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Automatic data processing of traction motor measured data and vibration analysis of test bench

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Abstract

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Arshey Shashank Dhangekar

One of the goals of ABB AB is to develop highly efficient electric motors for traction application. The demand for traction motors is increasing due to the rise in electric vehicles sale and railway locomotive engines. Highly efficient traction motors will assist in reducing the pollution caused by fossil fuels and help make the earth a better place to live by leveraging sustainable energy.

The electrical and mechanical characteristics of electric motors are measured and analyzed in the lab. The measured data of the electric motor in the lab are analyzed using the conventional way. One of the significant challenges in a conventional way is to isolate the system with various limitations, and it offers very few choices for measurement. The data management of measured observation readings is affected severely due to this, and it is then risky to determine and analyze the characteristics of electric motors.

The first aim is to develop an automatic data processing algorithm for the measurement data collected from the specific setup of electrical machine.

The data processing is done using the MATLAB tool. Statistical methods such as mean, median, moving mean, moving median, Gaussian model for handling missing data, outliers and data smoothing methods have been implemented to get accurate measured dataset as a part of this thesis.

In addition, a study of vibrational analysis of the test bench assembly was performed for the traction motor. The natural frequency of test bench assembly is computed on the Finite Element Method (FEM) tool. All the natural frequencies of the test bench assembly with the traction motor are analyzed, and some of them were closed to the excitation frequency of the traction motor. This study found that the resonance frequency of test bench assembly, has to be prevented while operating the traction motor during lab to strengthen the life of the test bench.

Keywords: Traction motor, MATLAB, data processing, data analysis, FEM, test bench, natural frequency

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Popular Scientific Summary

The thesis focuses on one specific data processing method and its importance in electrical machine measurement. The electrical parameters such as magnetic flux, voltage, current, power, and mechanical parameters such as speed and torque are crucial to determine accurate measurement. Based on those parameters, highly efficient and with minimum electrical and mechanical losses, electrical motors for traction application has been developed. According to the International Electrotechnical Commission standard (IEC), various tests, such as vibration, heat run, and more, were performed on the electric motor. Traction motors are essential for the electric vehicle and railway industries to reduce the carbon footprint; hence the goal is to make a highly efficient and affordable electrical machine for traction application. The literature review showed clearly that the traction motor demand is rising year by year in the automobile industry; hence, to achieve sustainability, a highly efficient traction motor will make the world greener.

The study also explains the importance of the test setup of the traction motor. Electric motor testing is essential to evaluate motor parameters. Motor testing is the initial step after manufacturing **to know about the motor build characteristics** and behavior in the real world. Usually, the motor's integrity is evaluated via the instruments that track trends within the motor, such as motor sensors. The motor testing is performed via advanced computer-assisted equipment that is becoming popular with digitalization. The fundamental goal of motor testing is to uncover underlying abnormalities and avoid premature failure.

Following the overview, the thesis proceeds with the discussion of the automatic data processing algorithm that will handle the problems of missing measurement at a particular interval of time, then data cleaning so that data is processed and is ready in its usable form. Presently at the ABB Corporate Research Center electrical machine lab at Västerås, the traction motor data is measured by temperature logger and power analyzer instrument.

Power analyzer and temperature logger together generate many files of measured parameters, and some of the files have missing values. Also, they have some unexpected sets of data during a particular period. Hence it is vital to pre-process the data to determine accurate parameters of the traction motor. The data processing method was applied to get the perfect data set of measured parameters of traction motor, which will be considered for analyzing traction motor electrical and mechanical characteristics measured by sensors such current, torque, temperature, and sensors data collected by temperature logger and power analyzer. The study investigated a statistical method to handle measured data with handling missing data, outliers, and noise filtering measured by power analyzer and temperature logger used for traction motor test setup.

To sum up, the data processing algorithm identifying missing values, cleaning the outliers, and smoothing curves has included all the essential techniques to handle these problems based on the mean method.

Furthermore, the study has discussed the vibration analysis of the test bench. During the lab test of the traction motor, the issue is that when a traction motor is mounted on a test bench and operated near or in resonances, it can produce unwanted vibrations. While measuring the electrical and mechanical parameters, special care should be taken to separate resonating frequencies. Otherwise, besides the desired working frequency, other frequencies of test bench assembly can be excited.

The study investigates the natural frequency of the test bench, where the test bench is used to analyze electric motors’ electrical and mechanical characteristics. In conclusion the study found the natural frequency of test bench using COMSOL Multiphysics.

Finding of these frequencies are crucial to avoid running the traction motor during the lab test.

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Abbreviations

MOU	Memorandum of Understanding
EV	Electric Vehicle
IPM	Interior permanent magnet
SyRM	Synchronous reluctance machine
SRM	Switching reluctance machines
FEM	Finite Element Method
MS Excel	Microsoft Excel
CRC	Corporate Research Center
BEV	Battery electric vehicles
PHEV	Plug-in hybrid electric vehicles
PM	Permanent magnet
PMSM	Permanent magnet synchronous motor
IM	Induction Motor
CPSR	Constant power speed rate
IEC	International Electrotechnical Commission
ISO	International Organization for Standardization
NaN	Not a number
IQR	Interquartile Range
MAD	Mean absolute deviation
P.U	Per unit
DE	Drive-end
NDE	Non-drive end

1. Introduction

Electric vehicles have become the current trend in the global automobile industry. The companies are investing huge capital in their research and development wing to create high sustainable electric vehicles and efficient railway locomotives to reduce carbon footprint in the automotive and railway industry. As a result of the increasing demand and shift towards electric vehicles, many primary organizations are signing Memorandum of Understanding (MOU's) with various efficient electric motors.

The traction motors are the primary propulsion system for an electric traction system that deals wide speed range, high efficiency, high power density, and mechanical durability. They feature a wide torque range at low speeds and considerable power output at cruise speeds. These high-performance electric motors are designed and tested in different categories and scenarios to achieve all possible targets [1].

Firstly, the objective of an electric vehicle propulsion system is to convert electrical energy to mechanical energy with durability and uniform performance throughout the life cycle. There are electric traction motors like induction motors and permanent magnet motors [2]. These are used based on the company's research and development and their brand uniqueness.

According to Agamloh [2], the electric vehicle manufacturers are gradually shifting from Induction motors to Permanent magnet motors due to high efficiency and high power to mass ratio, and current and future trends are going to focus more on the interior permanent magnet (IPM) motor and traction motor without rare earth magnets, for example, synchronous reluctance machine (SyRM) and switching reluctance machines (SRM).

Electric motor testing is essential to evaluate motor parameters. Motor testing is the initial step after manufacturing to know about the motor build characteristics and its behavior in the real world. Usually, the motor's integrity is evaluated via the instruments that track trends within the motor, such as motor sensors, or the motor testing is performed via advanced computer-assisted equipment that is becoming popular with digitalization. The fundamental goal of motor testing is to uncover underlying abnormalities and avoid premature failure. Static factors like insulation, wire damage, and electrical current leakage are evaluated during electric motor testing, as are more dynamic parameters like distortion, temperature changes, and balance [3].

The following three sections presents the importance of data collected from traction motor lab test. The data collected is in raw format and needs to be cleaned, imputed (imputation is the technique of filling the missing data with substituted values.) and there are various steps to be performed as a part of the data pre-processing steps on the traction motor data. Based on this pre-processing, different visualizations are prepared on the data to derive insights.

In chapter 2, the current electric vehicle market trend, followed by an overview of traction motor topology with the recent trend of traction motor technology elucidated, and more discussion about traction motor standards and motor test setup is being covered.

In the remaining chapters, the study discussed the two independents task, automatic data processing and vibration analysis of the test bench had been discussed in the study. The data processing techniques and finite element method discussed in the method section and their respective outcomes in the result sections and conclusion on the simulation performed and possible improvements for future work has been discussed in the study.

1.1Thesis Background

ABB AB is one of the world’s leading manufacturer of electrical machines. ABB manufactures electric motors and generators for various applications. The Energy Conversion Department is in-charge of electric motor and generator testing and verification. A greater emphasis on producing efficient traction motors. Energy-efficient electrical motor needs the development off reliable, repeatable analysis and testing methods for estimating motor electrical and mechanical characteristics. It is currently of great interest to design a highly efficient traction motor by lowering thermal and electrical losses.

The 21st century is known to be a revolutionary data century. Data since the last two decades has been growing exponentially. As a result, many businesses are utilizing data from their products in order to have a greater impact on the markets. Data is in various forms structured, semi-structured and unstructured. There are many data analysis tools available in the market. Open-source tools and technologies like R, Python, MATLAB, Microsoft Excel (MS Excel) are the popular data analysis tools used on a heavy basis by small- and large-scale companies as per their requirement. Presently at the electrical machine lab, all the data is captured from the traction motor, analyzed, and stored in MS Excel (which is captured in CSV). More than hundreds of CSV files of test motor and drive motor data with their electrical and mechanical parameters are generated while taking measurements and have to be pre-processed to analyze motor test results. Due to the limited data processing feature of MS excel, MATLAB is a good alternative solution for doing data analysis. Hence data processing using MATLAB allows more flexibility and provide extensive mathematical tools and library to pre-process measured motor parameters data from ABB Corporate Research Center (CRC) lab.

One of the goals at ABB CRC, Västerås, is to build an efficient traction motor from the designed prototypes. The test bench is then used to test this prototype without damaging the motor and test bench by preventing running motor in the range of natural frequency of test bench. After this, the motor is tested for real-world use; this process collects the data from motors via numerous sensors present at different motor parts. Once the data is collected from these motors, it is available in CSV format, and a detailed analysis is done on the collected motor data to evaluate its functional parameters. However, while performing the study of the large data set collected from various sensors of the motor, all the parameters and conditions for analysis needs to be taken into consideration and based on that, the initial step is taken where data has to be pre-processed and made available in accordance with the standard functioning of the motor. Data pre-processing is a tedious task where an analyst needs to spend most of their time studying the characteristics of data so that the data is available in its standard form, free from any abnormalities and outliers. For this, we leverage the power of MATLAB, starting with loading those CSV files and moving to the subsequent step, with data pre-processing being one of the major out of those steps.

1.2 Aim of the thesis

The aim is to develop an automatic data processing algorithm for the measurement data collected from the specific setup of electrical machine using MATLAB tool and to find and calculate the natural frequency of the test bench using the Finite Element Method (FEM) tool.

1.3 Scope of work

Testing electric motor for traction application requires an understanding of traction motor's measured electrical and mechanical data, which is essential to authenticate motor performance characteristics. In general, it is purely based on speed, torque, current at different temperatures, and the accuracy of measured parameters. This thesis deals with intelligent data processing for traction motor measurements that have been interfaced with sensors to collect data at ABB CRC Västerås lab. The data is captured via employing multiple sensors at different parts of the traction motors at ABB CRC Västerås lab. The raw data collected from motors via sensors differ from actual data due to environmental factors and human errors, so the captured data possess a severe problem of data storage because of which some of the observations captured by the sensors are not recorded, some are lost, and if in case they are recorded the observation readings are in an unusual form which can cause a severe problem for deriving or finding out the parameters like efficiency, rotational speed torque related to the motor. The significant impact of this is that it is difficult to estimate accurate measurement. Without proper data processing and analysis, one cannot have proper estimates of the measurements. It is not good practice to trust the data as it may consist of various discrepancies. Since our goal is to measure data accurately, there is a major emphasis on the significance of data, which can be achieved with data pre-processing.

Besides these uneven measurements of the motor parameters at different time intervals, another issue that needs attention is missing data. Nearest, previous, next, and constant value data processing techniques are studied in the thesis to handle and impute the missing data to make the data set completely normalized.

Moreover, during the lab test of traction motor, the issue is that it can produce unwanted vibrations when a motor and generator are mounted on a test bench and operated near or in resonances. So, while measuring the electrical and mechanical parameters, special care should be taken to separate resonating frequencies. Otherwise, besides the desired working frequency, other frequencies of test bench assembly can be excited. Therefore, it is crucial to find the natural frequencies of test bench assembly using the Finite Element Method (FEM) tool.

1.4 Assumptions

To process the measured motor data. The algorithm is sensitive to some of the vital prerequisitesThus it is essential to have some prerequisites for applying to the data set. The data set stored in the CSV file is considered as they have the same header name, which cannot be seen for temperature logger data. In that case, the user has to modify the header name in the MATLAB script. Secondly, it found that temperature logger and power analyzer stored data have the data type problem in some files. It is essential to have all the same data types for the given set of data, and its datatype should be double for the measured values.

1.5 Limitation of the study

One of the study's limitations is that the new data set is closer to the ideal data set, assuming that it is based on the statistical approximation. In reality, at a particular instance, the motor speed could be different at a different interval. Hence, the generalizability of the results is limited by the data processing algorithm studied in the thesis. In case when the measured data by torque, current, sensors is reported as NaN, in that case, it is impossible to approximate the data using statistical methods.

2 Literature study

2.1 Background of Traction machine and Electric vehicle

Electric car registrations have increased in major markets since the start of this decade despite the Covid pandemic. As seen from figure 1, there has been an exponential increase in the rise of electric vehicles. As per the market figures and facts, electric vehicles have almost doubled to 1.41 million, contributing to nearly 10% of the market share. The European market shrunk by 23% approximately in 2020. Still, the brighter side is the electric vehicle registration has increased. Electric vehicle sales in Sweden reached 30%, shown in figure 1 [4].

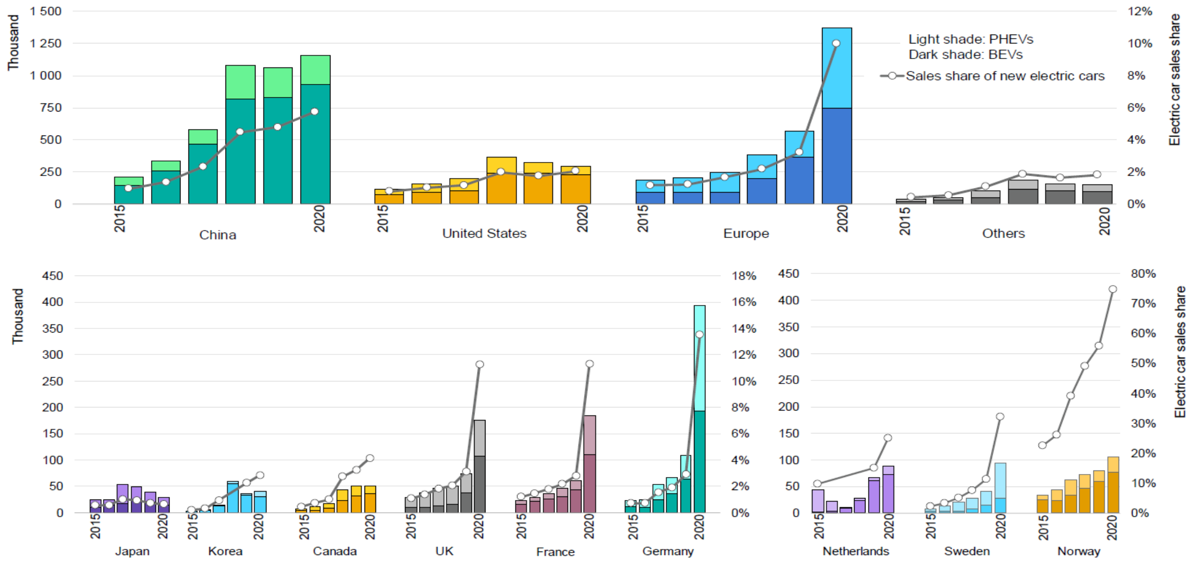

Figure 1: Electric car registration and sales share 2015-2020[4]

As seen from figure 2, there has been an exponential rise in the electric vehicle stock covering from all the light commercial vehicles to heavy-duty vehicles such as cars, trucks, and buses in the past decade. The progress for light commercial vehicles such as cars is high, and heavy-duty vehicles are moving towards this electric-based engine. As the trend suggests, all types of vehicles will be working on electric motors coming days.

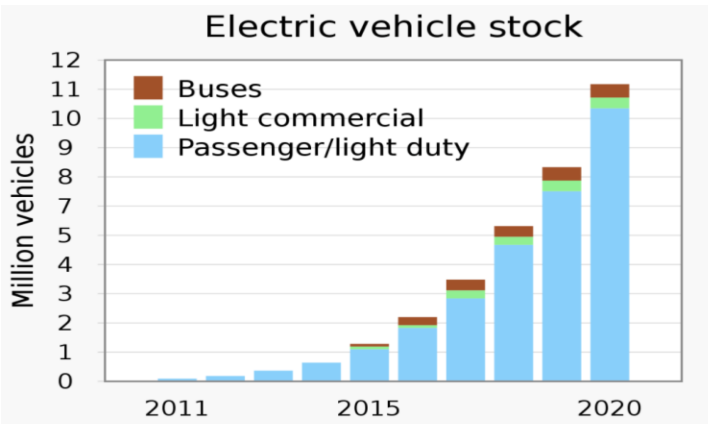

Figure 2:Electric vehicle stock [4]

Traction machines are expected to grow at a 17.4 percent annual pace, with the number of electric machines for electrified cars increasing from 44.6 million in 2013 to 147.7 million in 2023 [5].

Table 1 and Table 2 illustrates the type of traction motor utilized in commercial vehicle and heavy-duty vehicle. For commercial battery electric vehicles (BEV) and Plug-in hybrid electric vehicles (PHEV), and heavy-duty vehicles, it is seen that traction motor technology changed from asynchronous motor to permanent magnet synchronous motor (PMSM). Tesla model s60 launched with induction motor in 2013, then currently only Audi in 2020 launched with an induction motor, other hand current scenarios Tesla, Volvo, Jaguar, BYD, and Allison decided to implement permanent magnet synchronous motor due to their high efficiency. Even for heavy-duty manufacturers moving from IM to PM magnet motor. Hence the market share of PMSM traction motors has increased.

Table 1:EV and their motor used [7],[6], [5], [2]

Company and Model	**Year**	**Type of motor**	**Peak torque (Nm)**	**Peak Power (kW)**
Volvo XC40	2021	Permanent-magnet synchronous motor	330	150
Jaguar I PACE	2021	Permanent magnet synchronous motor	692	294
Tesla Model 3	2017	Permanent magnet synchronous reluctance motors	416	202
Tesla S60	2013	Induction motor	430	225

Table 2 Heavy-duty electric vehicle [8]

Company and Model	**Type of motor**	**Peak torque (Nm)**	**Peak Power (kW)**
BYD T9	Permanent-magnet synchronous motor	2*1500	2*720
BYD T7	Permanent magnet synchronous reluctance motors	550	149.8
Allison EP 40	Permanent magnet synchronous motor	1234	261

2.2 Traction Motor topology

Currently, there are several traction motors available in the market. AC motors dominate over DC motors. In AC, asynchronous and synchronous motors are utilized in commercial EVs [2]. High torque/power ratio vital for EV and railway. Some of the essential traction motor topologies are discussed in the thesis.

2.2.1 Induction motor (IM)

Induction motor is a widely used traction application for EV and various railway applications due to its low cost and toughness. Also, the unique ability to be used in multiple drives, where two or four motors are coupled in parallel to a single converter, has made them the favorite choice of train designers and constructors. [9].

For the past four decades, induction motors with aluminum or copper rotors have been the most common traction motor architecture in train propulsion. Aluminum or copper is chosen based on several factors, such as cooling method and performance requirements [10].

The losses in traction motors can be classified according to the location and origin of the loss. The significant stator losses are stator copper loss and stator iron loss. Consider the case of induction motor; the major rotor loss is the rotor copper loss. There is no major loss in the rotor for permanent magnet synchronous motor (PMSM) [11].

2.2.2 Permanent magnet synchronous motor (PMSM)

Most Electric vehicles (EVs) nowadays utilize PMSM. The demand for high power/torque and power density has shifted toward permanent magnet motors.

In the early 1979s, introducing high-coercivity neodymium iron boron magnets opened up new possibilities for Permanent Magnet (PM) motors. They are now being utilized more frequently in automotive applications [12].

A permanent magnet motor is designed to efficiently handle heavy loads at low and high speeds and operate for long durations. They are perfectly tailored for full battery electric vehicle operation.

PM motors are distinguished by their consistent rotor magnetization. Permanent magnets in the rotor provide large magnetic fields in the air gap without excitation currents, resulting in a high-power density. Excitation currents account for almost half of the losses in the form of Joule losses in non-self-excited synchronous motors. PM motors are therefore more efficient and require less cooling [9]. As a result, most automakers choose permanent magnet machines as the vehicle's traction motor.

In recent years, the demand for PM machines has shrunk in railway applications. The reason behind this is: there have been uncertainties in predicting the price of the magnet, which is the primary cost driver for PM motors. Because of their excellent performance and low-temperature sensitivity, rare-earth Neodymium magnets are the leading candidate for train applications. Though, due to high power/torque. PM machines are still in demand in high-speed trains [10].

Surface permanent magnet (SPM) and interior permanent magnet (IPM) are two significant types of PMSM based on their rotor design.

Surface permanent magnet motor (SPM)

The rotor design impacts several critical aspects of the machine, including the constant power speed range. The SPM machines have a fundamental structure, but because the magnet is positioned on the rotor's surface, the magnets may fly off during high-speed operation due to this. A bigger air-gap affects the machine's performance, particularly its constant power speed rate (CPSR). Although SPM machines can be designed with concentrated windings to achieve much higher CPSR, their use in automobiles is now minimal, especially in light of the trend toward high torque and high-power density machines with lower magnet content [2].

Interior permanent magnet motor (IPM)

Permanent magnets with varying orientations are hidden inside the rotor of an IPM motor. Because of its higher air-gap flux density, magnet security from armature reaction, higher mechanical stability due to buried magnets, armature reaction dominant extensive constant-power region. Additional salient torque due to saliency, IPM machines outperform surface-mounted PM machines in high-speed automotive applications [14].

IPM machines can be built to provide reluctance torque of 40–50 percent or more [2].

Because of this appealing characteristic, IPM machines have become the machine of choice for traction application.

IPM machines' rotor designs have advanced from simple flat magnets to various combinations of U, V, W-shaped magnets, double V-shaped magnets, and a variety of others, including variations in magnet sizes from pole to pole.

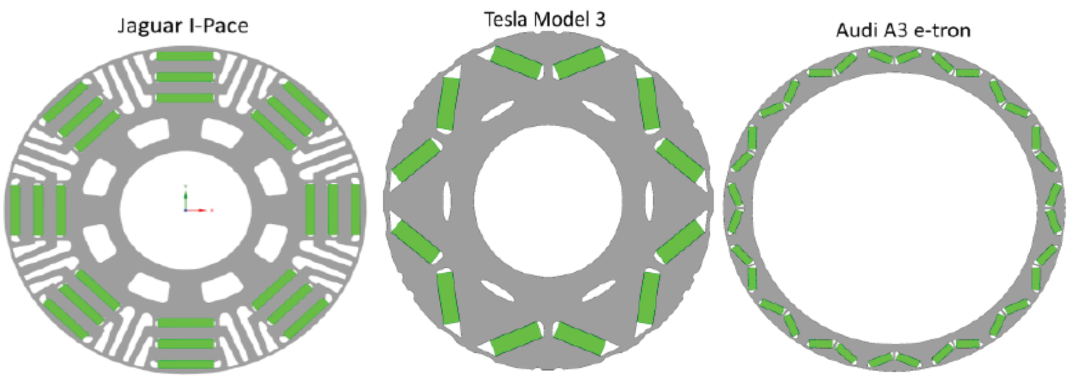

Figure 3: The IPM motors' rotor design geometries[7]

All motors contain buried magnets shown in figure 3 and special magnetic path guidance features in the rotor, which are used to reduce magnet material application; in addition to this, it also utilizes reluctance torque and creates a large constant power speed range for field weakening operation on the other hand [7].

Figure 3 shows a single V type arrangement of magnet in rotor design for Tesla model 3 and Audi A3 Etron, whereas flat arrangement can be found in Jaguar I-Pace

2.2.3 Traction motor without rare magnets

Designing a traction motor without a rare earth magnet is also an alternative option by eliminating the rare-earth magnets, the motor cost reduction is improved, but the dependence on this critical material is removed, as now the motors are not dependent on the magnet thus, the additional overhead of maintaining magnets is reduced [2]. Moreover, a simple and robust rotor structure allows high-speed operations for switching reluctance machines (SRM).

The synchronous reluctance machine (SyRM) and switching reluctance machines (SRM) work by removing magnets from the rotor. Both machines have a rotor made up of solely thin steel laminations. The SRM has a lot of noise, torque ripple, vibration, and the rotor is cheaper, but there is a need for part of the system that adds complexity to the system, and thus the cost of the entire system increases. SyRMs are also popular due to their durability, efficiency, low torque ripple, and ease of management. However, they have significant drawbacks, such as a reduced power factor, which impacts converter sizing and cost, and, more crucially, a limited CPSR [2].

In 2012, ABB became the first noteworthy modern industrial commercialization of SyRM. ABB has heavily developed highly efficient SyRM, and it is one of the leaders and trusted brands in the SyRM segments. SyRM motors rely on high reluctance torque, as a result of which the motor does not require expensive rare earth magnet material in the rotor structure make more cost-effective compared to PM motors [10,15]. Following this path currently, Kaiser Motoren, Koncar MES, and SIEMENS are, among others, provide solutions in the 0.6-310 kW range, in addition to ABB [15].

2.3. Thermal management of traction motor

2.3.1 Open-air Self ventilated cooling

Metros and Light Rail Vehicle are the most typical applications for self-ventilated traction motors. A radial shaft-mounted fan is used in this cooling approach. The volume flow rate is controlled in this cooling topology by the fan design as well as pressure losses over the motor [10].

Figure 4: For metro and LRV applications, an open self-ventilated motor is constructed [10].

2.3.2 Open-air forced ventilated cooling

Both framed and frameless traction motors for Electric Multiple Unit, locomotives, and high-speed trains are commonly forced ventilated. The exterior fan and the specified ducting system deliver cooling air in forced-ventilated motors. The purpose of forced ventilation is to achieve high torque and power levels [10].

Figure 5:For locomotive applications, a frameless forced-ventilated traction motor designed [10].

2.3.3 Enclosed ventilated cooling

An enclosed motor's cooling is divided into external and internal air regions that are separated from one another, unlike an open self-ventilated motor [10].

Figure 6: For Light Rail Vehicle applications, a closed self-ventilated motor is developed [10].

2.4. Thermal insulation for traction motor

From a thermal aspect, the insulation of the traction system is critical. For insulating the motor method, epoxy-based impregnation materials are used in the traction motors with thermal class 180 (H), whereas silicone-based resins are assigned thermal class 200. (C). The thermal class of the insulating system specifies the maximum permitted absolute temperature in conventional electrical gear [10].

According to the rail standard IEC 60349-2 [16], a Class H insulating system can work at a temperature rise of up to 220–225 °C. The thermal class of an insulating system is determined using the IEC 60034-18-31[17] testing technique.

2.5 Electric Motor test bench

Every idea that comes to the designer is a prototype, which is then implemented for the real world. This implementation goes through various processes to make it ready for real-world use. The test bench is one of the main and most important processes developed for electric motors and generators are used in research and development, quality assurance, auditing, and manufacturing [18]

Before the prototypes are available for production, electric motors undergo several processes during their development to ensure every condition is fulfilled. Therefore, it is critical to identify any product flaws or defects as early as possible to reduce or avoid the work and costs of correcting them. For this purpose, a test bench has been developed. Test bench developed for electric motors and generators are used in research and development, quality assurance, auditing, and manufacturing [19]. This test bench helps the manufacturer to note and correct all the shortcomings of the motor so that it can perform ideally as per the prototype. At ABB CRC Västerås, a test bench was developed for electric motors.

Figure 7: Test bench for electric motor (left-hand side) and generator (right-hand side) [20]

Figure 7 shows the test bench for the electric motor and generator. A test bench is a form of testing electric motor and generator system responsible for reproducing the testing of electrical and mechanical properties. It includes other parameters such as overload capacity, thermal design, and other application-specific measurands based on electrical drives. Noise from the motors is mainly due to the sound of rotors and their vibrations. There are also specific requirements to reduce this unwanted sound and vibration to make the motor ease of use for electric motors comprises a mechanical unit boundary to which various electric motor components are attached. It further includes a measuring system consisting of various sensors attached to the motor, their related application software, and an evaluation unit to analyze and control the test procedures associated with the system. The determination of the dynamics, power, efficiency, and stability of an electric motor is dependent on the measurement of electrical quantities, for example as current voltage, power, harmonic transients, winding resistances, insulation resistance, high-voltage test, shield resistances, and mechanical quantity for example torque, rotational speed, angle of rotation [19].

The development of drive systems for highly efficient motors and electromobility in the industrial sector. It is almost vital to cover various torque ranges, speed, and power, torques. Electric motor test benches must determine their energy efficiency in accordance with the "Minimum Energy Performance Standards". It is used to calculate the energy efficiency of electric motors introduced worldwide and comply with the legal regulations regarding measurement accuracy [19].

To follow up with the increasing market demands and meet the customer experience at a larger scale, standardization of the electric motor is vital. Various protocols need to be followed and implemented to implement the design for electric motors, and the exact needs to be manufactured as per the standard protocols. Worldwide International Electrotechnical Commission (IEC) and the International Organization for Standardization (ISO) are responsible for the standardization of the electric motor design IEC is the world's leading organization preparing and publishing International Standards for all electrical, electronic, and associated technologies [21].

Standards IEC 60034-30-1 and others define the efficiency classes and minimum requirements on electric motors in power class 0.75 to 375 kW [19].

2.6 Traction Motor standards

There are several important IEC standards for traction machines developed depending on their application. The IEC standards for electric motor performance, rating, and testing are described in detail and compared to IEEE standards. In terms of rating, performance, and testing, motors developed to IEEE standards should be adequate for the application. [22]. Every motor that is either a prototype or manufactured should be according to the standards set by IEC and IEEE for its use in real world by the customers. Some essential IEC and IEEE standards are discussed in the thesis.

- IEC 60349-1

It applies to rotating electrical machines that are not electronic converter-fed alternating current motors and are part of the electrical-powered rail and road vehicles' equipment. Power for the vehicles might come from either an external or internal source. Tests are used to check a machine's performance and offer a basis for evaluating its suitability for a particular task and comparing it to other machines [23].

- IEC 60349-2 2010

It applies to converter-fed alternating current motors forming part of the equipment of electrically propelled rail and road vehicles. Here, the main purpose of this component is to allow testing to confirm a motor's performance and offer a basis for evaluating its suitability for a specific duty and comparing it to other motors [17].

- IEC 60349-3

It applies to electrical machines for rail and road vehicles that meet the IEC 60349-2 standard. The losses supplied at the fundamental frequency are derived from measurements of the fundamental frequency load current and the fundamental frequency no-load power input because they cannot be detected directly [24].

- IEC 60349-4 2012

It covers converter-fed permanent magnet synchronous motors or generators that are part of the electrical-powered rail and road vehicles' equipment. Tests are used to check a machine's performance and offer a basis for evaluating its suitability for a certain task and comparing it to other machines. It covers traction motor and main generators, which provide power to the traction motor on the exact vehicle [25].

- IEEE Std 1812-2014

Permanent Magnet Machines Testing involves putting PM machines through tests to establish their performance characteristics and machine settings. Motors and generators can be subjected to the testing mentioned [26].

The traction motor's electrical and mechanical parameters are measured under IEC 600349 part 4 and IEEE Std 1812-2014 at ABB CRC lab at Västerås. Four categories of the test are involved in this measurement. These tests are standard type tests, reduced type tests, routine tests, and investigation tests. Electrical and mechanical parameters of traction motor are measured under these mentioned tests. Some of the significant standards, such as the environment test, are assumed for the test motor in the thesis.

The environmental condition for the ABB traction motor is defined under IEC 62498-1. The altitude from the sea level defined under Class A3 should not exceed where class A3 defined altitude range up to 1200 m and air shade temperature in shade class T1 where temperature setup according to middle Europe region [27].

2.7 Traction machine test setup

An input AC supply of 400 V is provided to the pre-charge circuit, which passes it to the line filter and distributes it to the generator and motor converter shown in figure 8. The Generator converter forwards it to the generator, whose power analysis is done via a power analyzer. On the other side, the motor and generator converter are operated via computer instructions responsible for operating the motor and generator. Black lines represent power flow, and the red lines are measurement flow, and all the measurement data of the motor is stored in the computer via these lines, as highlighted.

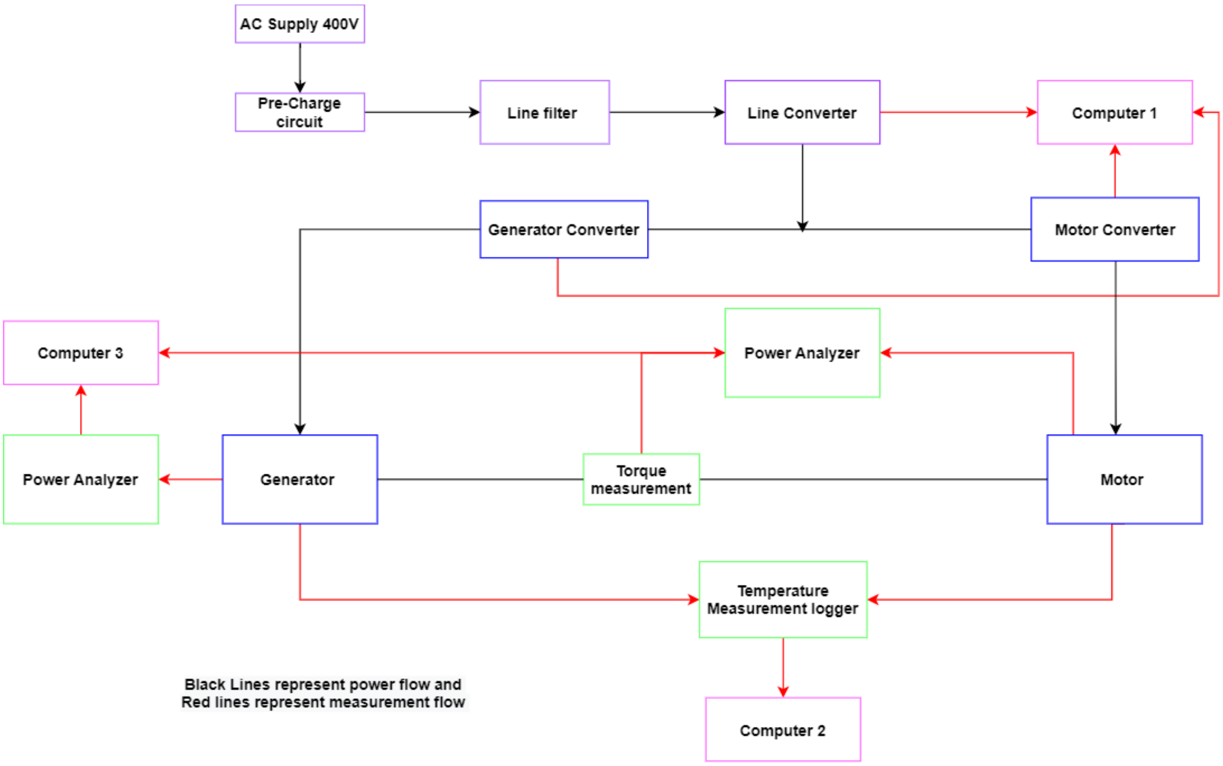

Figure 8: Block diagram of traction machine electrical and mechanical parameter measurement test setup

There are three computers in the lab, and one computer is connected to the line, motor, and generator converter. The line converter decides the DC link, so computer 1 controls it and controls the DC link for the line converter, the motor, and the generator. Computer 1 controls the dc level operational voltage and monitors the electrical parameters such as power, magnetic flux, and voltage. Out of those three computers, one computer controls the motor and generator, the second one collects the data from the power analyzer, and the third computer collects temperature data from the temperature logger connected to the motor and generator.

The power analyzed by the power analyzer of the motor and the temperature measurement logger is responsible for collecting temperature data from the motor and generator.

The motor and generator parameter measurements are taken using torque, current, and temperature sensors. Power, voltage, and remaining parameters are measured using a power analyzer, and all the temperature-related data and coolant flow rate are acquired at the temperature logger. Further, the data is logged with pressure at the inlet and outlet jacket and coolant flow to the motor. The motor and generator are coupled together, and an intelligent torque sensor is placed at the point of coupling. The torque sensor measures the traction motor and generator rotational speed.

To analyze and measure the vibration velocity of a traction motor through a vibration sensor when it mounted on test bench, the test setup has been established at ABB CRC lab, Västerås, shown in figure 9. To analyze the vibration velocity of the motor, a vibration sensor is used to collect the data from the motor as soon as vibration activity with respect to the sensor happens with respect to the motor captures the relevant data. It is then observed by an Oscilloscope which then forwards the values to the computer. The oscilloscope is used to analyze the vibrational velocity measurement. Triaxial Accelerometers KS943B100 sensor used to measure vibrational velocity also measure resonance frequency up to 32 kHz [28]

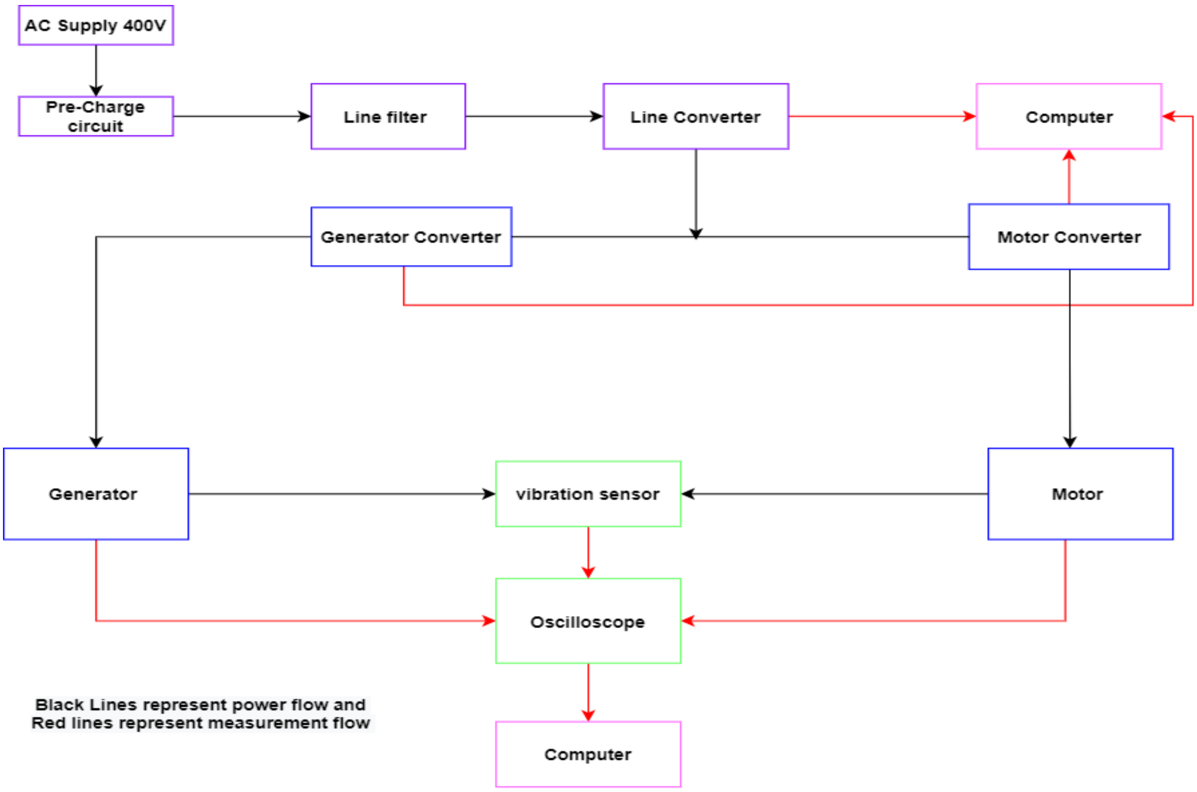

Figure 9:Block diagram of traction motor vibration test setup

3 Methods

3.1 Automatic Data Processing of traction motor measured data method

3.1.1 Data analysis background

Data analysis is a vital part of the system which is responsible for generating data. Data generated from various electrical equipment such as electrical motors, generators, transformers, etc., can be analyzed in electrical engineering.

Data from the electrical machines can help us build a predictive model based on their electrical parameters and improve efficiency and power production, which are cost-effective, save time, and reduce reliance on sensors. Numerous electric motors are running daily, doing vast amounts of work to deliver or accomplish specific tasks. These motors have various characteristics based on which it processes the run; various sensors are associated with electric motors to function smoothly. With the sensors that are connected to the electric motor, data can be collected from these motor-related electrical and mechanical parameters as per the requirements.

3.1.2 Data Analysis Process

The data analysis process is where the user needs to gather information from homogeneous or heterogeneous sources by using a proper application or tool that allows exploring the data and finding a pattern. Based on that information and data, decisions are made or get ultimate conclusions [29].

In this thesis, there is a focus on analyzing the measured data from the ABB traction motor. For the data analysis, essential data is collected through various tests that followed IEC standard 60034 part 4.

Data Analysis consists of the following phases:

Requirement Gathering

To reach the final aim of analyzing data in this thesis, it has been decided to perform data analysis on traction motor measured data. The traction motor at ABB CRC lab generated data using the sensors and data from the sensors used for the data analysis.

Collection of Data

After requirement gathering, a clear idea about what things must be measured and findings should be figured [30]. So, the data is collected from the sensors with the help of a power analyzer and temperature logger, and it is then stored in the form of CSV. Now the collected, measured data based on the requirements are processed and organized for analysis.

Cleaning of the collected data

Data in its natural form is very cumbersome. The traction motor measured data collected may or may not be helpful or irrelevant to the aim of the analysis. Due to the nonuniformity of data, it needs to be cleaned. The data in raw format collected from various sources contain duplicate records, white spaces, and errors. The measured data is then cleaned. Data cleaning is the first phase of data analysis and must be done before the initial data analysis steps. The output of the study will be closer to the expected outcome of the traction motor [31].

Analysis of the Data

Data analysis includes data collection, cleaning, and processing which is followed in the present data processing algorithm. It is ready for analysis. By manipulating measured data, the exact information needed is then identified. During this phase, MATLAB as a data analysis tool has been used to understand, interpret, and derive conclusions based on the requirements.

Interpreting the data

After analyzing the data, traction motor performance results were interpreted. Data analysis is expressed either in words and tables or in charts to express or communicate data. Then, use the data analysis process results to decide the best course of action [31].

Visualizing the data

Data visualization is a crucial part of analyzing the performance of the traction motor; this data then appears in various visualization forms of multiple graphs. Data visualization is a valuable tool and a powerful technique to draw inferences over data by just looking at graphs or charts. These visuals are then used to identify hidden facts and trends of the traction motor. Observing connections and examining traction motor datasets makes it easy to find a way to find out meaningful information [29].

3.1.3 Steps of Data Exploration and Preparation

The quality of inputs decides the quality of output. Data cleaning and pre-processing is the most important step to work with data as it makes the data used further [30]. Data Analysis involves various initial steps to understand, clean, and prepare data for building a predictive model, and the points are described as follows:

- **Identifying the variable**

The data set contains a whole set of variables in it, out of which input feature and output target should be identified correctly. For example, the impact of the rotational speed of the electric motor on mechanical torque. Next, there is a need to identify the data type of the input and output variables and the category of the variables in the given dataset [30].

- **Univariate Analysis**

At this stage, explore variables one by one. The method to perform univariate analysis will depend on whether the variable type is categorical or continuous. There is a need to look at these methods and statistical measures for categorical and continuous variables individually.

- **Continuous Variables**

In the case of continuous variables, the need is to understand the central tendency and spread of motor parameters.

3.1.4 Bi-variate Analysis

The relationship between two variables is calculated using bi-variate analysis. At a pre-defined significance level, association and disassociation between variables are checked initially in this analysis. Then the bivariate analysis is performed for any combination of categorical and continuous variables. The combination can be Categorical-Categorical, Categorical-Continuous, and Continuous-Continuous. Different methods are employed to tackle these combinations during the analysis process [31].

The Scatter plot shows the relationship between two variables but does not indicate the strength of their relationship [29]. To find the strength of the relationship, use correlation. Correlation varies between -1 and +1.

Correlation ($\rho_{X,Y}$) can be derived using the following formula:

$$\rho_{X,Y} = \frac{COV(X,Y)}{\sigma_X \sigma_Y} \tag{3.1}$$

Where COV is the covariance

σ_X is the X variable's standard deviation

σ_Y is the standard deviation of the Y variable

- $\rho_{X,Y} = -1$: perfect negative linear correlation
- $\rho_{X,Y} = +1$: perfect positive linear correlation
- $\rho_{X,Y} = 0$: No correlation

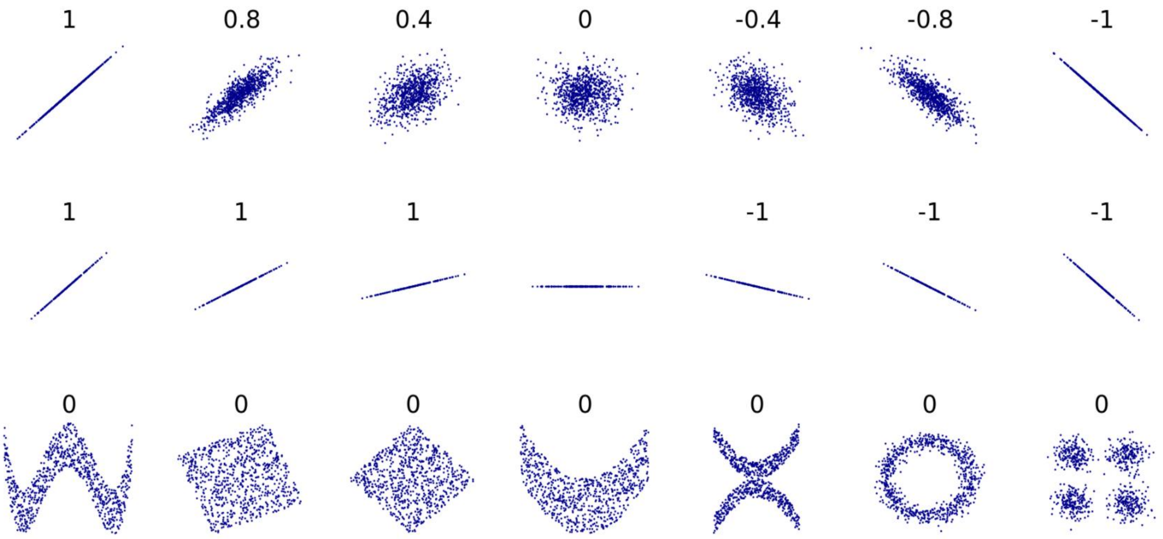

Figure 10: Several sets of (x, y) points, with the correlation coefficient of x and y for each set [32]

Correlation is often defined as the relationship between two variables. Two Variables can be negatively correlated or positively correlated, or not correlated at all. Scatter plots tell us about the distribution of the data points in the space. The scatter plot distribution has a lot to tell about the correlation of the data. The better the correlation between the two variables or the more robust the relationship, the closer the points are to each other and form a straight line [29].
Variables are positively correlated when the data points make a straight line, and both the data points move in the same direction. Variables are negatively correlated when the data are moving in the opposite direction. Now in the above correlation graph, all the positive values are showing positive correlation, with correlation one having all points close to each other, making it a straight line, and as the value decreases and moves towards 0, see that the points tend to move away in space and take more space rather they scatter in space taking more are as seen from the above figure 10.
If the line goes from a high value on the y-axis to a high value on the x-axis, the variables negatively correlate. As seen from the above figure 10, a negative correlation is the same as a positive correlation, but now the direction is opposite.
When the correlation is 0, then the data points can take any shape in the space. It mostly depends on how the data points are distributed randomly in a given space; it may be two-dimensional or three-dimensional.

3.1.5 Handling the Missing data

Missing data often causes a severe problem for processing data; training data can reduce the power/ fit or lead to a biased model because data does not correctly analyze the behavior and relationship with other variables. It can lead to wrong prediction, output, or classification [30,33].

Reasons for data having missing values:
The occurrence of these missing values may occur at two stages:

1. **Extracting the data**: There are various problems with the extraction process from current, temperature, and torque sensors connected to the traction motor. There is a lot of electromagnetic noise due to the switching of the converters, electromagnetic interference, and electromagnetic compatibility might be reasons behind the missing values. Errors at the data extraction stage are typically easy to find and can be corrected easily as well.

2. **Collecting the data** [29]: These errors occur at data collection and are harder to correct. At ABB CRC lab, data is collected from sensors connected to the traction motor. Now this collected data have missing values that can be categorized into three types:
    - **Missing completely at random**: It is a case when the probability of a missing variable is the same for all observations. For example: In terms of traction motor parameters like efficiency, power, torque. Here each observation has an equal chance of missing value. Temperature data for the traction motor may contain abnormalities where temperature values may exceed the operating values or certain threshold.
    - **Missing at random**: It is a case when the value is missing at random, and the missing ratio varies for different values/levels of other input variables. For

example, while collecting traction motor parameters data, the sensors may not give value regularly due to random issues at the sensor end.

- **Missing that depends on unobserved predictors**: This is the case when the missing values are related to the unobserved input variable. Some of the probabilities of a missing value are directly correlated with the missing value itself. For example, temperature with higher or lower values likely to provide non-response to the components of motor that are correlated to temperature.

3.1.6 Treating the missing values

a) **Deleting the missing values:** Based on the missing nature of missing data, deletion is performed in two types: Pair Wise Deletion and List Wise Deletion.

- **In listwise deletion**, observations where any of the variables are missing, are deleted. Simplicity is one of the significant advantages of this method, but this method reduces the model's power because it reduces the sample size.
- **In pair-wise deletion**, analysis with all cases in which the variables of interest are present is performed. This method is very powerful as it keeps as many possibilities available for analysis. One of the disadvantages of this method, it uses different sample sizes for other variables. For the data that is completely missing at random deletion, the method is best to apply. Else non-random missing values can bias the model output [30].

b) **Statistical Imputation**: Statistical Imputation is a method to fill in the missing values with estimated ones with the help of statistical methods such as mean, mode, median. The objective of this imputation is to apply a known specific fix seeing the pattern and relationships, and these patterns can be identified in the particular attributes or features having missing data. Statistical methods such as mean and median are some of the most redundantly used methods and computed using Equations 3.2 and 3.3. This statistical method focuses on imputing the missing data for a given feature by the mean or median of all known values of that variable [30].

$$Mean = \frac{1}{N}\sum_{i=1}^{n} x_i \tag{3.2}$$

For grouped data Median

The formula for grouped data median is used to find the median in group data with provided category interval. The middle position of the set when data is arranged in a particular numerical order is the median value of the data. The median class is then defined as the class where the the middle position is located.

The formula for finding the median in a grouped data is:

$$Median = m + \left(\frac{\frac{n}{2} - F}{f}\right)J \tag{3.3}$$

Where,
m is the lower boundary of the median class
n is the total number of observations
F is cumulative frequency before the median class.
f means the frequency of the median class
J is the size of the median class

Mean absolute deviation (MAD)

Mean and the average distance between each data point is termed the mean absolute deviation of a dataset. Mean Absolute deviation gives the idea about the variability in the dataset [34]. Given a random variable vector A made up of N scalar observations; the median absolute deviation is defined as:

$$\text{MAD} = \text{median}(|A_i - median(A)|) \tag{3.4}$$

Scaled MAD represented by equation 3.5

$$\text{MAD} = \text{c} * \text{median}(|A_i - median(A)|) \tag{3.5}$$

$$c = \frac{-1}{erfcinv(3/2) * \sqrt{2}} \tag{3.6}$$

The inverse complementary error function is Erfcinv.

Moving median

Moving median is used to find the median of data by operating over the moving window function. For each window, the moving median return the middle value in terms of rank found in the window.

Moving mean

Moving mean, also called rolling average or running average, involves creating a series of averages of different subsets on the given dataset. An analysis is done on those data points. Moving mean is also a type of finite impulse response filter. Its variation includes simple, cumulative, or weighted forms. For data smoothing and defining outliers moving mean and moving median applied for data set.

Window length

An extended sequence in data is usually broken into pieces called a window. The length of the window is termed window length. It is specified as a two-element vector, an integer scalar, or two-element vectors of positive duration. The window can be positive or even integer scalar. When positive, it is centered on the current element. If a window is even then, it is centered on the previous element and the current [34].

Interquartile Range (IQR)

Interquartile Range is a computation/ estimation of the data spread used to define outliers present in the data. Upper and lower quartile ranges define the boundaries of IQR. These ranges can be seen in the boxplot (figure 11). IQR is often calculated as the difference between Q3 and Q1, where Q3 corresponds to the 75th percentile and Q1 top 25th percentile. The mid-line between Q1 and Q3 is the median of the dataset. Data points below Q1- 1.5*IQR and above Q3+ 1.5*IQR are outliers, where IQR =Q3-Q1. IQR, also known as midspread, is variability based on dividing a data set into quartiles.

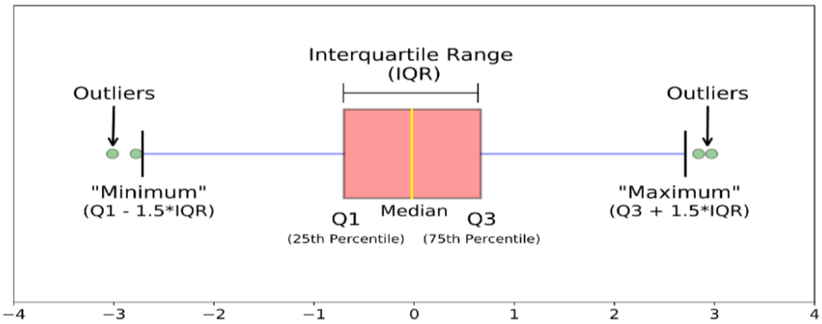

Figure 11: Boxplot with whiskers from minimum to maximum [35]

Data Smoothing

Data smoothing is used to make the data follow a normal distribution curve. Smoothing is a popular technique to remove the noise from data. A data analyst can easily find trends in the data by removing noise and figuring out the data's crucial/ essential points and patterns. In the given case where the data related to the motor is being analyzed, we apply to smooth over various columns to observe the data trends. Gaussian Curve is often referred to as a normal distribution curve, and it is a prevalent technique for analysts to make data smooth and free from any noise. Gaussian Curve is in the form of a bell with interquartile ranges at its tips (start and end)

The Gaussian distribution is in the form of a bell-shaped curve, and it is commonly called the normal distribution. The Gaussian component contains the majority of peak counts. This component arises from the statistical noise, which broadens the sharp line response of an ideal detector. The fitted parameters for Gaussians are the Position, centroid, the Amplitude of the peak, and the peak width [36].

$$y = \sum_{i=1}^{n} p_i e^{\left[-\left(\frac{x-b_i}{c_i}\right)^2\right]}$$

In the above formula,
The number of peaks to fit is n,
p_i represents the amplitude of the peak,
b represents centroid (location),
c is related to the peak width.

Relational operators

For defining an ideal data set, the data should be within certain limits means there should be no inconsistencies with the data. The data should be in certain bound to be represented ideally, and for this relational operator are be used such as <, >, <=, >=, ==, and ~=¨.

Outliers

Once the missing values are dealt with, the next target is to deal with outliers and fix them in our dataset. Often, it is intended to neglect outliers while building models. This is a discouraging practice. Outliers tend to make data skewed and reduces accuracy. Outliers are data points that vary enormously from the rest of the data. These points significantly differ from the actual issues and show unusual behaviors as they appear far from the data points with normal behavior in a sample [29,32].

Causes of Outliers:

There are several different reasons for having outliers in the data. Whenever outliers are seen in the data, the ideal way to tackle them is to find out the cause behind those outliers. The method to find the cause depends on their occurrence. Causes of outliers can be classified into two broad categories:

1. Artificial (Error) / Non-natural
2. Natural

3.1.7 Classification of outliers:

- **Human Errors:** Errors caused during data collection, observation from a system, and entering data into the system are some of the human errors.
- **Errors while taking measurement:** When the instruments are faulty, the reading is inaccurate, leading to measurement errors, and it is one of the most common outliers.
- **Experimental Error:** These are caused when the experimental setup is done incorrectly or inaccurately.
- **Intentional Outlier**: Self-reported data are the common cause for intentional errors, and it is most commonly found in the data with sensitive information.
- **Data Processing Error:** Whenever performing data mining, analysts need to extract data from multiple sources. This extraction of data may lead to errors causing outliers.
- **Natural Outlier:** The influence of the environment, such as wind, temperature, etc., causes a natural outlier.

Outliers impact on the data

Outliers have a significant impact on data, and in most cases, they can drastically alter or change the statistical modeling and data analysis results. There are numerous unfavorable impacts of outliers in the data set; some of them are listed as follows [31]:

- Error variance is increased
- Outliers reduce the power of statistical tests
- Outliers decrease the normality of the data if they are non-randomly distributed.

- Outliers can impact assumptions related to statistical models.

3.1.8 Outliers Detecting method

The most frequently used method to detect outliers is visualization. Using various visualization methods, like Boxplot, Histogram, Scatter Plot [30,31].

3.1.9 Removing Outliers

Most ways to deal with outliers are similar to the methods of missing values like deleting observations, transforming them, binning them, treating them as a separate group, imputing values, and other statistical methods. Here, the standard techniques used to deal with outliers are described [31]:

- **Deleting observations:** Delete outlier values due to a data entry error, data processing error, or outlier observations that are very small in numbers. To remove outliers at the end, trimming can also be used.

- **Transforming values:** To remove outliers, the variables can be transformed from one form to another. For example, a variable z can be transformed by scaling down or scaling up its value. one of the widespread transformations used is logarithm; to reduce the variation caused by extreme values natural log can be used.

- **Binning:** Binning is similar to the grouping of values. Binning is performed on the set of ranges and based on the range limit, and various bins are formed. It is a way to group fewer or more continuous values into a smaller subset/ groups/ bins.

- **Imputing:** Like imputation of missing values, also impute outliers. Use mean, median, moving mean, moving median imputation methods. Before assigning values, analyze if it is a natural outlier or artificial. If it is artificial, go with imputing values.

- **Treat separately:** If there are a significant number of outliers, then treat them separately in the statistical model. One approach is to treat both groups as two different groups, build individual models, and combine the output.

3.1.10 Outlier fill method

Outliers are the data points that differ or show different characteristics from all other data points in the dataset. Many factors are responsible for generating outliers in the dataset. Handling outlier is one of the common challenges. One of the most straightforward methods for detecting outliers is the use of box plots. Filling the outlier is the next step after its detection. There are numerous outlier fill methods based on the nature of outliers.

Previous fill the previous non- outlier value, and constant fills the static value decided by the data analysts, next fill the preceding non-outlier value, nearest fills the nearest non-outlier value.

Summary of the automatic data processing algorithm

Source data from sensors connected to the motor and stored in CSV format. The first step is to read the data from CSV shown in figure 12 and study the data characteristics for preprocessing it. In the initial steps, the data is imported from the CSV and preprocessed (shape, datatype, null values are studied), the source data has outliers, missing values at random, and noise in data. So first, data processing will include handling missing values steps. Missing values are handled with the next, previous, constant method for filing the missing data, then the second step handling outliers present in data. The current data scenario can be done by two methods: the first is by removing outliers, and the second is to fit the outliers. Suppose outliers are very few, around 1-5% or less than that. In that case, removal of outliers will be selected to get true data set; otherwise, fit the outliers method (moving mean, mean, moving median, median method) will be used to handle this large data set of outliers. The final step of data processing is to remove noise from the data using Gaussian, moving mean, or moving Median method to visualize data and trends from charts and graphs for further work. So, these are the data processing algorithm steps performed based on the source data as a part of essential stages in data preprocessing without much modifying the ideal data set of the parameters.

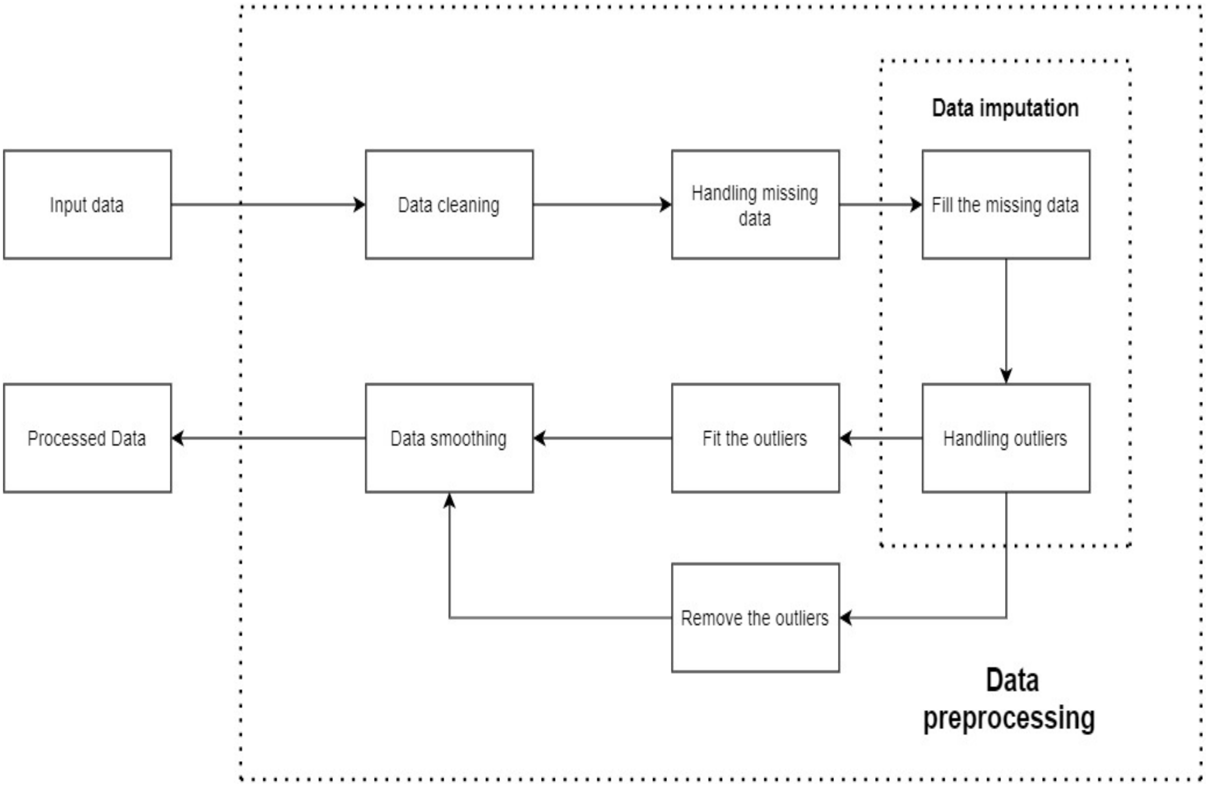

Figure 12: Data processing algorithm steps

3.1.1.1 Data pre-processing of traction motor measured data

Data collection and data reading

The data collected by temperature sensors measure the temperature of various motor parts such as rotor, stator and collecting accurate data from sensors is essential to determine motor performances. Sometimes sensors cannot collect accurate data due to human errors, which can cause problems while checking the performance of motors. The sensor collects unusual data as harmonics present in motor temperature, speed, current, and torque with wrong values. The storage of data is one of the main issues.

The data collected from motors happens via the sensors that are present or connected to various motor components. It may be a temperature sensor, sensors measuring rotational speed, torque, current, voltage, etc. After collecting the data, the next step is to process the data files. All measured data files are flat in CSV format stored at the ABB CRC lab computers. There are various tools and technologies supporting data analysis for CSV files. In the thesis, the MATLAB tool for used for data analysis.

While reading the CSV files in MATLAB, it is found that MATLAB can read the data. Still, specific points/ parts are skipped, such as the header of CSV files, and it is unable to identify their data types of temperature and motor parameters. It causes errors while reading the CSV file and evaluating motor characteristics. It leverages MATLAB advanced and customized commands to read the files per our requirement and automate multiple CSV files.

The data generated by the power analyzer and temperature logger while taking measurements in the computer from the traction motor results in many temperature logger and power analyzer files. The challenge is to clean these files for further processing. Cleaning this data manually is a tedious and time-consuming task. MATLAB has some command that needs to be imported for its usage and with these commands perform data cleansing, but those commands have limitations to read data.

11459x20 table

	1 Var1	2 Var2	3 Var3	4 Var4	5 Var5	6 Var6	7 Var7	8 Var8	9 Var9	10 Var10	11 Var11	12 Var12
1	1	2020-11-19	NaN	23.3720	23.3840	23.4740	23.4820	23.2750	23.4480	23.3390	23.3160	24.177
2	2	2020-11-19	NaN	23.3870	23.3910	23.4800	23.4880	23.2840	23.4510	23.3430	23.3190	24.179
3	3	2020-11-19	NaN	23.3850	23.3920	23.4830	23.4890	23.2860	23.4520	23.3430	23.3230	24.177
4	4	2020-11-19	NaN	23.3690	23.3890	23.4830	23.4940	23.2910	23.4490	23.3450	23.3240	24.177
5	5	2020-11-19	NaN	23.3920	23.3950	23.4900	23.4970	23.2900	23.4510	23.3480	23.3250	24.178
6	6	2020-11-19	NaN	23.3740	23.3940	23.4920	23.5010	23.2900	23.4520	23.3520	23.3300	24.179
7	7	2020-11-19	NaN	23.3750	23.3960	23.4930	23.5030	23.2940	23.4520	23.3530	23.3320	24.177
8	8	2020-11-19	NaN	23.3800	23.3980	23.4960	23.5060	23.2950	23.4510	23.3570	23.3350	24.180
9	9	2020-11-19	NaN	23.3820	23.4000	23.5000	23.5080	23.2980	23.4530	23.3570	23.3380	24.178
10	10	2020-11-19	NaN	23.3820	23.4000	23.5040	23.5110	23.2990	23.4540	23.3630	23.3410	24.179
11	11	2020-11-19	NaN	23.3850	23.4030	23.5050	23.5140	23.3010	23.4530	23.3650	23.3440	24.178

Figure 13:Example of motor temperature data before pre-processing

Figure 13 shows temperature data, the CSV file imported, and read it using MATLAB. The data in this file is not uniform. The temperature file has unwanted data on some rows and columns, causing the main error by the uniform. It can be seen in figure 13 before pre-processing and cleaning data, and the MATLAB read the header of temperature file detected as Var1, Var 2,..,Var 18 instead of motor temperature variable. In the main CSV file, all-temperature files have a constant of 18 columns, and rows vary with recorded measured temperatures. Most CSV files of motor measurement have the delimiter comma "," or a semicolon to separate rows and columns stored. MATLAB can separate distinguish rows and columns using these delimiters.

Data collection and data reading solution

Now that the measured data from temperature sensors of the motor is captured and written into CSV. These CSV files are then stored in some repository. These are naming conventions with initials as "inst0*" where * can be elongated for temperature data filename. So, there are n number of CSV files for data analysis.

The first task is to read that multiple temperature CSV files at once and process them further automatically. So, we provided the path where all CSV is stored combined and then initialized an empty directory where those CSV will be read one by one sequentially. The CSV is imported with MATLAB built-in functions "detectImportOptions" as CSV files contain comma-separated values use the specify delimiter as comma (,).

Then, a structure initialized as T= {} (all the CSV files are read by this, for example, if there are ten CSV files, then all ten CSV files will be read using this structure T= {} and will be cached here for further reference) where there is need to scan all the CSV sequentially and analyze their headers. There is also a check provided to skip CSV files that are empty to simplify our system, thus preventing further processing abnormalities.
MATLAB has Textscan command in MATLAB that reads data from an open text file into a cell array, C, to solve header reading issues while reading and importing CSV files. The file identifier, fileID, indicates the text file. The command which is used to open the file is fopen, and after opening the file to obtain the fileID value, fclose command is used to close the file. The command textscan attempts to match the data in the file to the conversion specifier in formatSpec. The textscan function reapplies formatSpec throughout the entire file and stops when it cannot match formatSpec to the data.
It is the feature that enables to read find desired header text in CSV files. It searches all significant header columns Scan, Time, and many more shown in figure 14 and all the measured temperature readings. It uses cell2mat the cell2mat command in code converts all the data into the required table. All the tables read by MATLAB it will store it in the struct. The measured temp files accessed by inside by struct.

	1 Scan	2 Time	3 x101_M1_RW1__C_	4 x102_M1_RW2__C_	5 x103_M1_RS1__C_	6 x104_M1_RS2__C_	7 x105_M1_RN2__C_	8 x106_M1_RD2__C_
1	1	'2020-11-2...	23.1790	23.2070	23.2090	23.2200	23.1100	23.3330
2	2	'2020-11-2...	23.1930	23.2120	23.2090	23.2180	23.1240	23.3310
3	3	'2020-11-2...	23.1820	23.2090	23.2010	23.2150	23.1180	23.3330
4	4	'2020-11-2...	23.1870	23.2150	23.2070	23.2090	23.1180	23.3330
5	5	'2020-11-2...	23.1870	23.2150	23.2090	23.2090	23.1240	23.3310
6	6	'2020-11-2...	23.1850	23.2090	23.2010	23.2090	23.1240	23.3330
7	7	'2020-11-2...	23.1820	23.2090	23.2070	23.2090	23.1240	23.3360
8	8	'2020-11-2...	23.1820	23.2120	23.2040	23.2150	23.1270	23.3330
9	9	'2020-11-2...	23.1850	23.2120	23.2070	23.2090	23.1210	23.3330
10	10	'2020-11-2...	23.1820	23.2120	23.2040	23.2090	23.1210	23.3280
11	11	'2020-11-2...	23.1850	23.2070	23.1980	23.2090	23.1210	23.3330
12	12	'2020-11-2...	23.1850	23.2090	23.1980	23.2040	23.1240	23.3280
13	13	'2020-11-2...	23.1870	23.2090	23.2010	23.2070	23.1160	23.3310

Figure 14:Pre-processed Temperature sensor measured data

The correct data file with headlines shown in figure 14 shows the headers after pre-processing, and it is very relevant as per the data, and it can also refer to the tags for the data of a particular column. After the initial pre-processing of the input file, something can be inferred from the input file.

Data types and missing data

After pre-processing the file, they still have some abnormalities. For example, the values of temperature are not in the same format. It is essential to have correct data types of measured data to measure further motor temperature and other motor parameters in the data processing. The most problem is processing the data temperature and motor parameters in MATLAB. The data is detected as cell type instead of double because most data measured are double type. Missing data and data are not defined for a particular time instance by the power analyzer; therefore, overall calculation and performance might influence such missing values.

The problem arises when sensors cannot measure parameters such as speed and torque due to momentary error. Missing data and data are not defined for a particular time instance; therefore, overall calculation and performance might influence such missing values. The values specified here as Not a Number (NaN), shown in speed sensor recorded values in some places in figure 15, are 159. Hence, while measuring temperature, it does not record or record slightly or largely different for certain small seconds, which can be ignored and filtered by the application of data pre-processing. The temperature file recorded middle of the stator core temperature of 10^{38} °C that can be impossible to have temperature also in motor parameter the maximum temperature and motor speed restricted using the relational operators available on MATLAB.

	Speed_1_Total_WT1	GroupCount
233	2.5001e+03	1
234	2.5001e+03	1
235	2.5002e+03	1
236	2.5002e+03	1
237	2.5003e+03	1
238	2.5004e+03	1
239	2.5005e+03	1
240	2.5010e+03	1
241	2.5022e+03	1
242	2.5047e+03	1
243	2.5106e+03	1
244	2.5234e+03	1
245	2.5457e+03	1
246	2.5529e+03	1
247	2.5925e+03	1
248	2.6112e+03	1
249	NaN	159

Figure 15: The group summary of speed

Data types and Missing data solutions

Given that the data type of motor parameters is in other formats like strings cell, it needs to be converted to double data type. In MATLAB, str2double is used to convert string datatype to double-precision values. After the temperature data and power analyzer data with all the values in double data type, the following step is to fill in the missing data. This filling of missing data can be done in many ways, such as the feedforward (next value), feed backward data (previous value), nearest value imputation method. Other methods include statistical techniques such as mean, mode, median to fill in the missing data.

To solve the missing value with NaN, they defined it as zero by using "issming" command in MATLAB. Once values are defined, they are ready to be used for analysis and which does not impact result strongly. Motor temperature and other parameter data are further filtered using relational operators such as etc. The group summary of motor parameters showed the range of values and their count. It is found that motor efficiency, torque, and motor rotational speed data restricted their range of data, and relational operators filtered those unusual data.

The speed test of the motor was conducted around a maximum of 1.4 p.u, but figure 16 shows the torque sensor detected a speed range of 7600 to 8000 rpm. Similarly, some unusual motor efficiency of more than a hundred percentage recorded. So, these are unusual measurements restricted by applying relational operators.

	Speed_1_Total_WT1	GroupCount
430	3.1209e+03	1
431	3.1211e+03	1
432	7.6145e+03	1
433	7.6699e+03	1
434	7.6986e+03	1
435	7.7094e+03	1
436	7.7447e+03	1
437	7.7841e+03	1
438	7.7891e+03	1
439	7.7925e+03	1
440	7.7987e+03	1
441	7.8530e+03	1
442	7.9408e+03	1
443	8.0521e+03	1
444	8.0861e+03	1
445	8.0905e+03	1

	Eta1_1_Total_WT1	GroupCount
1340	95.4880	1
1341	95.5040	1
1342	95.5150	1
1343	95.5810	1
1344	95.7880	1
1345	95.9950	1
1346	96.1990	1
1347	96.2420	1
1348	96.4050	1
1349	96.4270	1
1350	96.4620	1
1351	96.6650	1
1352	244.0200	1
1353	257.3550	1
1354	343.8610	1
1355	851.6810	1
1356	NaN	3840

Figure 16: Group summary of speed and efficiency.

With the data pre-processed, the data is ready for the next step that is data visualization. Plots and graphs use various data points against each other to understand the data and its trend in data visualization. The graphs are Current, Speed, Temperature Vs. Time which shows the trend of Current, Speed, Temperature varying concerning time. Similarly, there can provide different graphs that can be plotted further, which can infer different results.

3.2 Vibrational analysis of test bench method

3.2.1 Background

The structural analysis of the test bench is essential to analyze the vibration of a motor when a motor is running at a high rotational speed. Analyzing the motor suppression of unwanted vibration induced by traction motors has been an important research topic in the automotive and railroad industries. It is due to the increasing use of electrified components in passenger vehicles and electric locomotives [37].

3.2.2 FEM formulation

In this thesis, structural analysis of the test bench has been implemented without mounting the motor and mounting the motor on the FEM tool. FEM formulation is similar for both cases. In this study, the case when the motor is not mounted on the foundation of the test bench has been discussed. The test bench model is assumed as a spring model. The free vibration case is considered in our study. The assumption made in this case was that vibration would be small and that the strain induced by the displacement would be linear and its linear deformation along the x, y, and z-axis, respectively [38]. The initial condition of the surface displacement of the test bench is defined as $u(x, y, z) = 0$
The test bench displacement field (u) is a function of the material coordinates (x, y, z), and the value of u describes the point's displacement relative to its initial position [38]. The displacement is calculated as a function of the coordinates of the test bench material (x, y, z).

The test bench material property is assumed isotropic, and the ratio of stress (σ) and strain (ε) is specified as the test bench modulus of elasticity,

$$\text{Modulus of elasticity (E)} = \frac{\sigma}{\varepsilon} \tag{3.2.1}$$

Various possible inelastic strain (ε_{inel}) contributions have been examined as per equation 3.2.2

$$\varepsilon_{inel}[u] = \varepsilon_0[u] + \varepsilon_{ext}[u] + \varepsilon_{th}[u] + \varepsilon_{hs}[u] + \varepsilon_{pl}[u] + \varepsilon_{cr}[u] + \varepsilon_{vp}[u] \tag{3.2.2}$$

Where ε is total strain, the initial strain is ε_0, ε_{ext} is external strain, ε_{th} is thermal strain, ε_{hs} is hygroscopic strain, $\varepsilon_{pl}$is plastic strain, $\varepsilon_{cr}$is creep strain, ε_{vp} is viscoplastic strain

The elastic strain ε_{el} is the difference between the total strain ε and all inelastic strains ε_{inel}

$$\varepsilon_{el}[u] = \varepsilon[u] - \varepsilon_{inel}[u] \tag{3.2.3}$$

The elastic strain is computed in geometrical linear analysis by subtracting the inelastic strain from the total equation 3.2.3. The elastic strain tensor is obtained after removing any inelastic deformation contribution from the total deformation from the displacements [38].

Material models define how stress is related to the displacement field u. For the linear Hookean model, Strain tensor ($\varepsilon[u]$) is defined as

$$\varepsilon[u] = [(\nabla u)^T + (\nabla u)] \tag{3.2.4}$$

Where ∇u is displacement gradient

The tensor form of strain representation ($\varepsilon_{xy}, \varepsilon_{xz}, \varepsilon_{yz}$) is utilized in COMSOL.

test bench elastic strain along x, y, and z-axis represented as

$$\varepsilon_x = \frac{\partial u_x}{\partial x} \tag{3.2.5}$$

$$\varepsilon_y = \frac{\partial u_y}{\partial y} \tag{3.2.6}$$

$$\varepsilon_z = \frac{\partial u_z}{\partial z} \tag{3.2.7}$$

$$\varepsilon_{xy} = \frac{1}{2}\left(\frac{\partial u_x}{\partial y} + \frac{\partial u_y}{\partial x}\right) \tag{3.2.8}$$

$$\varepsilon_{yz} = \frac{1}{2}\left(\frac{\partial u_z}{\partial y} + \frac{\partial u_y}{\partial z}\right) \tag{3.2.9}$$

$$\varepsilon_{xz} = \frac{1}{2}\left(\frac{\partial u_x}{\partial z} + \frac{\partial u_z}{\partial x}\right) \tag{3.2.10}$$

Strain tensor represented by equation 3.2.11

$$\varepsilon = \begin{bmatrix} \varepsilon_x & \varepsilon_{xy} & \varepsilon_{xz} \\ \varepsilon_{xy} & \varepsilon_y & \varepsilon_{yz} \\ \varepsilon_{xz} & \varepsilon_{yz} & \varepsilon_z \end{bmatrix} \tag{3.2.11}$$

It is possible to have an extra stress contribution σ_{ex} with contributions from σ_0 initial stresses, σ_{ext}external and viscoelastic stresses $\sigma_q$on test bench [38].

$$\sigma_{ex}[u] = \sigma_0[u] + \sigma_{ext}[u] + \sigma_q \tag{3.2.12}$$

The test bench assembly's displacement field u(x, y, and z) concerning the stress and strain follows. Cauchy stress tensor determined by using equation 3.2.13

$$\sigma[u] = \sigma_{ex}[u] + C{:}\, \varepsilon_{el}[u] \tag{3.2.13}$$

":" represents a double dot product, C is the elasticity tensor,

By Hooke's law for a linear elastic material, the stress tensor is related to the elastic strain tensor of the test bench in equation 3.2.13 [38]

Stress tensor: Due to its symmetry, the strain tensor can be expressed as the following matrix [38]

$$\sigma = \begin{bmatrix} \sigma_x & \sigma_{xy} & \sigma_{xz} \\ \sigma_{xy} & \sigma_y & \sigma_{yz} \\ \sigma_{xz} & \sigma_{yz} & \sigma_z \end{bmatrix} \quad (3.2.14)$$

The symmetric 6-by-6 matrix can perfectly represent the elasticity tensor [38]

$$C = \begin{bmatrix} C^{1111} & C^{1122} & C^{1133} & C^{1112} & C^{1123} & C^{1113} \\ C^{1122} & C^{2222} & C^{2233} & C^{2212} & C^{2233} & C^{2213} \\ C^{1133} & C^{2233} & C^{3333} & C^{3312} & C^{3323} & C^{3313} \\ C^{1112} & C^{2212} & C^{3312} & C^{1212} & C^{1223} & C^{1213} \\ C^{1123} & C^{2223} & C^{3323} & C^{1223} & C^{2323} & C^{2313} \\ C^{1113} & C^{2213} & C^{3313} & C^{1213} & C^{2313} & C^{1313} \end{bmatrix} \quad (3.2.15)$$

For isotropic material elasticity matrix case, the elasticity matrix becomes [38]

$$C(E, \upsilon) = \frac{E}{(1+\upsilon)(1-2\upsilon)} \begin{bmatrix} 1-\upsilon & 0 & 0 & 0 & 0 & 0 \\ 0 & 1-\upsilon & 0 & 0 & 0 & 0 \\ 0 & 0 & 1-\upsilon & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{1-2\upsilon}{2} & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1-2\upsilon}{2} & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{1-2\upsilon}{2} \end{bmatrix} \quad (3.2.16)$$

Where E is Young modulus v is Poisson's ratio

Eigenfrequency determined using the following two equations for the test bench

$$-(2\pi f)^2 \rho u = \nabla . \sigma[u] \quad (3.2.17)$$

the relationship between eigenvalue λ and eigenfrequency is shown in equation 3.2.18

$$f = -\frac{\lambda}{2\pi i} \quad (3.2.18)$$

COMSOL executes all the given equations by solving all equations, investigating structural analysis, and test bench eigenfrequency.

3.2.3 Eigenfrequency analysis

Natural frequencies, also known as eigenfrequencies, are discrete frequencies at which a system is likely to vibrate without the driving force. A structure deforms into a specific shape while vibrating at a particular eigenfrequency [39]. The determination of a structure's eigenfrequencies is an essential aspect of structural mechanics.

Eigenfrequency analysis has the following goals: Confirm that a periodic stimulation results in resonance and ensure that a periodic stimulation does not generate a resonance that could result in excessive strains [39].

Free vibration

Free vibration is analyzed when no external force acting on the body,

According to Newton's law of motion, the equation of motion for a single degree of freedom

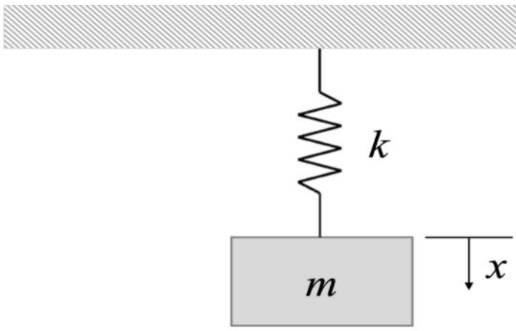

Figure 17: Free vibration single degree of freedom system [39]

$$m\ddot{x} + kx = F(t) \tag{3.2.19}$$

When the free vibration case is considered, the equation of motion becomes

$$m\ddot{x} + kx = 0 \tag{3.2.20}$$

Natural frequency (ω) of the system

$$f = 2\pi\sqrt{\frac{k}{m}} \tag{3.2.21}$$

Where k stiffness and m are mass of the system

Regarding how stiffness and mass affect eigenfrequencies, the expression for the eigenfrequency equation 3.2.21 illustrates typical behavior [39].

The test bench system with multiple degrees of freedom can be characterized by a matrix equation of the type [39]

$$M\ddot{u} + C\dot{u} + Ku = F(t) \tag{3.2.22}$$

F(t) is forces, M is the mass matrix, C is the damping matrix, u is the displacement vector, K stiffness matrix.

In the case of free vibration, the system's equation of motion becomes

$$M\ddot{u} + Ku = 0 \tag{3.2.24}$$

Forced vibrations occur if an external agency continuously drives a system, represented by equation 3.2.22. The assembly is subject to magnetic-force excitation on the surface of the stator's teeth, causing forced vibration [41].

Synchronous speed for a permanent magnet motor

$$N_s(rpm) = \frac{120p}{f} \tag{3.2.25}$$

Where $N_s$is shaft rotation speed, p is the pole, and f is frequency.

3.2.4 COMSOL Multiphysics

The FEM is a method for numerically solving differential equations arising in structural mechanics [42].

FEM consists of three phases, the first phase. It starts with the problem statement that is turned into a discrete computer model. Following this, the first phase is further extended, which includes the geometry, meshing, physics, and boundary conditions used to accomplish. The second phase includes the computer computing the eigenfrequency using a numerical algorithm, and the third phase deals with analyzing and visualizing the eigenfrequency result [43].

In this thesis, eigenfrequency analysis of the test bench model was implemented using the COMSOL Multiphysics tool.

3.2.5 Model Information

The test motor and drive motor are mounted on a steel foundation, and this system is mounted on a test bench foundation shown in figure 18. The steel casing consists of a circular hollow profile to which the machine is screwed. Structural steel frame foundation is the surface where the motor is mounted, so the motor feet are in the middle of the hollow profiles concerning the front view of the shaft. The steel frame foundation is designed so that a second motor can be mounted on the steel frame and coupled to the drive motor later.

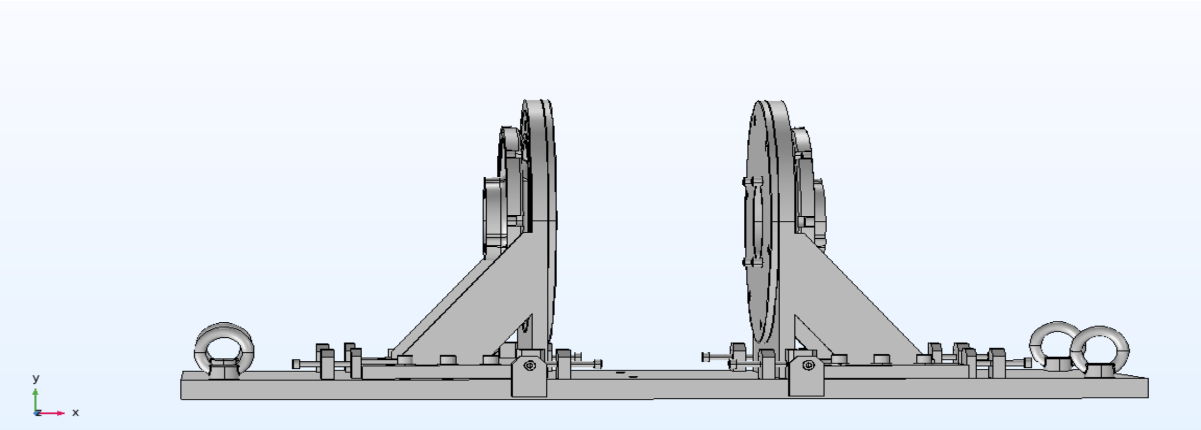

Figure 18: Test bench model

Triaxial Accelerometers KS943B100 sensors are mounted on the test bench at the drive end (DE) holder and the non-drive end (NDE) shield holder of the motor to calculate vibrational velocity.

3.2.6 Geometry

The test bench, test motor, and drive motor were designed on CAD. The geometry of the test bench and PM motor was constructed on a CAD tool. In this study, the 3D geometry of the test bench was analyzed by forming a union on the COMSOL tool.

3.2.7 Solid mechanics

The elastic material property Young modulus and Poisson's ratio depending on the selected material. In this study, structural steel is utilized for all the test bench and motor domains, and the assumption in thesis eigenfrequency analysis is the case of free vibration.

3.2.8 Meshing

The accuracy of the FEM model is directly related to the finite element mesh that is used. The finite element mesh is used to divide the test bench and traction motor model into smaller domains then used to solve equations. These equations approximate the governing equation of interest by defining a set of polynomial functions over each element. The computed solution will approach the actual solution as these elements are reduced, and the mesh is refined. The finite element model must go through mesh refining before it can be validated [44].

In FEM, structured and unstructured are two categories of meshing operation. Free triangular, free quad, and free tetrahedral are unstructured procedures that generate unstructured meshes. Unstructured operations provide the ability to mesh any geometry, which is a crucial feature. The free tetrahedral unstructured tetrahedral mesh generates a mesh on the test bench's remaining domains, boundaries, edges, and points. To obtain a mesh optimized for computations in the FEM tool, both element quality and the supplied size parameters are taken into account when an unstructured mesh is generated. In general, for the meshing, the mesh's total number of elements has grown, and the minimum element quality has nearly doubled, implying that the mesh's overall quality has improved [44,45].

Meshing is a challenging part of the COMSOL tool. By applying various meshing types give an accurate result. When applying normal mesh on the model, it must be looked where the mesh fails to apply. It applies physics to the entire geometry of the model. Finer mesh can be calibrated to resolve the problem of mesh.; however, applying finer or more calibrated meshing takes more simulation time. Instead of applying extra fine or above, the mesh can be applied on specific domains and boundaries. The error found in meshing is related to its geometry. The most common errors were found when edges intersected and failed to create mesh near sharp edges.

The thesis has followed an approach which involves creating the free tetrahedral mesh for the test bench and applied mesh for a specific part of the domain by selecting the edges with respective boundaries and then calibrating element size for the model and selected the mesh type for the model. If still there is an error, we again check the boundary and interesting edges and calibrate them. So basically, we divided the model's geometry into the specific part of the domain and applied precise mesh to resolve the mesh error.

In this study, two different meshings were used for the same test bench. The mesh was calibrated normal to the test bench foundation, and for the remaining part of the test bench, fine meshing shown in figure 19 in blue color is calibrated.

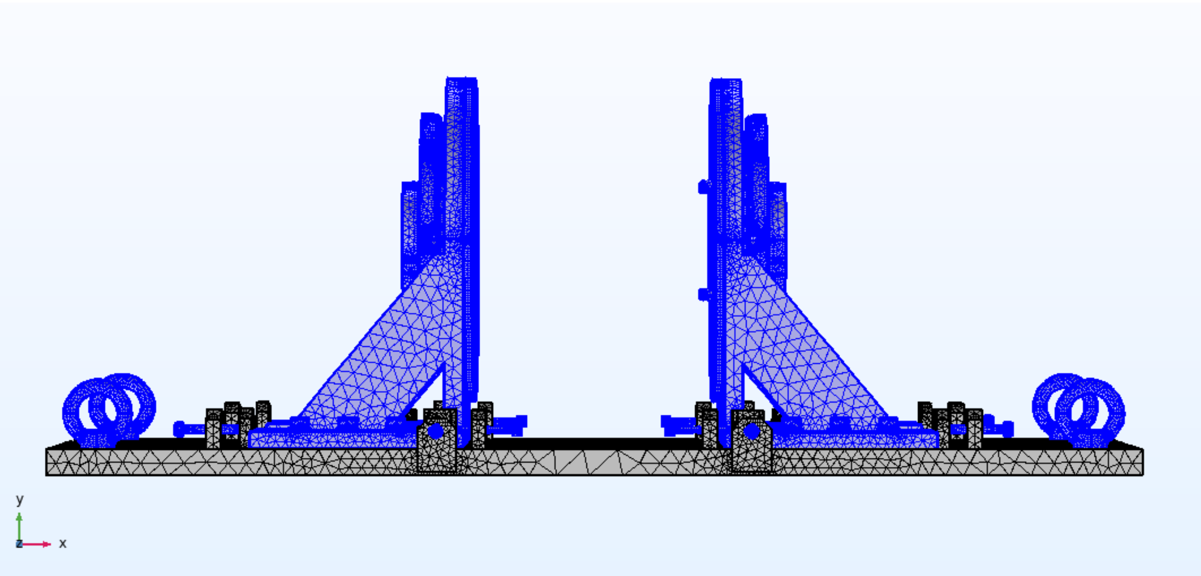

Figure 19:Test bench with two different mesh

3.2.9 Mesh Quality

To investigate mesh quality, the skewness of the test bench model is mentioned in this study. The best possible quality is 1 for all quality measures and indicates an optimal element in the chosen quality measure. 0 represents a degenerated element at the other end of the interval. If the geometry results in a poor-quality mesh, the mesh returns the poor-quality mesh for inspection rather than no mesh at all. To get accurate findings, minimum and average element quality levels appropriate for test bench assembly must be determined at first. [46].

The number of boundary elements increases for the more calibrated mesh for the same part of the test bench, as shown in tables 3 and 4. Two different meshes were applied to improve the accuracy of the eigenfrequency result. Finer meshes were implemented in which the number of boundary elements is more than the normal mesh setting, and simulation time also increased. The same procedure applies to the foundation.

Table 3: Mesh for test bench foundation

Mesh	Number of elements	Number of boundary elements
Fine	52732	16946
Normal	43327	15406

Table 4: Mesh remaining part of test bench

Mesh	Number of elements	Number of boundary elements
Finer	1158505	265086
Normal	875459	213525

Table 5: Skewness of test bench

	Minimum quality	Skewness
Test bench foundation	0.01018	0.6209
Remaining part of the test bench	0.5407	0.762

Table 5 shows the skewness of the test model that was implemented for eigenfrequency analysis. The model is built with a normal and finer mesh, resulting in high skewed face cells.

3.2.10 COMSOL SETUP

Due to free vibration, no excitation forces act on the test bench; hence F(t) is zero. For the eigenfrequency calculation, all the forces acting on the system are set to be zero in COMSOL.

In this study, the default eigenfrequency solver "ARPACK" is selected and then chosen eigenfrequency search region-wise. It computes eigenfrequency for the entire geometry of the FEM model. In the largest eigenfrequency search for the test bench, 1000 Hz is selected to search all the eigenfrequency related to the selected range and give the output close to the frequencies. The physics applied for the test bench was solid mechanics, and the model runs on a 3D space dimension with eigenfrequency for the numerical part. In materials, structural steel is applied to the entire geometry of the test bench without changing any thermal and mechanical properties. Since the test bench has finer meshing, the memory allocation problem occurs with running out of space with solver configuration with PARDISO linear system solver. MUMPS solver configuration was utilized for structural mechanics analysis [38].

4 Results

4.1 Automatic data processing results

4.1.1 Analysis of Power analyzer measured data

The traction motor electrical and mechanical parameters at ABB CRC lab were measured according to the IEC 60034-part 4 standard.
The motor speed data have been measured from the torque sensor. The data has been processed by filling out the missing value, removing, and filling the outliers, and smoothing data. These three phases are investigated in our study for motor speed data.
Motor parameter measured by power analyzer containing torque, current, speed, and other containing data with a sample size of 10101 is processed. The motor temperature data recorded by the temperature logger has zero missing data values, so it did not require going through the data imputation process filling out the missing data values stage. However, by measured speed data on the power analyzer, it was found that 3752 data points out of 10101 were missing at random, and relevant filling methods were used to compensate for the missing data. All the values are mentioned in Table 6.

Table 6: Method to fill the missing speed data

Nearest value	Previous value	Constant value	Next value
3752 (filled value)	3711	3752	3537

To cover for the missing data points: one method could be ignoring those values using the data deletion method and making analysis; however, it could be problematic to determine the motor speed and its characteristics based on that result. Data deletion shrinks the data size of measured motor parameters and makes it biased. To solve this issue, statistical methods are used, and the most convenient nearest value method to fill 3752 has been applied. Based on that nearest values and comparing nearest, previous, and constant data arrived from table 6 at a final check, selection for the suitable method based on their mean of original data set and new data set of motor speed is computed. Table 7 can be referenced that the nearest value method has a close mean of data to the original mean of speed data. The mean of the original speed data set found was 0.6648 p.u (Where p.u represents per unit), and the mean of the new data set was 0.6587 p.u after applying the nearest value method, and the error comes around 1% for this filling missing value method. Figure 20 shows the filled 3752 missing values using the nearest value method of measured data.

Table 7: Mean of fill the missing speed data value method

Mean (original)	Nearest value method	Constant value method	Previous value method	Next value method
0.6648 p.u	0.6587 p.u	0.3889 p.u	0.6171 p.u	0.6871 p.u

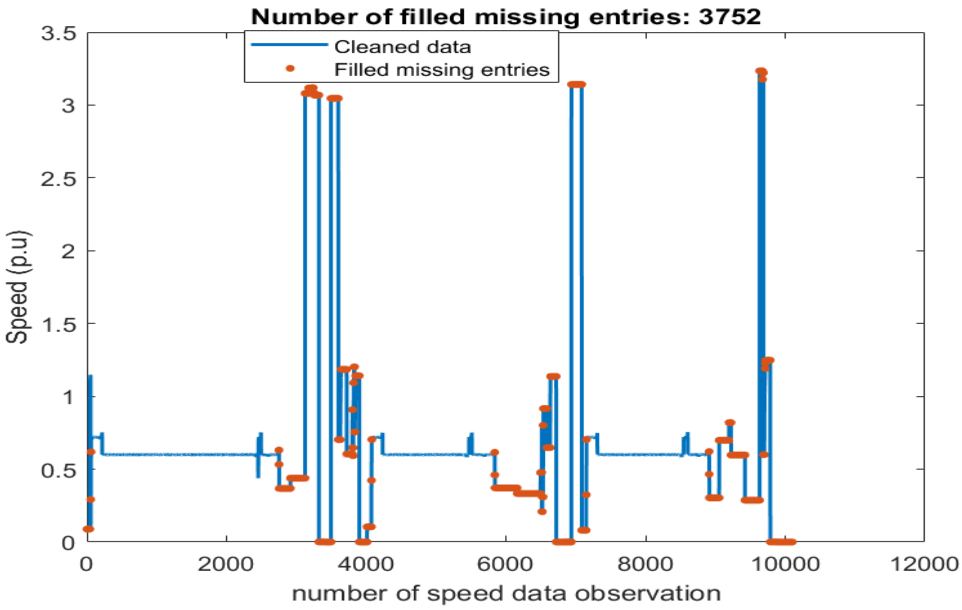

Figure 20: Filling the missing data using the nearest value method

4.1.2 Handling Outliers

The motor is operated maximum of up to 1.64 p.u during the lab test. However, some unusual measurements were recorded around 3. 2 p.u; it may be due to some glitch in the torque sensor. The total number of recorded observations beyond 1.64 p.u was 507 measurements out of 10101, so it is reasonable to neglect such values since it does not affect the test result**.** It means around 1% of the data of the whole table is not considered**.** The updated array table size is 9594. The outliers are removed in this case by using relational operators. So, for defining the ideal motor speed data set, the relational operator method is suitable. When the outliers are defined with other methods, in that case, the new data of speed same as the filtered data with the relational operator seen from table 8, it also tells about the various statistical method such as mean, median, moving mean, and moving median applied to the data for handling outliers.

Table 8: Outlier defining method and their respective mean for speed data

Mean (relational operator)	**Mean method**	**Median Method**	**Moving median Method**	**Moving mean Method**
0.3851 p.u	0.3883 p.u	0.4278 p.u	0.4349 p.u	0.3891 p.u

There are different methods to fit such unusual measurements for neglecting the data. We have used the mean method to define the outliers of the speed data, and figure 21 illustrates that the 264 outliers were determined by the moving mean method.

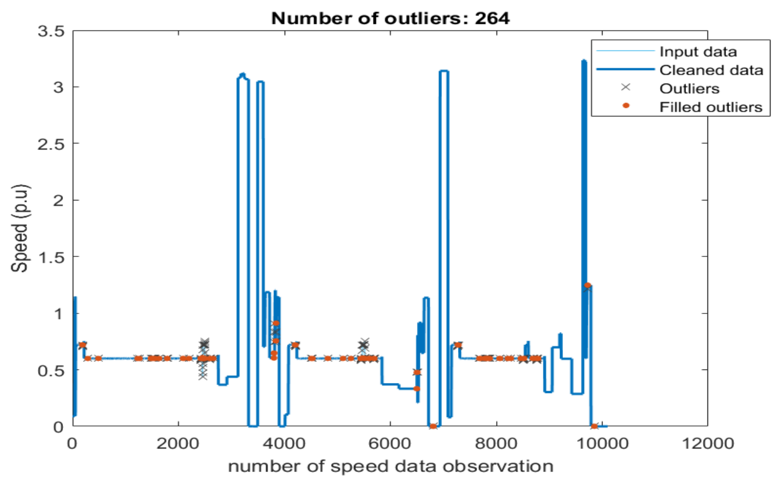

Figure 21: Outliers samples with respect to the speed of the motor

4.1.3 Speed data smoothing

In the final step, the motor speed is now simplified to analyze it further. As an inference from figure 22, there are two legends: input data and smoothed data. Now from the input data curve, one can infer that various small points are spiking too much, causing the data to be disturbing; after applying smoothing on the given input data, it has been found out that the spikes in data points have decreased further; this helps in analyzing data properly within the correct limits rather than considering the abnormal and usual spiked data. Also, the smoothing curve shows that the data points are appropriately distributed with a smooth curve reducing noise in the data points. Table 9 shows the newly created speed dataset after data smoothing and the close dataset mean found with Gaussian filter nearest to the perfect filtered dataset using relational operators.

Table 9: mean of smoothed speed data

Mean (relational operator)	**Moving mean**	**Moving median**	**Gaussian filter**
0.3851 p.u	0.3858 p.u	0.3860 p.u	0.3856 p.u

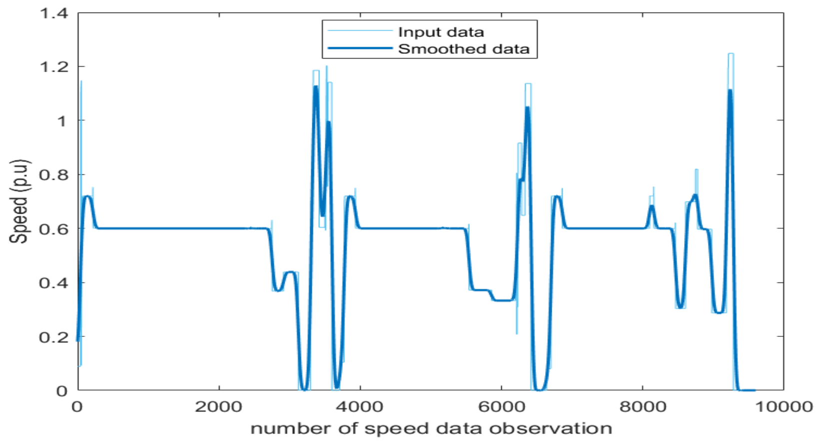

Figure 22: The smoothened data of motor speed with respect to the number of observations

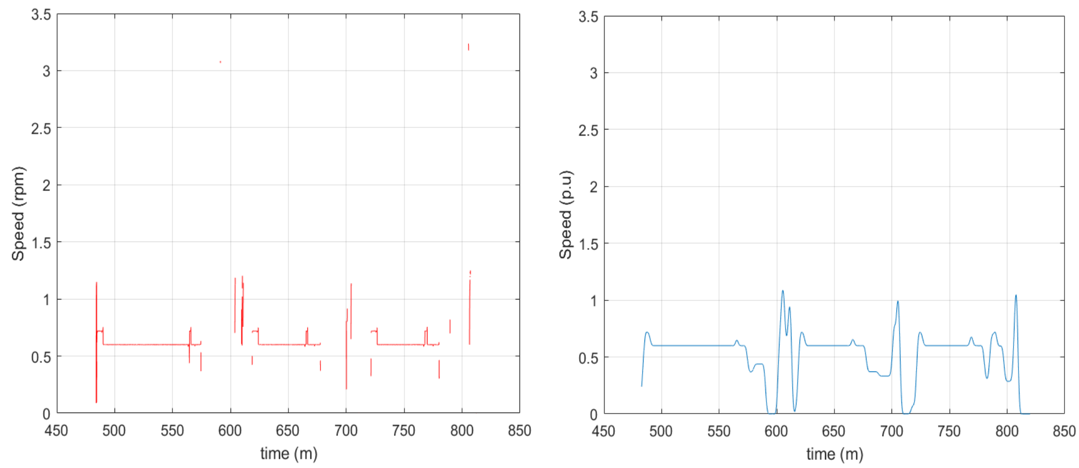

Figure 23: Speed vs. time before left and after data processing right

As seen in figure 23, the left-hand side graph, the speed data seems to be discontinuous, meaning there are specific motor issues in terms of speed given the motor's time. This is caused due to missing values of data that the sensors were not able to capture timely. Analyzing such data will provide distorted or improper results. The graph on the right-hand side, figure 23, covers all those issues by filling in the missing data. Now the analyst can derive results and conclusions on the speed of motor varying with respect to time.

4.1.1.1 Temperature logger measured data

A sample of motor temperature data has been taken from all the temperature sensors used to measure various motor parts for the data processing. Those measured data consist of a 9762-sample size. The motor temperature data do not have missing values at random recorded by the temperature logger, so handling the missing data value step for temperature data analysis is skipped.

4.1.1.2 Analysis of temperature data outliers

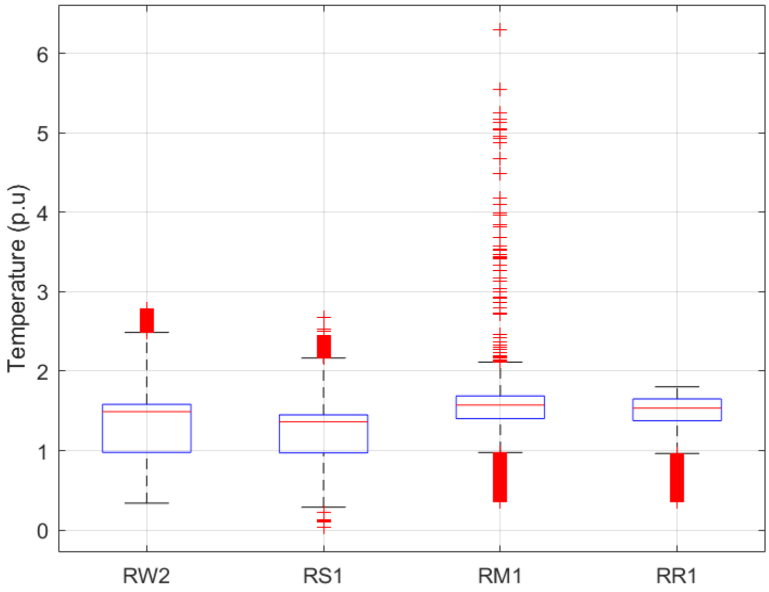

Figure 24: Boxplot of PM temperature data

Where temperature sensors RW1 is the Middle of NDE side end winding**,** RW2 is Close to the stator core of NDE side end winding**,** RS1 is the middle of the stator core (axially) in a slot belonging to phase U**,** RM1 is Permanent Magnet (PM) temperature

Figure 24 shows the boxplot, the median for various legends, that seems to be shifted to the right or left, meaning that the data is either right-skewed or left-skewed. The IQR ranges of the temperature of location of RW2, RM1, RS1, and RR1 data starts from somewhere near to 0.3 p.u and continues till around 2.5 p.u motor temperature approximately. All the data points beyond and above these points can be treated as outliers. There are two methods for PM temperature data to do first, by filling the outliers, and second, by removing the outliers.

The relational operator method for the PM(RM1) temperature data was applied to remove outliers. In this method, the number of temperatures measured data shrink but only 30 values going beyond the temperature range of 2.2 p.u, so it does not impact the result. Also, the whole data set is used subsequently for processing. Therefore, removing outliers is more accurate in this case.

Table 10: PM temperature mean using statistical method

Mean (original)	Mean relational operator method	Mean method	Median method	Moving mean method	Moving median Method
1.5047 p.u	1.4953 p.u	1.4962 p.u	1.5217 p.u	1.5011 p.u	1.4982 p.u

The new dataset was created by mean, median, moving mean, and moving media. The data set was created by the moving mean method without reducing the array size of original data of PM temperature sample size of 9762 close to the relational operator method data.

Table 10 compares the mean of the reduced data of the relational operator, which is a true data set. As seen from the table, the mean of original data containing outlier is 1.5047 p.u, and the mean filtered with relational operator is 1.493 p.u, so there is not much significant difference. In this case the outliers are defined keeping the original data size. It is found from the table that the mean method is close to the reduced data size of the relational operator data set.

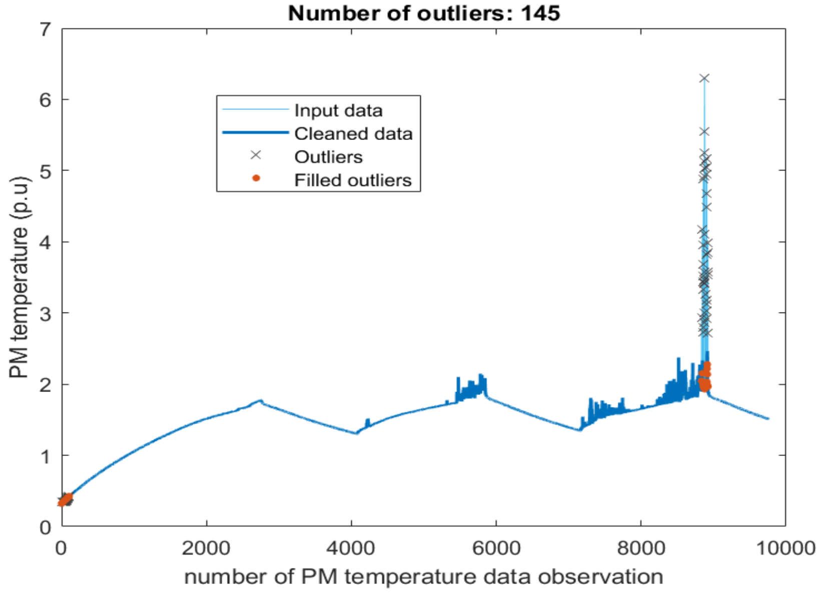

Figure 25: PM Temperature data outliers

Figure 25 shows 145 outliers present in the original temperature data, and the mean method was suitable.

4.1.1.3 Temperature data smoothening

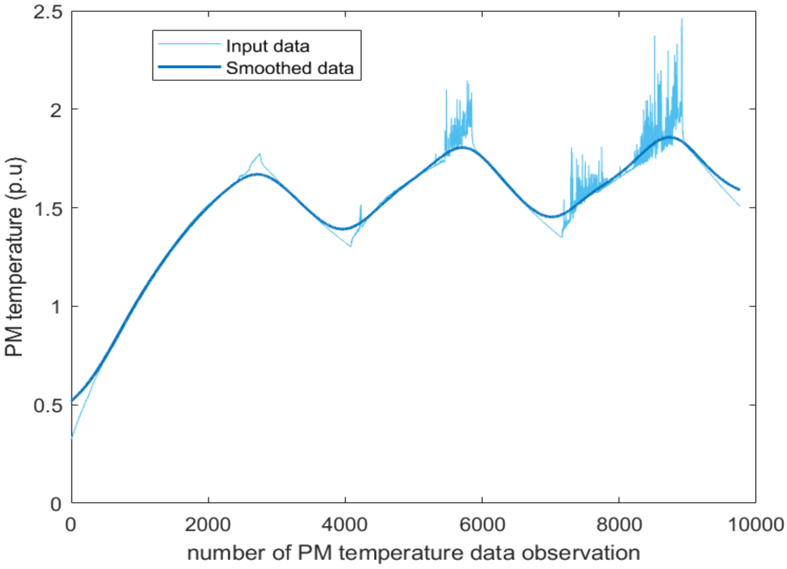

Figure 26: Smoothened data keeping the same data set

The temperature range of PM is from 0 to 2.2 p.u. Since it was essential to keep PM measured data close to the actual data. The main reason for the non-linearity of the temperature sensors is because of the temperature change. This nonlinearity is mostly observed when there is an abrupt change in the temperature reading.

To analyze PM temperature embedded in the motor, a gaussian filter is used to perform smoothing on the data, and it is best suitable for analyzing the temperature. Table 11 explicitly shows that new smoothed data created has been less altered than other data filters when the Gaussian filter is implemented. Their mean of data is close to the relational operator filtered data mean. The Gaussian filter has a bell curve shape showing the normal distribution; as seen from figure 26, the gaussian method helps suppress the noise in the input data providing a smooth normal distribution. The normal distribution can then further help in studying the characteristics of the PM temperature with respect to the number of observations**.**

Table 11: mean of noise filtered PM temperature data

Moving mean	1.5237 p.u
Moving median	1.5216 p.u
Gaussian filter	1.5137 p.u
Mean (relational operator)	1.4953 p.u

Figure 27 shows the plot of PM temperature vs. time before pre-processing. It has noise in the data, and figure 28 represents data processing followed by defining outliers and the data smoothing method. The PM temperature was analyzed further with respect to time and other motor, electrical and mechanical parameters as per the requirement.

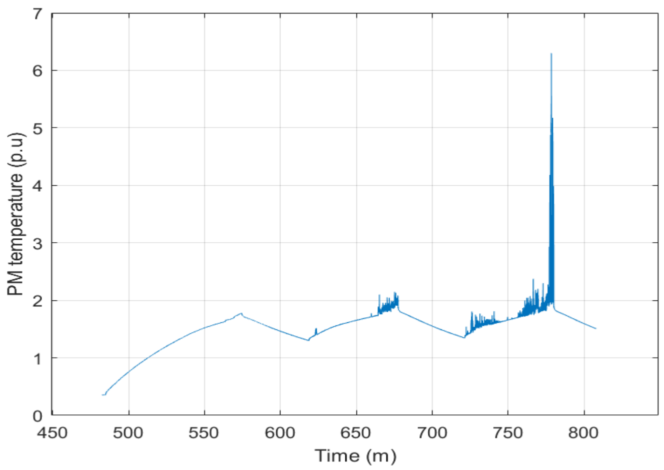

Figure 27: PM temperature vs. time plot without data processing

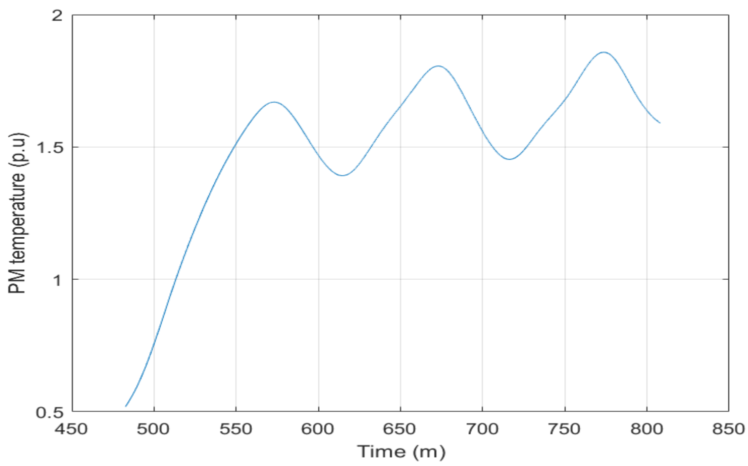

Figure 28: PM temperature vs. time plot after data processing

4.2 Vibration Analysis results

4.2.1 Experimental vibration analysis

The vibrational analysis of the traction motor was done under IEC 60034-14, and the motor was tested in the speed range of 0 to 1.64 p.u at ABB CRC lab Västerås. Stator frame of test motor and test bench form a rigid body where they connected at drive end (DE) and Non-drive ending (NDE) holder of test bench foundation. Moreover, the DE holder is close to the test bench casing.

The vibrational velocity of NDE and DE holder of test bench with motor measured using vibration sensors in ABB Västerås lab. It found that test bench assembly when motor and generator mounted on structural steel foundation, when speed corresponding to the eigenfrequencies of test bench coincides, then resonance occurs. The resonance peak of the motor NDE shield was observed in the frequency range of 1.16 to 1.24 p.u, and vibrational velocity reached the peak along the x and y direction when frequency close to 1.2 p.u was found in this study.

Note: The experimental graph is confidential. Therefore, it is excluded

4.2.3 FEM eigenfrequency analysis

The result obtained from the FEM simulation of the test bench (without mounting test and drive motor) is shown in table 12. The eigenfrequency of the test bench found in this study and only the first four eigenfrequencies are considered for the resonance frequencies study since those falls under the operational speed range of the motor. The operating range of traction motor up to 1.64 p.u.

Table 12: Natural frequency of test bench

Eigenfrequency (p.u)
0.46
0.82
1.2
1.57

The result obtained from the FEM simulation, the natural frequency 1.2 p.u of test bench is approximately near to the excited frequency range and speed of NDE holder of motor which found in the experimental result. When the test motor's rotational speed reaches the natural frequency of 1.2 p.u, the test bench vibrates directly with the exciting force of the test motor.

At 1.2 p.u, the test bench resonates along the x and y-axis. The maximum displacement of the test bench casing is 1.38 µm, and the minimum displacement is 0.06 µm test bench foundation seen in figure 29.

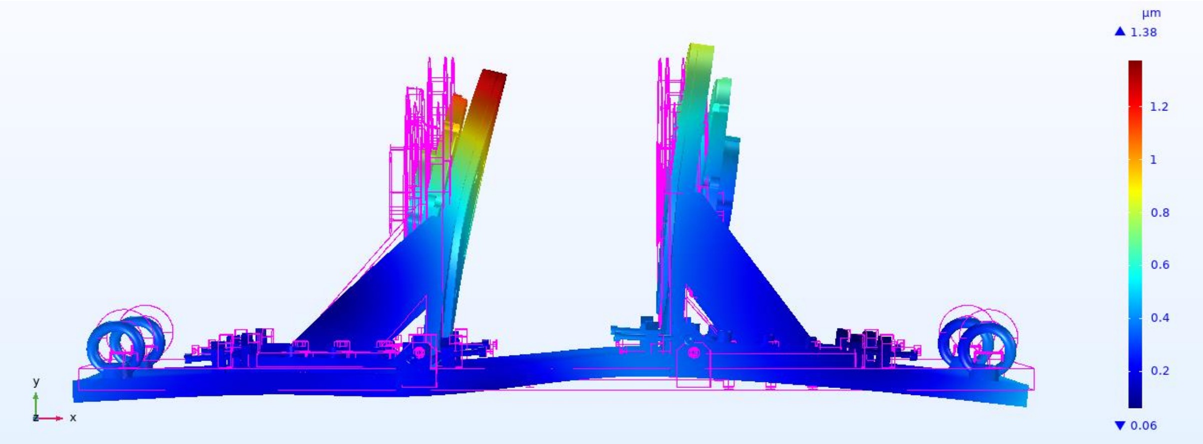

Figure 29: Test bench natural frequency at 1.2 p.u

The vibrational velocity of the NDE side along the y axis reaches the peak around 12 mm/sec and along the x-axis, 6 mm/sec, due to the excitation of magnetic forces along the x and y directions.

4.2.3 Bending case of test Bench

While analyzing the motor performance in the lab, operating the motor at a certain speed range must be avoided because it has a significant impact on test bench structure when it is close to the range of test bench natural frequencies.

The study shows possible bending of the test bench, which leads to fatigue and the possibility of breaking small parts of the test bench and even possible with the motor's casing. The bending of the test bench we studied and even though it does not fall in the range resonance frequency, it is still essential to avoid those natural frequencies due to bending the test casing and foundation.

Figure 30 shows the maximum surface displacement of 1.37 µm at the tip of the test bench casing at 0.46 p.u frequency along the negative x-axis. The minimum displacement of 4.52 nm occurred at the end of the second foundation of the test bench. It increases at the end of the foundation, the displacement of the foundation, and the steel casing shown in black color in figure 30. The steel casing bends more than the foundation. The longitudinal strain of the left side casing is maximum along the negative x-axis.

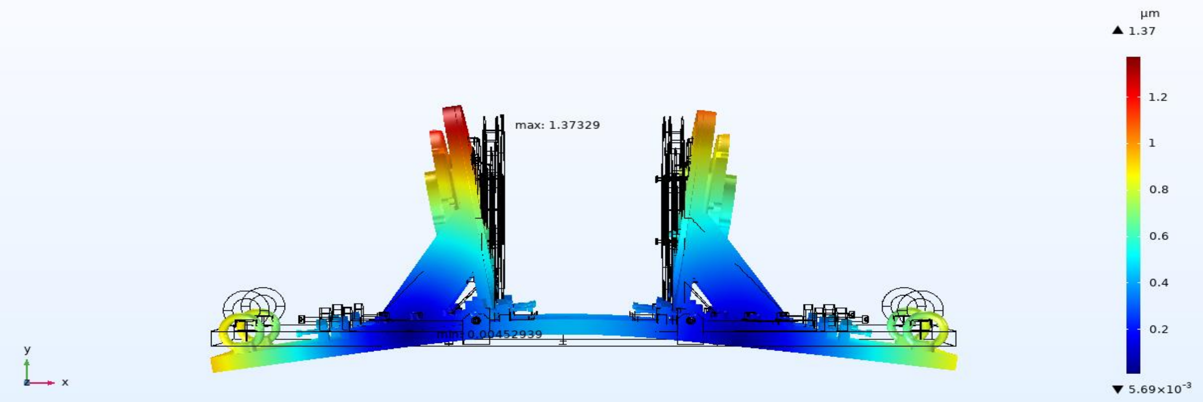

Figure 30: Surface displacement of the test bench at a natural frequency of 0.46 p.u

At the second eigenfrequency 0.82 p.u, the maximum surface displacement of the hook bolt is 1.34 μm left side of the casing along the negative y-axis. The minimum displacement near to joint of left side of casing. Figure 31 shows maximum displacement at all the corners of the foundation and the tip of both casings. So, this frequency is crucial to avoid due to its twisting of the basement in the middle of the test bench.

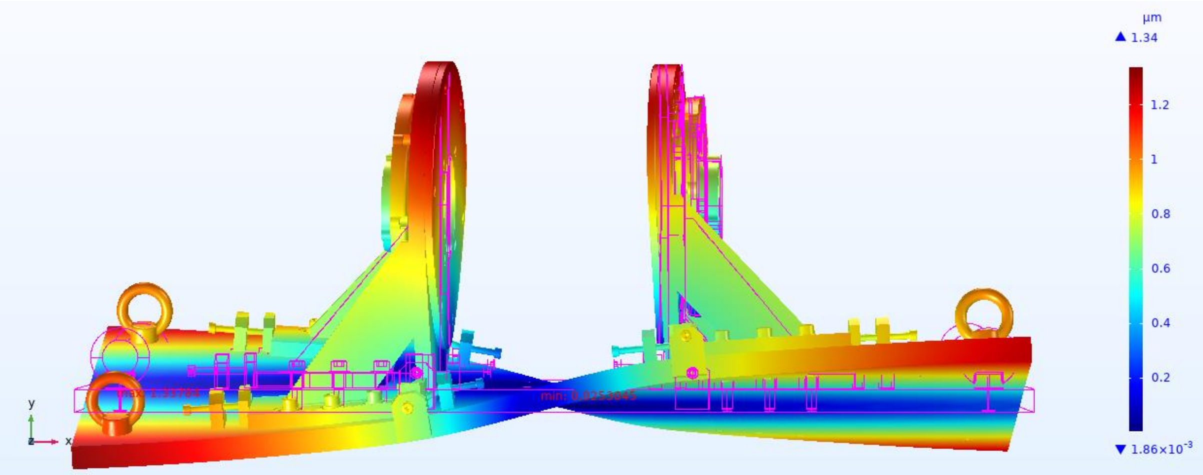

Figure 31: Surface displacement of the test at a natural frequency of 0.82 p.u

From figure 30,31 and 32, the study has been found that as the frequency increase from 0.46 to 1.57 p.u, the bending of the test bench foundation also increases.

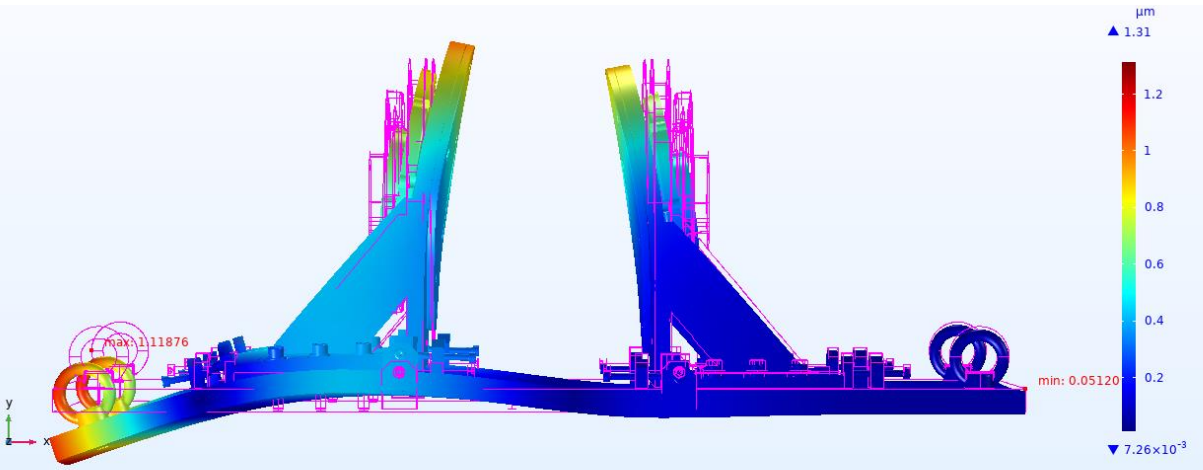

Figure 32: Surface displacement of the test at a natural frequency of 1.57 p.u

5 Discussions

5.1 Automatic data processing of traction motor measured data discussion

Another result shows that the PM magnet temperature data collected by the temperature logger in the study helps to understand the PM temperature trend with respect to time. It provides essential information about possible losses present in the traction motor. The same is true for the speed of the motor; around 38% of the data were missing, and the data processing algorithm assisted in analyzing the speed during the time interval when data is missing. The result can also be used to identify the faultiness of sensors such as temperature, torque, and current sensors used during the lab test.

5.2 Vibration analysis of test bench discussion

The result obtained using the FEM tool of resonance frequency was validated with the experimental result. Besides the resonance frequencies, other frequencies of the test bench were found using FEM are also important because the surface displacement of the test bench foundation and casing was found to be maximum. Surface displacement increases the chances of breaking the small part of the test bench. It can damage the traction motor during the lab test. Hence those frequencies are essential to avoid while operating the motor in the lab test.

However, in the experimental result, resonance frequencies were found in the range of 1.16 to 1.24 p.u. There are many resonance frequencies that the COMSOL Multiphysics tool could not find out during the simulation. Therefore, only one resonance frequency was found in that range using the FEM tool due to that constraint. There are many other FEM tools such as SimScale and ANSYS that can calculate the natural frequencies of the test bench. It can be useful to validate the experimental result by comparing the result of natural frequencies of the test bench.

6 Conclusion

6.1 Automatic data processing of traction motor measured data conclusion

In this thesis work, data collected from sensors connected to the traction motor was studied, and data analysis was performed on traction motor measured data. Various steps were performed on the captured data, and then the data was visualized to represent the behavior of the motor with respect to the data captured.

In this study, the statistical method has been implemented in data processing for handling the missing data, removing and filling outliers, and noise filtering. Deciding how to handle those problems which how to apply statistical methods depends on the column data and its data. This decision will determine which method is suitable for that column data. The proposed algorithm in this research work for data processing can handle data reading, pre-processing, removing and filling outliers, and noise filtering.

The data in raw format is present in the form of CSV. The existing tools for processing CSV have some limitations discussed in the data analysis section. The method developed explained in this thesis revolves around the MATLAB tool. Using MATLAB, one can read the measured data efficiently. The thesis has covered all the necessary steps for data processing, starting from reading the multiple CSV, data pre-processing, and all the required steps to make data ready to analyze the motor parameters effectively. The automated data processing developed with the help of MATLAB can address the automated data reading and the data cleaning.

Further missing data were imputed, and outliers in that data were handled using statistical methods. The mean method was used in the thesis for suppressing outliers, data cleaning, and removing noise from the data. From the statistical study, it can be concluded that selecting the most suitable statistical model for filling the missing values, defining the outliers, and filtering noise based on the average value of parameter dataset filtered with relational operator helped make the suitable data set for the measured parameter of the motor. Based on the closest average of the data set, the statistical method has been chosen in our thesis.

The study also visualizes the processed data via charts and graphs; some are curves and graphs related to the power analyzer and temperature logger instrument. More than two hundred records that measured all the power analyzer data were scanned; it was found that only the Power analyzer instrument has the problem of missing values at random when it stores the incoming data from the motor. Various statistical methods were used and applied to handle missing data values, and the best amongst them was chosen. In the present data processing algorithm identifying missing values, cleaning the outliers, and smoothing curves, all the essential techniques to handle these problems based on the mean method were included. Further, the user has to apply a suitable approach to get the desired output. As a result, it is likely to analyze the efficiency, speed-torque characteristics, and temperature influence motor efficiency from the data processing more adequately. This data processing algorithm can be used to push sensors beyond capabilities for improving measurement systems.

6.2 Vibration analysis of test bench conclusion

A finite element model was used to calculate the test bench natural frequency. The findings of the experiment and the finite element analysis were compared. The experimental result found the resonance frequency in the range of 1.16 to 1.24 p.u, and the FEM result found resonant frequency at 1.2 p.u. The results of the finite element model fit the experimental results well, according to the eigenfrequency analysis. The study found that at 1.2 p.u frequency, the motor resonates during the lab test, which validated with experimental and COMSOL results. Vibrational velocity was reached at the peak along the x and y direction of the NDE holder, which can be catastrophic for the test bench and motor assembly.

The result shows that 0.46,0.82,1.2, and 1.57 p.u natural frequencies, the test bench casing, and the foundation bends reduce the test bench's lifespan. Even though the magnitude of maximum displacement is negligible, there is the possibility of breaking some small part of the test bench, causing a fracture to the test bench. The study shows the frequencies at which resonance occurs, and the same should be avoided during the vibration test of the motor. Also, it is possible to predict the lifespan of the test bench of the traction motor and its reliability.

7 Future work

Data Analysis is performed on the measured data from ABB CRC lab related to traction motors. There were many challenges for using that data, for which suitable pre-processing steps were applied further, the missing data were imputed, and data characteristics were plotted to study the behavior of the data. After the data analysis, analysts were able to conclude on the motor characteristics of the electric motors at ABB labs. Further study could investigate the scope of Machine learning implementation on this data to predict the future behavior of the motor. Machine learning models such as regression can be applied to predict the motor values, and steps can be taken before any wear tear. It can help detect or predict any failure before it occurs, which can help save a lot of cost in terms of time and capital.

In this thesis, the majority of the work was done on data analysis, starting from data reading, various data pre-processing steps, including data imputation, data smoothing. The processed data is then available for future studies as the output of data analysis

The current algorithm will make data ready for a machine learning model for predicting the temperature of various motor parts. Currently, some of the temperature sensors measure exceptional values, and retaking measurements could be time-consuming. Based on temperature sensor location, developing a model like linear regression predicts the motor's temperature based on other sensors. Also, it could be possible to analyze the data live with the user-friendly graphical user interface. Machine learning models could be implemented further after data processing to correlate various parameters based on the data.

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