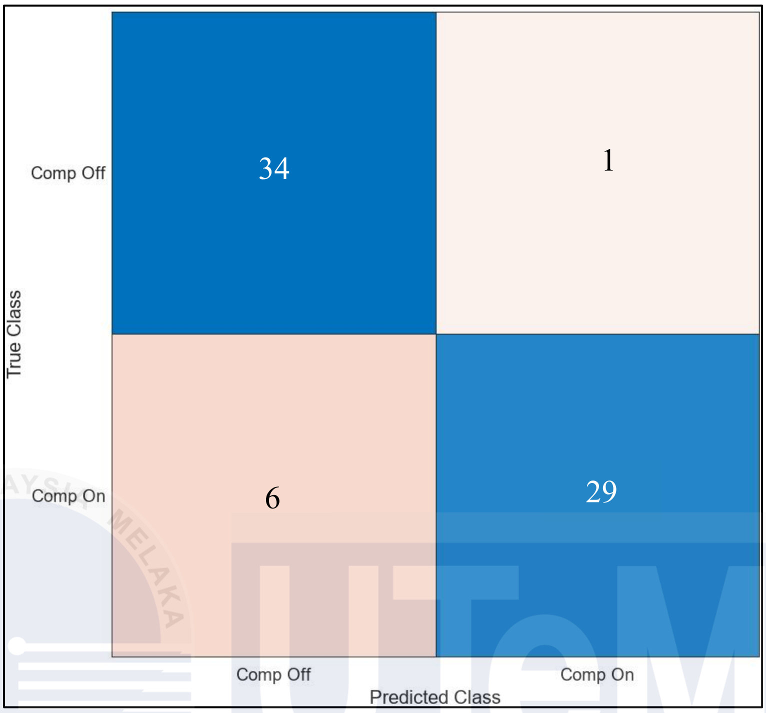


Figure 4.18a SVM Confusion matrix of Z Freq 2D of Refrigerant parameters

The accuracy obtain from the classification learner for specific parameters which for refirgerant R134a is about 90% with the precision of 85%. Figure 4.18b shows the result of Z - Freq 2D classifier for k-NN method which obtain only 74.3% of accuracy with precision of 73% out of 70 Z - Freq 2D coefficients for all speed of compressor. Data comparisons clearly show that the SVM method is more efficient than the k-NN method for this study, proving that this coefficient method can be used to detect or predict faults in the vehicle air conditioning system, particularly regarding compressor health.

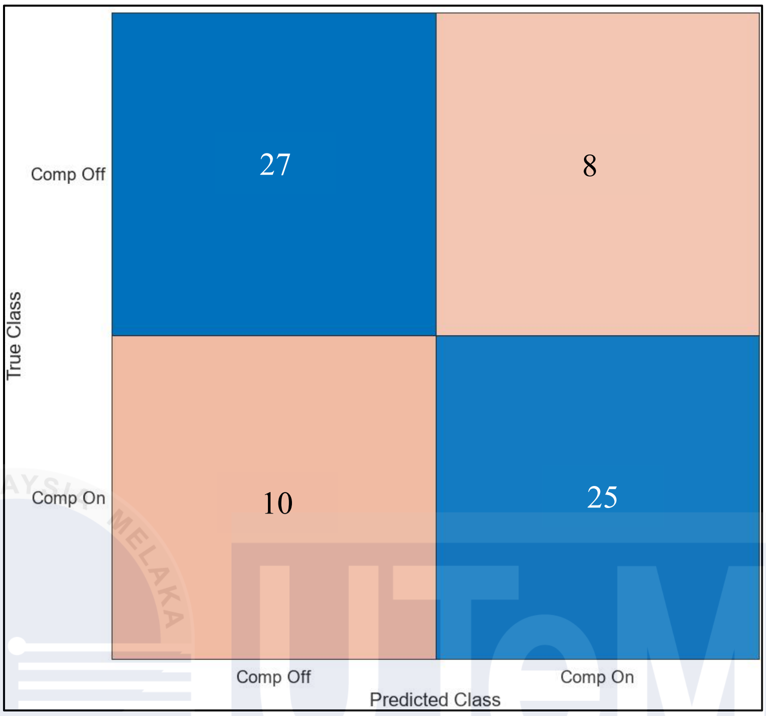


Figure 4.18b k-NN Confusion matrix of Z Freq 2D of Refrigerant parameters

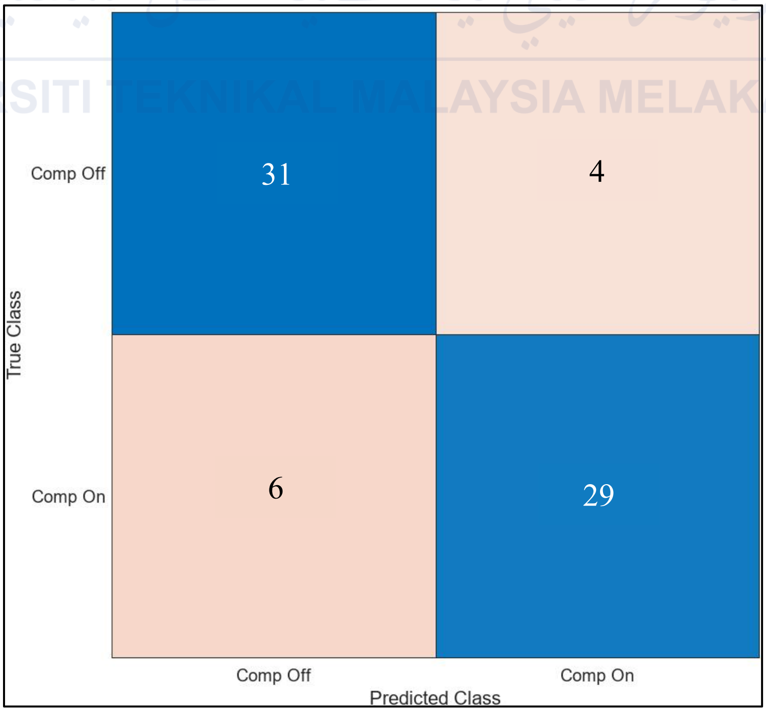


Figure 4.18c SVM Confusion matrix of Z Freq 2D of Oil parameters

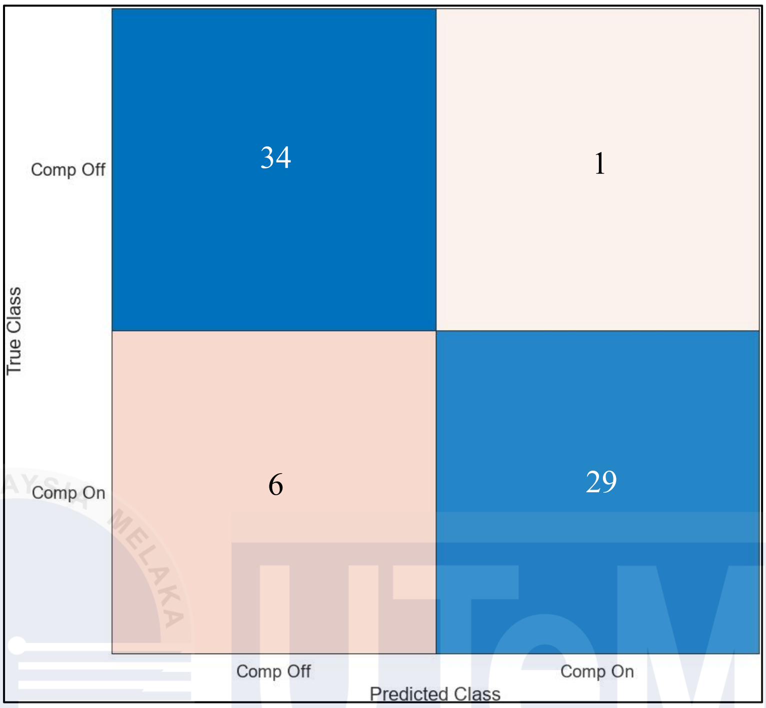


Figure 4.18d k-NN Confusion matrix of Z Freq 2D of Oil parameters

Figure 4.18c and 4.18d shows the confusion matrix for the parameters of oil versus the speed of the compressor. The SVM shows about 85.7% of accuracy while the k-NN is 90%. This shows the k-NN values are higher than that of SVM for oil. Figure 4.18e shows the confusion metrics when the data of both refrigerant and oil is combined.

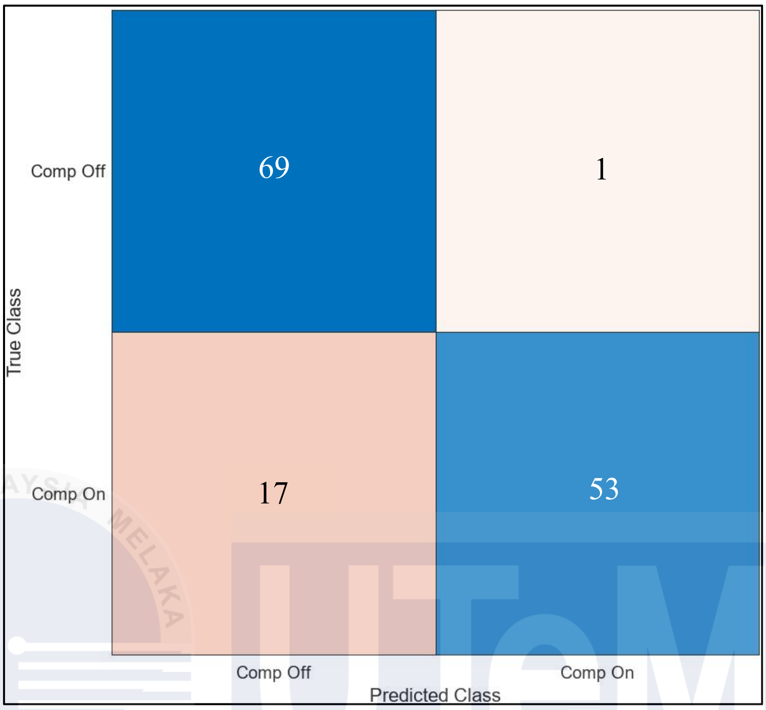


Figure 4.18d SVM Confusion matrix of Z Freq 2D of Refrigerant - Oil parameters

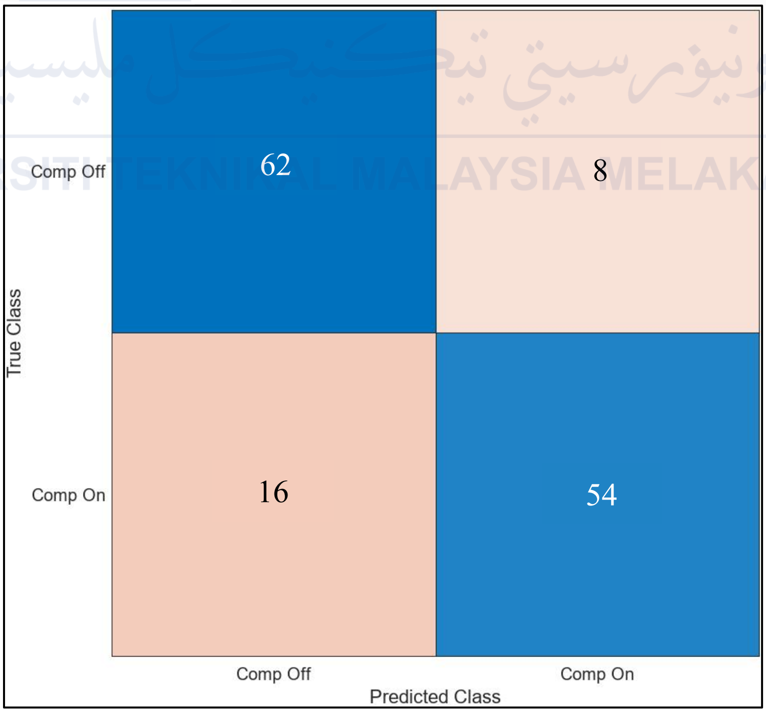


Figure 4.18d k-NN Confusion matrix of Z Freq 2D of Refrigerant - Oil parameters

The figures above show that the accuracy of the confusion matrix of both parameters are around 87.1% for SVM while 82.9% for k-NN. The values of SVM are greater than k-NN values which satisfied the requirement of good indication as the value of sensitivity are 98.6% for SVM and 88.6% of k-NN. The values of true positive rate (TPR) or sensitivity and false positive rate (FPR) of precision, are considered good when the percentage are high. More than 90% is the great results of machine learning of the experimentation. By this ANN confusion matrix for Z - Freq 2D coefficient, can be summarized that the method of Z - Freq 2D as diagnostic tools can be legit for further and future real time prediction. However this method are still in developing method which it will be need more research and experimentation for it be more efficient for upcoming diagnostic.

Table 4.5 and table table 4.6 below shows the output of classification metrics which included accuracy, precission, sensitivity, and specificity of the research experiments results. The data obtain from the equation from (1) to (4), equation of performance metrics.

Table 4.5 Table of Evaluation Metrics for SVM

		Evaluation Metrics (SVM)			
		Accuracy	**Precision**	**Sensitivity**	**Specificity**
Parameters	**Oil Volume**	0.857	0.838	0.886	0.829
	Refrigerant	0.9	0.85	0.971	0.829
	Refrigerant Vs Oil	0.8714	0.802	0.986	0.757

Table 4.6 Table of Evaluation Metrics for k-NN

		Evaluation Metrics (k-NN)			
		Accuracy	**Precision**	**Sensitivity**	**Specificity**
Parameters	**Oil Volume**	0.90	0.850	0.971	0.829
	Refrigerant	0.743	0.730	0.771	0.714
	Refrigerant Vs Oil	0.829	0.795	0.886	0.771

4.3 Summary

Based on all the research findings, we can summarize that the effectiveness of the wireless diagnostic system greatly depends on the network signal strength. It can be observed that the performance metrics of the support vector machine (SVM) surpass those of k-Nearest Neighbors (k-NN) in terms of accuracy, precision, and sensitivity.

SVM performs well in high-dimensional spaces, particularly in situations with more features than samples. With a sensitivity of 98.6%, the support vector machine (SVM) significantly surpasses the k-Nearest Neighbors (k-NN) classifier's 88.6% sensitivity. This suggests that SVM is more effective in accurately recognizing positive examples in this classification test.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

In conclusion, this study offers valuable insights into the impact of refrigerant and compressor oil volumes on the performance of automotive air conditioning systems. The application of a wireless vibration accelerometer and the newly developed Z-Freq 2D statistical technique enabled precise measurements and a nuanced understanding of the relationship between the studied variables and the air conditioning system's performance. The incorporation of machine learning algorithms further validated the findings, providing a robust framework for performance evaluation. The outcomes of this investigation offer practical guidelines for the automotive industry to improve vehicle comfort and energy conservation. The study highlights the importance of integrating advanced sensor technology, sophisticated statistical analysis, and machine learning validation techniques in automotive research, paving the way for future innovations in vehicle climate control systems.

5.2 Summary of the Research Objectives

Thorough evaluation of the data obtained from field tests is essential to achieve reliable outcomes, particularly in addressing potential issues such as weak network signals during experimentation. Several factors need to be considered during experimentation, including human error, network signal strength, noise from the connected framework, and environmental surroundings.

A critical aspect of this research is the precise measurement of the percentage of both refrigerant and oil in the vehicle HVAC systems. This ensures that the data collected matches the set values, enabling the identification of potential faults in the HVAC system related to the quantities of refrigerant and oil. From the results and discussion, it is shown that either during low or high amount of refrigerant and oil in the systems, contribute a high vibration which would highly affect the performance of the compressor to perform well. This can be regards as a faulty in the systems. The proper amount of refrigerant in the system is exactly around 320g to 330g while about 80ml to 90ml of oil in the systems prove the same as standardized automotive industrial recommendation.

The use of performance metrics provides precise, unbiased measurements for assessing and comparing models, guiding improvements, monitoring progress over time, and streamlining stakeholder communication. In order to ensure regulatory compliance, comprehend the advantages and disadvantages of the model, and make well-informed judgments based on task needs, they are helpful.

Results from performance metrics using a classification learner in MATLAB indicated that the support vector machine (SVM) is the best choice for this research, as it provides a strong foundation for model selection and ongoing development initiatives based on data.

5.3 Research Contributions

The authors extend their heartfelt gratitude to the Faculty of Technology and Mechanical Engineering (FTKM) at Universiti Teknikal Malaysia Melaka (UTeM) for their unwavering support and generous provision of resources.

This research would not have been possible without access to the state-of-the-art laboratory facilities, the automotive test vehicle, and the financial backing provided under project grant no. FRGS/1/2020/TK0/UTEM/03/3. The collaborative environment and technical assistance from the faculty and staff of FTKM have been invaluable in the successful completion of this project.

5.4 Practical Implications and Beneficiaries

This research project offers several benefits for real-world applications, further research, and technological developments. The Z-Freq 2D coefficient can be used as a new problem-solving tool for detecting faults in compressor performance, thereby identifying potential issues within HVAC systems. There are several practical implications and beneficiaries of this research, where the Z-Freq 2D coefficient can be applied, including:

- Application in automotive industry : Integration of faulty detection software with Z - Freq 2D as its basic system detection,
- Technology Adoption : Broaden the Z- Freq 2D coeeficient not only for automotive departments but also in building and creationg of new technology sytem,
- End Users : People or entities that will directly use the outcomes or profit from Z - Freq 2D, such customers of a new good or services.

5.5 Limitations of The Present Study

As mentioned in Chapter 3.2.7, there are several limitations in this research project that can be addressed in future studies. The limitation of the research is as follows:

1. Since the Phantom Vibration Sensor (PVS) uses Wi-Fi to send vibration data, fluctuations in network traffic and signal strength can affect the sensor's ability to provide reliable wireless diagnosis data,
2. It is difficult to distinguish between problems with internal equipment and external factors such as vibration interference from other vehicles or surrounding environments,
3. As inaccurate time readings during signal transfer to the cloud system can result in flawed analysis, meticulous monitoring and precise timestamping of each incoming signal are essential.

5.6 Future Works

For future research projects aimed at improvements, the accuracy of data results can be enhanced as follows:

1. Increase the number of experiments. Conducting more tests improves the statistical significance, accuracy, and reliability of the data, allowing for stronger conclusions and more effective identification of patterns and anomalies,
2. Improves the network signal by remove any possible network interference, to ensure the data obtain are accurate and precise,
3. Create an efficient data table for each recorded dataset, including the timestamps of downloaded vibration data from the experiments. Repeat the experiments to confirm results.

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APPENDICES

Appendix A

Yuszairie

ORIGINALITY REPORT

15%	10%	11%	5%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

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Publication

Exclude quotes	Off	Exclude matches	Off
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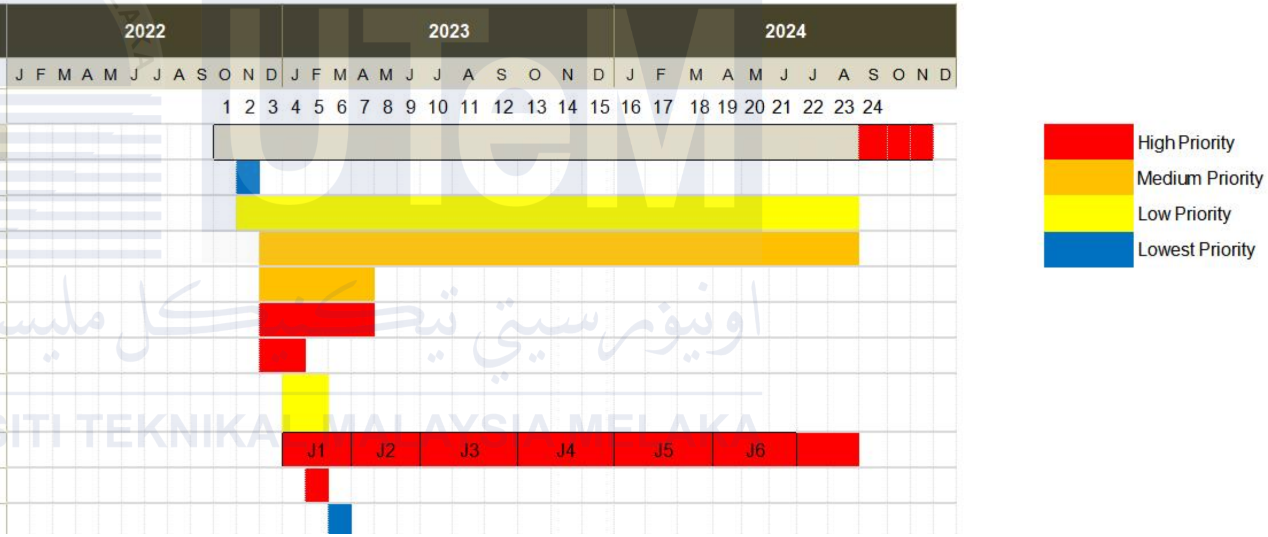
Appendix B

Master Programme Milestones

Muhammad Yuszairie Bin Yusri

TASK DESCRIPTION	PLAN START	PLAN END	TYPE
Semester 1			
Registration Master Program	22/11/2022	23/11/2022	B
Master Discussion With SV	29/11/2022	29/08/2024	Y
Literature Review	1/12/2022	1/08/2024	O
Experimental Setup	5/12/2022	5/04/2023	O
Data Acquisation	5/12/2022	5/04/2023	R
Progress Report Semester 1	26/12/2022	2/01/2023	R
Uploading Progress Report and Asessment	2/01/2023	12/02/2023	Y
Journal Publication	16/01/2023	1/08/2024	R
Research Proposal Defend	27/02/2023	28/02/2023	R
End Of Sem I	12/03/2023	12/03/2023	B



Semester 2			
Sem II Registration	13/03/2023	13/03/2023	B
Result Analysis	1/02/2023	1/04/2023	O
Progress Report Semester 2	21/02/2023	5/08/2023	R
Result Validation	1/04/2023	1/06/2023	O
Field Testing	1/06/2023	1/09/2023	O
End Of Sem II	8/10/2023	8/10/2023	B
Semester 3			
Sem III Registration	12/03/2023	14/03/2023	B
Project Management	1/10/2023	1/04/2024	Y
Progress Report Semester 3	5/02/2024	7/02/2024	R
Semester 4			
Sem IV Registration	7/03/2024	12/03/2024	B
Thesis Writing	1/04/2023	1/05/2024	R
Progress Report Research Review	10/06/2024	12/07/2024	Y
S & VP	1/03/2024	1/09/2024	
Progress Report Semester 4	10/06/2024	12/07/2024	R
Thesis Submission and Viva	1/06/2024	30/08/2024	R