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REVIEW ON MACHINE LEARNING ALGORITHM FOR THE FAULT DETECTION IN ELECTRICAL SYSTEM

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Abstract : This research paper focuses on the investigation of detecting broken rotor faults in AC induction motors through the analysis of both electrical and vibration signals. AC motors, commonly powered by three-phase converters or industrial power supplies, may experience failures in the rotor bars, manifesting in diverse signals such as voltages and currents across the three phases. Additionally, information from acceleration and velocity signals in radial, axial, and tangential directions provides valuable insights. The experimental setup comprises a three-phase induction motor linked to a direct-current machine serving as a generator to simulate load torque. This system is interconnected through a shaft incorporating a rotating torque meter.

Keywords: Machine Learning, Fault detection, Induction motor.

1 INTRODUCTION

Induction motors (IMs) stand as the predominant electric motor type in a wide array of industries such as oil and gas, cement, petrochemicals, and electric traction, primarily owing to their durability and cost-effectiveness. Remarkably, they constitute approximately 85% of the industrial sector's total energy consumption. Given this prevalence, the implementation of a robust fault detection and diagnosis (FDD) system becomes imperative for industries to preemptively address issues, prevent unplanned shutdowns, curtail maintenance expenses, and minimize downtime. Failures in IMs can emanate from various sources, encompassing faults in the stator, rotor, motor mechanical components (such as bearings and shaft), or external influences. Numerous surveys have been conducted to discern the distribution of failures across these components, revealing that the percentages vary based on factors such as motor size, application type, and manufacturing standards. For instance, medium voltage motors exhibit heightened susceptibility to faults like broken bar and end ring issues compared to their smaller counterparts. The critical role of IMs in industrial energy consumption underscores the necessity for a comprehensive understanding of the factors contributing to their failures. Not only does this knowledge aid in the development of effective FDD systems, but it also enables industries to tailor maintenance strategies according to specific motor characteristics, ultimately enhancing overall operational efficiency and minimizing the economic impact of unexpected motor failure

1.1 MACHINE LEARNING

Machine learning is a computational process that produces a particular outcome without being explicitly programmed. These methods adapt themself by learning from experience to produce a better outcome. This learning from experience is the training process, where input data is given together with the desired outcome. Machine learning is a field of computer science that is concerned with developing algorithms and models that enable computers to learn from data and improve their performance on a given task over time. The machine learning model then learns itself to link the input data to the desired outcome. This is done in a way that not only the training data can be identified, but also new, previously unseen data.

In essence, machine learning is a way of teaching computers to make predictions or decisions based on examples, without being explicitly programmed to do so.

There are several types of machine learning algorithms, including supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, the algorithm is trained on a labelled dataset, where each example is associated with acorresponding label or target value. The goal of the algorithm is to learn a mapping from the input features to the output label, suchthat it can accurately predict the label for new, unseen examples. Examples of supervised learning are logistic regression, decisiontrees (DTs), and support vector machines (SVM).In unsupervised learning, the algorithm is trained on an unlabeled dataset, where there are no corresponding target values. The goalof the algorithm is to find patterns or structure in the data, such as clusters or latent variables. Examples of unsupervised learning are hierarchical clustering, k-means, and k-nearest neighbors (K-NN).

Then there is also a category called semi-supervised learning. Here, only part of the data is labelled. In this situation, the labelled data can be used for the learning of the unlabeled part. Examples of semi-supervised learning are expectation maximisation (EM) with generative mixture models, cotraining, and transductive SVM.

In reinforcement learning, the algorithm learns to make decisions based on feedback from the environment. The algorithm receivesa reward or penalty for each action it takes, and its goal is to learn a policy that maximises the cumulative reward over time.

One of the key advantages of machine learning is its ability to automate complex decision-making tasks that are difficult for humansto perform manually. For example, machine learning can be used to detect fraud in financial transactions, predict customer churn in marketing, or diagnose diseases in medical imaging.

2. LITERATURE REVIEW

1. Ravi C. Bhavsar Condition Monitoring of electrical machines is increasing due to its potential to reduce operating costs, enhance the reliability of operation and improve service to customers. Condition Monitoring of induction motors is a fast emerging technology for online detection of incipient faults. This paper includes a comprehensive review of different types of faults occurring in induction motors and also points out the latest trends in condition monitoring technology. Most frequent electric faults in the case of induction motors have been described over here along with their detection techniques. It also contains the different monitoring methods of three phase induction motors which are used previously and also important for nowadays like AI based detection techniques.

2. Sudhanshu Goel This work is aimed to act as a guide for an industrial or academic user to choose the right technique for condition based maintenance of their equipment and to present a comprehensive review of prevalent condition monitoring technologies, i.e. Vibration signal analysis, Acoustic emission testing, Ultrasound condition monitoring, Infrared thermography and lubrication oil analysis. A detailed review of condition monitoring techniques which can be used to detect a particular type of fault is presented with an aim to identify the most suitable technique for fault diagnosis. It is concluded that the most suitable condition monitoring technique for a particular operation can only be decided by taking in consideration the factors like equipment under test, its loading, defect type and ambient conditions, etc.

3. Praveen Kumar Shukla CM (Condition Monitoring) is a process of monitoring the operating parameters of machines to know the monitored characteristics and to predict machine health. In industries protection of devices such as motors has become challenging work. Further in this paper, various condition monitoring techniques are given with specific advantages and disadvantages. For the condition monitoring of alternating motors, the economical and latest method is analysing the stator current through LabVIEW. An intelligent diagnostic condition monitoring system has been proposed. This system will provide continuous real time tracking of different faults occurring in the system and for automatic decision making estimates the severity of faults. a variety of condition monitoring techniques are available but acoustic emission and stator current analysis have proven to be the most accurate and suitable techniques. Current analysis technique is however most economical. Also, an intelligent diagnostic CM system for AC motors has been proposed. This technique provides continuous real time tracking of different faults and estimates severity of faults for automatic decision making. It is expected that the motor protection system as proposed in this research will be faster, more efficient and user friendly than the other techniques.

4. Neelam Mehra Small single phase Induction machines are used for home appliances hence the machine monitoring plays an important role for industrial as well as domestic appliances growth. Various fault detection methods have been used in the past two decades. Special attention is given to non-invasive methods which are capable of detecting faults using major data without disassembling the machine. The Motor Current Signature Analysis (MCSA) is considered the most popular fault detection method nowadays because it can easily detect common machine faults such as turn to turn short ckt, cracked /broken rotor bars, bearing deterioration etc. The present paper discusses the fundamentals of Motor Current Signature Analysis (MCSA) plus condition monitoring of the induction motor using MCSA . This technique can be fairly simple, or complicated, depending on the system available for data collection and evaluation. MCSA technology can be used in conjunction with other technologies, such as motor circuit analysis, in order to provide a complete overview of the motor circuit. The result of using MCSA as part of the motor diagnostics program is a complete view of motor system health.

5. Khadim Moin Siddiqui, et al.The author in this paper, uses primarily nondestructive testing techniques, visual inspection, and performance data to assess machinery condition.

6. Partha Sarathee Bhowmik, Sourav Pradhan et al. This paper delves into the various faults and study of conventional and innovative techniques for induction motor faults with an identification of future research areas.

7. Neelam Mehala, Ratna Dahiya. In this paper, the author presents theory and some experimental results of Motor current signature analysis. The MCSA uses the current spectrum of the machine for locating characteristic fault frequencies. The spectrum is obtained using a Fast Fourier Transformation (FFT) that is performed on the signal under analysis.

8. Sulekha Shukla, Manoj Jha, M. F. Qureshi, In this paper, the author presents the implementation of broken rotor bar fault detection in an induction motor using motor current signal analysis (MCSA) and prognosis with interval type-2 fuzzy logic. In this study, MCSA is applied to an induction motor to detect broken rotor bar faults. Here they discuss the fundamentals of Motor Current Signature Analysis (MCSA) plus condition monitoring of the induction motor using MCSA and interval type-2 fuzzy logic. In addition, this paper presents four case studies of induction motor fault diagnosis.

9. Ajagekar, Akshay, and Fengqi You. In this paper, the author proposes a hybrid QC-based deep learning framework for fault diagnosis of electrical power systems that combines the feature extraction capabilities of conditional restricted Boltzmann machines with an efficient classification of deep networks.

10. Dang, Hoang-Long, et al. In this paper, the author, chosen and analysed several typical loads, especially nonlinear and complex loads such as power electronic loads, and five time-domain parameters of the current—average value, median value, variance value, RMS value, and

distance of the maximum and minimum values—were chosen for arc fault detection. Various machine learning algorithms were used for arc fault detection and their detection accuracies were compared.

3. METHODOLOGY

In this research paper, the focus is on investigating faults in induction motors using machine learning (ML). The initial step involves the acquisition of sensor data, which includes both electrical and mechanical signals. The dataset comprises voltage readings for each phase (V_a, V_b, V_c), current draw for each phase (I_a, I_b, I_c), and various mechanical vibration signals such as tangential speeds (Vib_carc, Vib_base), axial speed (Vib_axial), and radial speeds on the driven side (Vib_acpi) and non drive side (Vib_acpe). Subsequently, the dataset undergoes preprocessing, involving the extraction of ensemble member data and signal processing techniques. This preprocessing step is essential for refining the raw sensor data, ensuring its compatibility with machine learning algorithms.

The next phase involves the development of a detection or prediction model to identify conditions or indicators of faults in the induction motor. This encompasses the selection of appropriate ML algorithms, feature engineering, and model training using the preprocessed data. The model is designed to recognize patterns and anomalies within the signals that may indicate potential faults or deviations from normal motor behaviour.

Once the ML model is trained and validated, it is deployed and integrated into MATLAB Simulink. The integration with Simulink allows for real-time monitoring and evaluation of the induction motor's condition using the developed ML model. Simulink provides a platform for incorporating the ML model into the broader control and monitoring system, enabling continuous assessment of the motor's health and facilitating timely responses to potential faults.

3.1 WORKING

In this research project, we aim to develop a fault detection system for induction motors utilizing machine learning (ML) techniques. Initially, sensor data encompassing electrical and mechanical signals such as voltage readings for each phase, current draw for each phase, and various mechanical vibration signals are acquired. This dataset undergoes preprocessing to refine raw sensor data and make it compatible with ML algorithms. Subsequently, a detection or prediction model is developed using appropriate ML algorithms, feature engineering, and model training. This model is designed to identify patterns and anomalies within the signals indicative of potential faults in the induction motor. Once trained and validated, the ML model is deployed and integrated into MATLAB Simulink for real-time monitoring and evaluation. Integration with Simulink enables continuous assessment of motor health, allowing for timely responses to potential faults within the broader control and monitoring system.

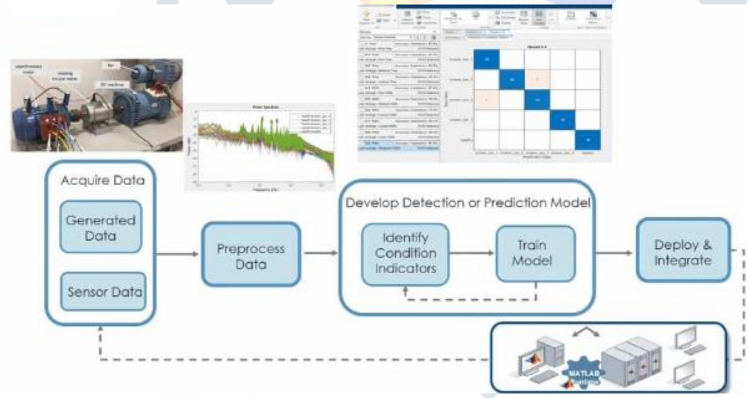


Fig: 3.1 Block diagram

4 . SYSTEM REQUIREMENT

SOFTWARE REQUIREMENT

- Matlab Software

IMPLEMENTATION

The system implementation was executed utilising a dataset described in a paper provided by Mathworks. The following setup serves as our point of reference

The Implementing Step Carried out in below 4 Step.

STEP 1] : Data Acquisition:

- The research project focuses on investigating faults in induction motors using machine learning (ML).
- Sensor data acquisition involves gathering both electrical and mechanical signals from the motor.

- The dataset includes:
  - Voltage readings for each phase (V_a, V_b, V_c).
  - Current draw for each phase (I_a, I_b, I_c).
  - Various mechanical vibration signals such as tangential speeds (Vib_carc, Vib_base), axial speed (Vib_axial), and radial speeds on the driven side (Vib_acpi) and non-drive side (Vib_acpe).

STEP 2] : preprocessing:

- The acquired dataset undergoes preprocessing to refine the raw sensor data and make it compatible with machine learning algorithms.
- Preprocessing involves the extraction of ensemble member data and signal processing techniques.
- This step is crucial for preparing the data for further analysis and ensuring its quality for training machine learning models.

Extract Ensemble Member Data

Convert the original motor data files into individual ensemble member data files for all combinations of health condition, load torque, and experiment index. The files are saved to a target folder and used by the fileEnsembleDatastore object in the Diagnostic Feature Designer app for data processing and feature extraction.

Processing data file struct_rs_R1.mat

Creating the member data file rotor0b_torque05_experiment01.mat
Creating the member data file rotor0b_torque05_experiment02.mat
Creating the member data file rotor0b_torque10_experiment01.mat
Creating the member data file rotor0b_torque10_experiment02.mat
Creating the member data file rotor0b_torque15_experiment01.mat
Creating the member data file rotor0b_torque15_experiment02.mat
Creating the member data file rotor0b_torque20_experiment01.mat
Creating the member data file rotor0b_torque20_experiment02.mat
Creating the member data file rotor0b_torque25_experiment01.mat
Creating the member data file rotor0b_torque25_experiment02.mat
Creating the member data file rotor0b_torque30_experiment01.mat
Creating the member data file rotor0b_torque30_experiment02.mat
Creating the member data file rotor0b_torque35_experiment01.mat
Creating the member data file rotor0b_torque35_experiment02.mat
Creating the member data file rotor0b_torque40_experiment01.mat
Creating the member data file rotor0b_torque40_experiment02.mat

Processing data file struct_r1b_R1.mat

Creating the member data file rotor1b_torque05_experiment01.mat
Creating the member data file rotor1b_torque05_experiment02.mat
Creating the member data file rotor1b_torque10_experiment01.mat
Creating the member data file rotor1b_torque10_experiment02.mat
Creating the member data file rotor1b_torque15_experiment01.mat
Creating the member data file rotor1b_torque15_experiment02.mat
Creating the member data file rotor1b_torque20_experiment01.mat
Creating the member data file rotor1b_torque20_experiment02.mat
Creating the member data file rotor1b_torque25_experiment01.mat
Creating the member data file rotor1b_torque25_experiment02.mat
Creating the member data file rotor1b_torque30_experiment01.mat
Creating the member data file rotor1b_torque30_experiment02.mat
Creating the member data file rotor1b_torque35_experiment01.mat
Creating the member data file rotor1b_torque35_experiment02.mat
Creating the member data file rotor1b_torque40_experiment01.mat
Creating the member data file rotor1b_torque40_experiment02.mat

Processing data file struct_r2b_R1.mat

Creating the member data file rotor2b_torque05_experiment01.mat
Creating the member data file rotor2b_torque05_experiment02.mat
Creating the member data file rotor2b_torque10_experiment01.mat
Creating the member data file rotor2b_torque10_experiment02.mat
Creating the member data file rotor2b_torque15_experiment01.mat
Creating the member data file rotor2b_torque15_experiment02.mat
Creating the member data file rotor2b_torque20_experiment01.mat
Creating the member data file rotor2b_torque20_experiment02.mat
Creating the member data file rotor2b_torque25_experiment01.mat
Creating the member data file rotor2b_torque25_experiment02.mat
Creating the member data file rotor2b_torque30_experiment01.mat
Creating the member data file rotor2b_torque30_experiment02.mat
Creating the member data file rotor2b_torque35_experiment01.mat
Creating the member data file rotor2b_torque35_experiment02.mat
Creating the member data file rotor2b_torque40_experiment01.mat
Creating the member data file rotor2b_torque40_experiment02.mat

Processing data file struct_r3b_R1.mat

Creating the member data file rotor3b_torque05_experiment01.mat
Creating the member data file rotor3b_torque05_experiment02.mat
Creating the member data file rotor3b_torque10_experiment01.mat
Creating the member data file rotor3b_torque10_experiment02.mat
Creating the member data file rotor3b_torque15_experiment01.mat
Creating the member data file rotor3b_torque15_experiment02.mat
Creating the member data file rotor3b_torque20_experiment01.mat
Creating the member data file rotor3b_torque20_experiment02.mat
Creating the member data file rotor3b_torque25_experiment01.mat
Creating the member data file rotor3b_torque25_experiment02.mat
Creating the member data file rotor3b_torque30_experiment01.mat
Creating the member data file rotor3b_torque30_experiment02.mat
Creating the member data file rotor3b_torque35_experiment01.mat
Creating the member data file rotor3b_torque35_experiment02.mat
Creating the member data file rotor3b_torque40_experiment01.mat
Creating the member data file rotor3b_torque40_experiment02.mat

Processing data file struct_r4b_R1.mat

Creating the member data file rotor4b_torque05_experiment01.mat
Creating the member data file rotor4b_torque05_experiment02.mat
Creating the member data file rotor4b_torque10_experiment01.mat
Creating the member data file rotor4b_torque10_experiment02.mat
Creating the member data file rotor4b_torque15_experiment01.mat
Creating the member data file rotor4b_torque15_experiment02.mat
Creating the member data file rotor4b_torque20_experiment01.mat
Creating the member data file rotor4b_torque20_experiment02.mat
Creating the member data file rotor4b_torque25_experiment01.mat
Creating the member data file rotor4b_torque25_experiment02.mat
Creating the member data file rotor4b_torque30_experiment01.mat
Creating the member data file rotor4b_torque30_experiment02.mat
Creating the member data file rotor4b_torque35_experiment01.mat
Creating the member data file rotor4b_torque35_experiment02.mat
Creating the member data file rotor4b_torque40_experiment01.mat
Creating the member data file rotor4b_torque40_experiment02.mat

Construct File Ensemble Datastore

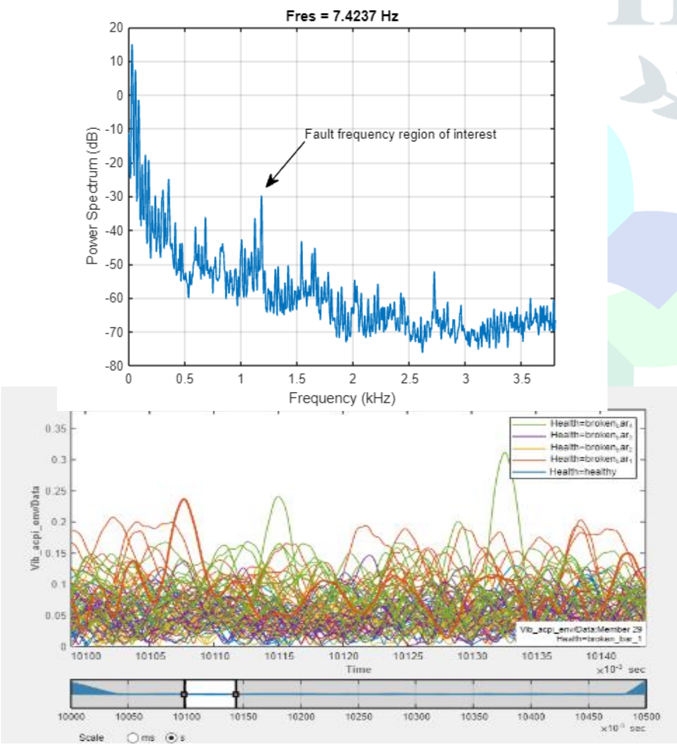
In These We Create a file ensemble datastore for the data stored in the MAT-files, and configure it with functions that interact with the software to read from and write to the datastore. Before interacting with data in the ensemble, Neet created functions that tell the software how to process the data files to read variables into the MATLAB workspace and to write data back to the files. Finally, set properties of the ensemble to identify data variables, condition variables, and the variables selected to read. These variables include ones that are not in the original data set but rather specified and constructed by readMemberData: Vib_acpi_env, the band-pass filtered radial vibration signal, and Ia_env_ps, the band-pass filtered envelope spectrum of the first-phase current signal.

POWER SPECTRUM

T=80×6 table

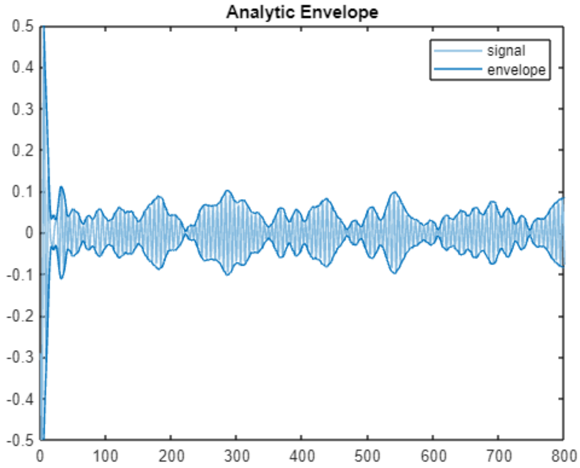
Ia	Vib_acpi	Vib_acpi_env	Ia_env_ps	Health	Load
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque05"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque05"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque10"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque10"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque15"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque15"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque20"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque20"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque25"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque25"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque30"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque30"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque35"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque35"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque40"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque40"
⋮					

From the power spectrum of one of the vibration signalsVib_acpi, observe that there are frequency components of interest in the [900 1300] Hz region.Hz region.



ANALYTIC ENVELOPE

The envelope of signals after band-pass filtering them can help reveal demodulated signals containing behaviour related to the health of the system



STEP 3] Model Development:

The next phase involves developing a detection or prediction model to identify conditions or indicators of faults in the induction motor.
By Open the Diagnostic Feature Designer app import the file ensemble datastore into the app by clicking the New Session button and selecting the ens variable from the list.Once preliminary data is read by the app, uncheck the Append data to file ensemble option.

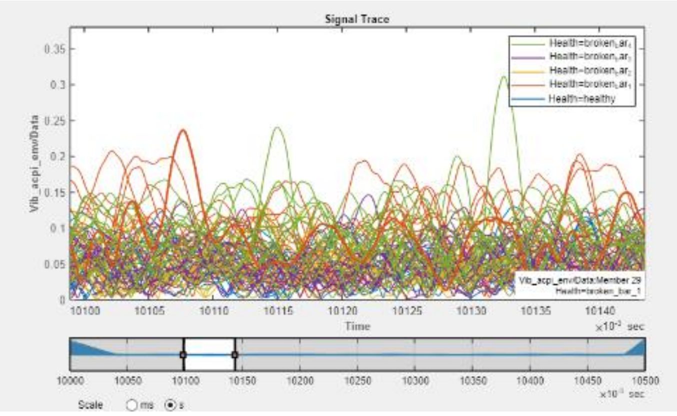
Data in table Format

T=80×6 table

Ia	Vib_acpi	Vib_acpi_env	Ia_env_ps	Health	Load
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque05"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque05"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque10"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque10"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque15"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque15"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque20"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque20"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque25"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque25"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque30"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque30"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque35"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque35"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque40"
{50001×1 timetable}	{7601×1 timetable}	{7601×1 timetable}	{25001×2 double}	"healthy"	"torque40"
⋮					

SIGNAL TRACE DATA

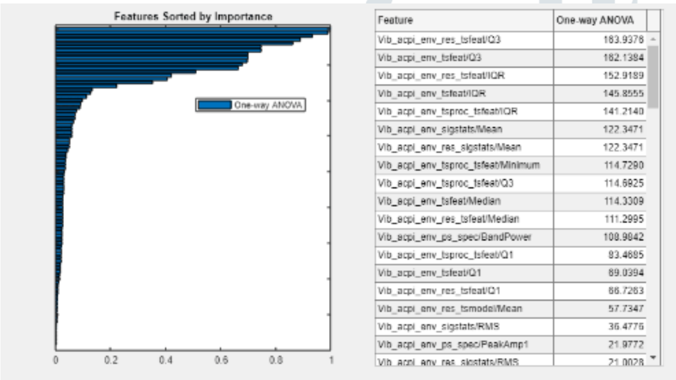
Signal Trace plots and grouping the plot colors based on the Health status of the experimental data. The function loads only the data between 10.0 and 11.0 seconds.



PREDICTIVE FEATURES

This large number of features from available signals and ranking them according to their power in separating various health classes. large number of features automatically and ranks them according to their importance with respect to the One-way ANOVA criterion.

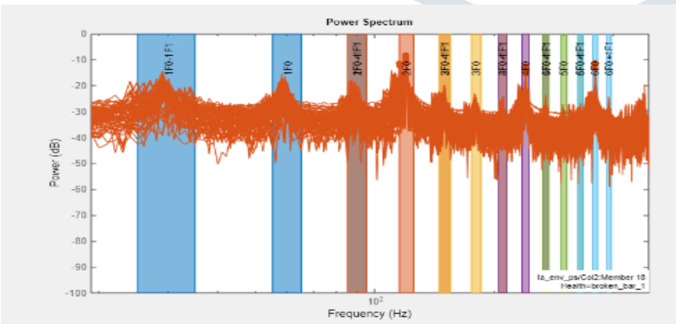
FEATURES RANKING



Feature	One-way ANOVA
Vib_acpi_env_res_tsfeat/Q3	183.9378
Vib_acpi_env_tsfeat/Q3	182.1384
Vib_acpi_env_res_tsfeat/IQR	152.9189
Vib_acpi_env_tsfeat/IQR	145.8555
Vib_acpi_env_tsproc_tsfeat/IQR	141.2140
Vib_acpi_env_sigstats/Mean	122.3471
Vib_acpi_env_res_sigstats/Mean	122.3471
Vib_acpi_env_tsproc_tsfeat/Minimum	114.7290
Vib_acpi_env_tsproc_tsfeat/Q3	114.6925
Vib_acpi_env_tsfeat/Median	114.3309
Vib_acpi_env_res_tsfeat/Median	111.2995
Vib_acpi_env_ps_spec/BandPower	108.9842
Vib_acpi_env_tsproc_tsfeat/Q1	83.4685
Vib_acpi_env_tsfeat/Q1	69.0394
Vib_acpi_env_res_tsfeat/Q1	66.7263
Vib_acpi_env_res_tsmodel/Mean	57.7347
Vib_acpi_env_sigstats/RMS	36.4776
Vib_acpi_env_ps_spec/PeakAmp1	21.9772
Vib_acpi_env_res_sigstats/RMS	21.0028

POWER SPECTRUM

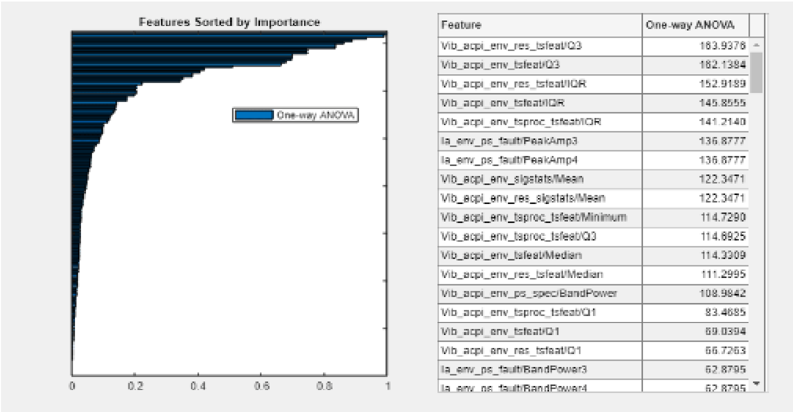
This Power Spectrum is Generated by envelope Spectrum Data. by Selecting the Ia_env_ps signalFault bands around a fundamental frequency of 60 Hz and its first 6 harmonics along with a sideband of 30 Hz to cover most of the spectral peaks in the envelope spectra. Use a fault band width of 10 Hz.



This Spectrum generated a large number of features from the various electrical and vibration signals of the AC motor system.

RANK FEATURES

The final ranking table indicates that the first 10 to 15 features, based on One-way ANOVA ranking, help classify the motors according to the number of broken rotor bars in them.

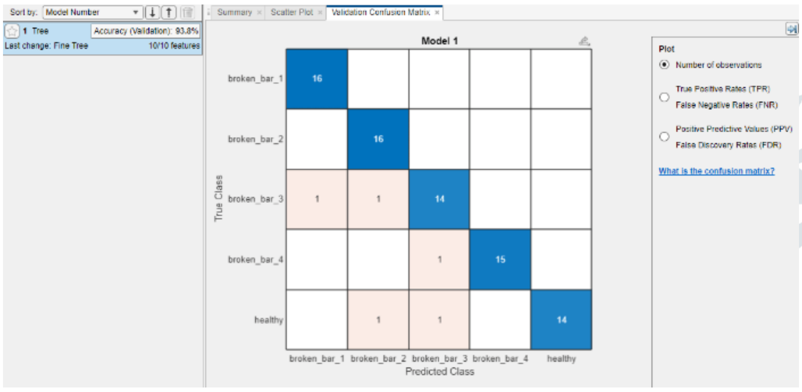


STEP 4] : Integration with MATLAB Simulink

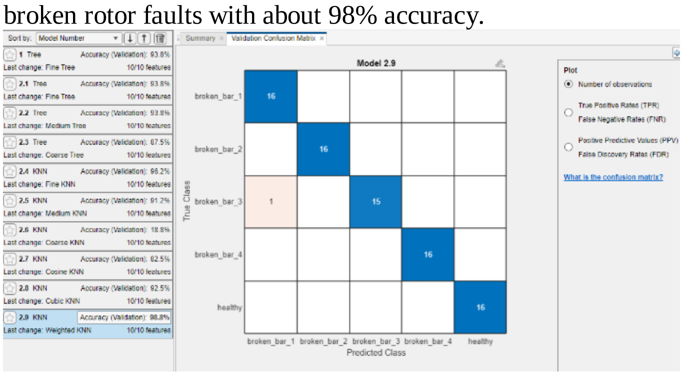
- Once the ML model is trained and validated, it is deployed and integrated into MATLAB Simulink.
- Integration with Simulink allows for real-time monitoring and evaluation of the induction motor's condition using the developed ML model.
- Simulink provides a platform for incorporating the ML model into the broader control and monitoring system.
- It enables continuous assessment of the motor's health and facilitates timely responses to potential faults by providing a real-time monitoring interface

4. RESULT

As a result of this project, a tree model has been developed that achieves approximately 94% accuracy in classifying motor faults, specifically the number of broken rotor bars. This model utilises 10 features imported into the application to accurately predict and classify the faults within the motor system.



To generate a selection of fast-fitting models Train all model.The weighted KNN model number 2.9 in the figure is able to classify broken rotor faults with about 98% accuracy.



5. CONCLUSION

This research delved into the realm of fault detection in induction motors using a comprehensive dataset comprising electrical and mechanical signals. Through the integration of machine learning techniques, particularly in preprocessing and model development, the study successfully showcased the potential for accurately identifying fault indicators within the motor system. The utilisation of advanced signal processing methods and the careful selection of ML algorithms facilitated the creation of a robust model capable of recognizing patterns indicative of motor faults. The integration of this model into MATLAB Simulink enables real-time monitoring, thus offering a proactive approach towards maintenance and ensuring the continued operational integrity of induction motors.

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