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Current Based Condition Monitoring of Three Phase Induction Motor Using Deep Learning

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Abstract –

Condition Monitoring and Predictive maintenance of induction motors might prove quite profitable in the long run since these machines constitute the majority of the industries. Many factories spend lots of money on Reactive and Preventive maintenance which can be lessened using predictive maintenance. Usually, it involves estimating when faults will occur (Remaining useful life aka RUL) of the machine. Motor Current Signature Analysis is one of the techniques employed to identify these faults. However, it's limited to a certain extent. In this paper, we try to predict the voltage faults and RPM of the motor using only the current signals

Index Terms- MCSA, Machine Learning, Deep Learning, LSTM, Condition Based Monitoring

I. INTRODUCTION

This Our on-going intention is to perform Predictive maintenance by capturing supply current readings of the motor using Current Transformer Sensors (CT). CTs are much cheaper than Hall effect sensors and are easier to install such that it is just a matter of clamping into the wires of the voltage supply. The motor is driving a vibrating conveyor in capping section of the line.

The current waveform of an induction motor contains information about the magnetic fields in the motor, which are influenced by the rotor and stator windings, as well as any load on the motor. When a fault occurs in the motor, such as a broken rotor bar or a bearing fault, the magnetic field of the motor is affected, which can result in changes in the current waveform.

In this paper, we focus on Deep Learning algorithms can be used to detect some of the features and faults only using Current Signals. However this can be challenging since current readings are one of the many condition indicators of the motor. And in that, MCSA constitutes the niche in the field due to Vibration analysis.

Still looking at the easy installation of CTs and advancements in Machine Learning we hope to achieve complete condition based monitoring of the motor only using Current signature. One of the major bottleneck in our research is lack of data and few unknown variables regarding the motor. These variables include slip, RPM, temperature, Voltage. Further in the paper we will discuss how will we tackle these bottlenecks for the initial stage of our research.

II. LITERATURE REVIEW

Since the late 90s and early 2000s various researches took place in the field of maintenance. Motor Current Signature Analysis (MCSA). Through literature review, we wanted to know what others have done only using current signals whilst keeping a keen eye on other methods too.

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[1]This paper proposes an accelerated CNN method that simultaneously compresses and speeds up CNN by removing less important connections and sharing the weights. Further, this method is compared to basic CNN model. Their CNN architecture implements pruning and weight sharing technique. Their proposed method was observed to perform up to three times faster than basic CNN without losing the quality of performance, and it is also robust against high levels of noise. The proposed method achieves this by using deep neural networks that can learn invariant and complex features from raw data without any additional feature extraction.

In [2], Altaf et al. presents a study of fault diagnosis in industrial motor networks using knowledge-level modelling techniques. Multiple ANN architectures are tested to recognize patterns in electric current data indicative of specific fault types. The study compares the performance of different neural network architectures and looks at the accuracy of diagnosing broken rotor bar faults in particular. The results show that accuracy of up to 96-97% can be achieved in the diagnosis of BRB faults.

In [3], Antonino-Daviu and Popaleny discusses the use of Advanced Transient Current Signature Analysis (ATCSA) to detect different types of mechanical faults in induction motors. They discussed a method involving analysis of transients which occur during change of state, especially when starting the motor. They study these transients in the form of current signals. The viability of studying starting currents for transients to identify faults has been discussed at length. It is concluded that this technique is a reliable indicator of the presence of these faults and avoids false diagnostics caused by classical methods.

In [4], B et al. presents a machine learning approach to fault prediction in induction motors using a conjugate gradient-based training technique and the Scaled Conjugate Gradient (SCG) algorithm. The trainlm method is used for training networks of modest size, and is the fastest for this purpose. Results demonstrate that this method is effective in predicting motor faults.

In [5], Bazan et al. discusses the use of data optimization and machine learning techniques for multi-fault diagnosis in three-phase induction motors (TIMs), with a focus on bearing and rotor failures. The authors compare various conventional methods and highlight the advantages and disadvantages of model-based and knowledge-based approaches. They use principal component analysis (PCA) to reduce the influence of different load conditions and extract relevant characteristics from the voltage, current, vibration, and acoustic signals of the machine. They also use mutual information (MI) and shifted mutual information (SMI) to extract important features from stator line current signals, which are used for pattern recognition. The extracted patterns are then used as an input matrix for a multilayer perceptron artificial neural network (MLP ANN). The results show that the proposed approach can effectively diagnose multiple faults in TIMs with high accuracy.

In [6], Hussain et al. proposes a method for detecting and identifying supply imbalances in loaded three-phase induction motors using Long Short-Term Memory (LSTM) networks. The authors used a dataset of 3-phase induction motor signals with different levels of supply imbalances to train and test their LSTM network. The proposed method achieved an accuracy of 98.5% in detecting supply imbalances and 97.5% in identifying the type of supply imbalance.

In [7], Benbouzid et al. proposes a method for detecting and localizing faults in induction motors using advanced signal processing techniques applied to the stator current. The authors used a dataset of stator current signals from a 3-phase induction motor with different types of faults to train and test their method. The proposed method achieved an accuracy of 100% in detecting and localizing faults in the induction motor.

In, [8] and [9] ,Mohanty presents the latest techniques in fault diagnosis and prognosis, provides many real-life practical examples, and empowers you to diagnose the faults in machines all on your own.

Navaz et al. [10] provide an overview of the algorithms and processing technologies used for real-time data streaming. They explain the different types of data commonly streamed in real-time and discuss the programming models used for real-time data processing. The authors also provide examples of real-world applications of real-time data streaming and discuss the challenges associated with it.

With reference to [11] and [12] by Bhoite et al., our mentor, we gained significant insights on LSTM as well as ensemble models. These techniques have proved their importance in various fields and these two papers have shown what can be done to solve everyday problems using such techniques and to build a successful model and improve real world accuracy.

III. DATASET

The three-phase induction motor is a type of electric motor that uses a rotating magnetic field to generate torque. It consists of two main parts: the stator, which contains three pairs of coil windings carrying three-phase AC, and the rotor, which is a loop of conducting material that rotates due to the electromagnetic force generated by the stator. The speed of the motor is controlled by the frequency of the current, and anomalies in the current waveform can indicate faults in the motor.

The motor specifications include an RPM of 1380, current of 1.05 A, power factor of 0.74, voltage of 415 V with a tolerance of 10%, and frequency of 50 Hz with a tolerance of 5%. The motor has a power rating of 0.37 kW or 0.50 HP, efficiency of 66.0%, and is designed for frame size 71 with an ambient temperature of 50 degrees Celsius. The motor is used for vibration filtering of caps during the capping stage in a balm manufacturing plant.

The dataset contains files with 10,000 readings, each representing 1.83 seconds of data, with a sampling frequency of 5460 samples per second. The frequency resolution of the FFT is therefore 5460/2 Hz, allowing accurate detection of frequencies up to that limit. The motor type designation is 2FD1 073-04, with a torque of 0.26 kgm, GD^2 of 0.0022 kgm2, weight of 20 kg, and ratios of I(ST)/I(N) = 3.5, T(ST)/T(N) = 1.9, and T(PO)/T(N) = 2.1. The motor efficiency and power factor vary depending on load.

However, due to the motor being new and no historical faulty data was present, we had to simulate the same motor in MATLAB Simulink.

IV. DATA PROCESS

Calibrating Current

The function given is for calibrating raw sensor data into current for a 3-phase induction motor. The motor's stator current is monitored as faults in the motor are reflected in the stator current.

Motor Current Signature Analysis

Motor Current Signature Analysis (MCSA) is a technique used to analyse the electrical signals produced by an electric motor. MCSA involves taking current readings from each phase of the motor and analysing the frequency spectrum of these readings. By analysing the spectrum, anomalies or patterns that may indicate a potential fault or failure in the motor can be identified. MCSA can detect various types of faults, such as broken rotor bars, bearing defects, and winding faults.

One common fault that MCSA can detect is broken rotor bars. Bearing faults can also be detected using MCSA, and eccentricity is a fault that can occur when the motor's rotor is not perfectly centered in the stator. MCSA can be used to identify these faults by analyzing the difference in current readings between different phases of the motor.

Predictive maintenance involves predicting when faults will occur to prevent unplanned downtime and reduce costs. Regular maintenance is costly and may not be effective in preventing all faults. Predictive maintenance is a better option as it can predict when faults will occur, allowing maintenance to be scheduled only when necessary.

V. DATA CLEANING

a. Removing DC offset

In order to remove a DC offset from a signal, you can subtract the mean of the signal from each sample. This effectively removes any constant voltage or signal level that is added to the original signal, which is the DC offset. However, this method does not filter out any other low-frequency components in the signal, so it is not equivalent to applying a high-pass filter.

A high-pass filter is specifically designed to remove low-frequency components in a signal, including the DC offset. The choice of cut-off frequency determines which frequencies are considered "low-frequency" and are therefore filtered out. While subtracting the mean can be a quick and simple way to remove the DC offset, it does not provide the same level of control as a high-pass filter and may not be sufficient in cases where other low-frequency components need to be removed as well.

b. Modulation

Modulation (fig. 1) is the process of adding information to a carrier signal. Motor faults cause variations in the amplitude and phase of the signal, which produces a modulated signal with frequency components at the fundamental frequency and its sidebands.

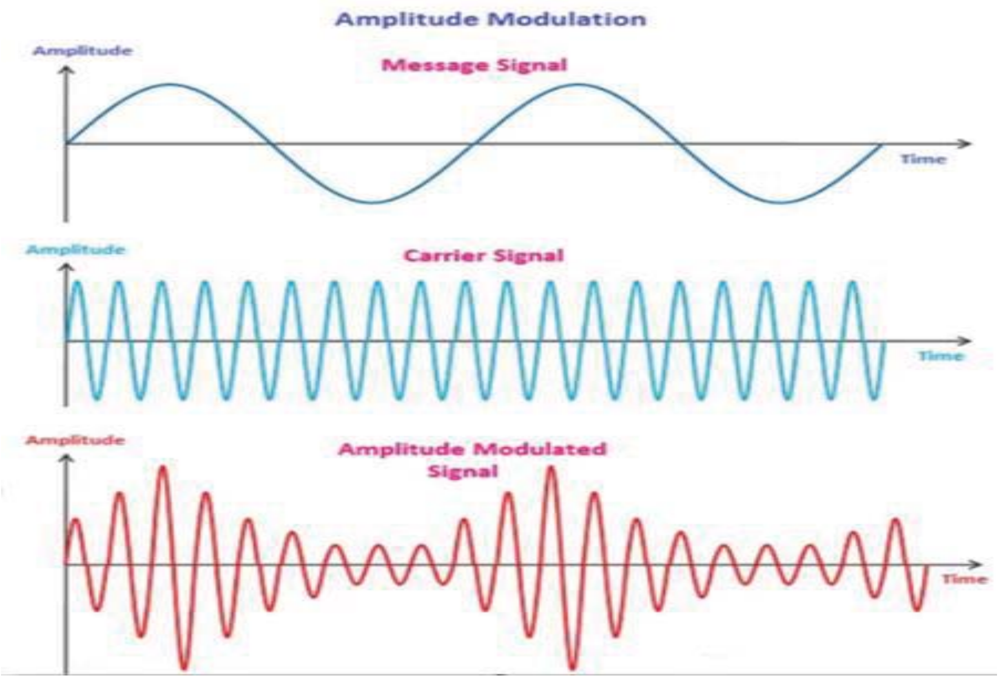

Figure 1: Modulation Visualization

The Technique of multiplying the signal with a carrier signal and removing the carrier frequency is called amplitude demodulation, which is commonly used to extract the low-frequency components of a modulated signal in Motor Current Signature Analysis (MCSA). Demodulation separates the modulated signal into its original components: the carrier wave and the information signal, allowing analysis of low-frequency components related to motor faults.

This allows selective extraction of the low-frequency components related to motor faults without affecting the rest of the signal. High-pass filters can be used to remove low-frequency components that subtracting the mean does not reduce sufficiently. Slip speed, the varying RPMs of induction motors depending on the load, should also be taken into account when analyzing the motor signal.

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VI. SIMULATING THE MOTOR

a. The Simulink Model

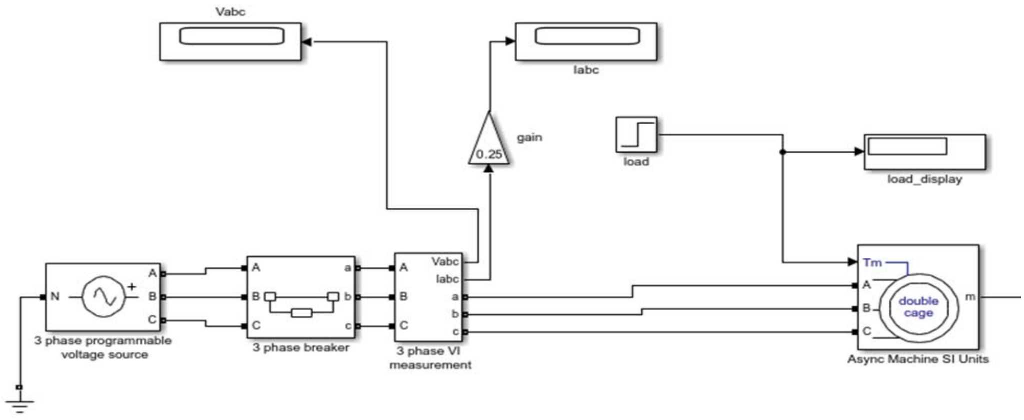

Figure 2: Simulated Model in Simulink

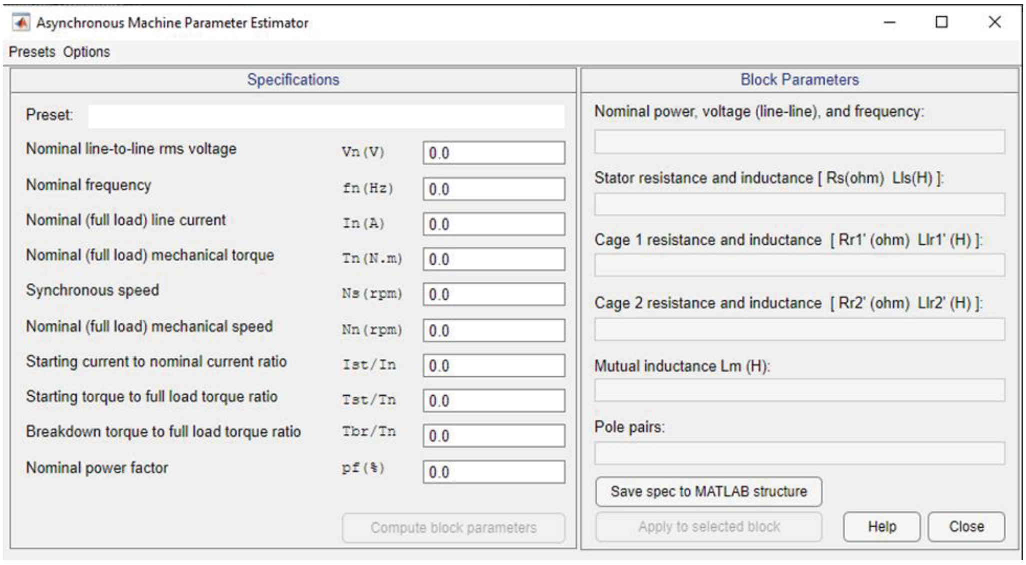

Figure 3: Setting Parameters of the motor

It is important to understand the nominal values of devices and systems. Nominal values are the rated or specified values of a device or system, such as voltage, speed, frequency, power, etc. In the case of an induction motor, the nominal voltage refers to the line-to-line RMS voltage, which can be different from the operating voltage. It is important to research the nominal values of an induction motor to ensure that it operates within its rated voltage range.

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The nominal mechanical torque can also be calculated by converting the given torque value in kgm to Nm. using the gravitational acceleration on Earth's surface.

When analysing the current readings of an induction motor, it is important to note that the starting current is typically higher than the full load current.

Figure 4: Normal Three Phase Currents

This is because the rotor is stationary during start-up, and the relative speed between the stator's rotating magnetic field and the rotor is at its maximum, resulting in a large induced electromotive force (EMF) in the rotor windings, which causes a large current to flow in the rotor and stator windings.

To simulate gradual faults in a 3-phase induction motor, MATLAB's Simulink environment can be used to create a model of the motor and gradually change the motor parameters over time. This can include introducing changes in the rotor inertia, friction, or load to simulate changes in the motor's operating conditions. By running the simulation over a period of time and recording the motor current (4), voltage, and speed readings, data can be generated to train a machine learning model to predict the remaining useful life (RUL) of the motor.

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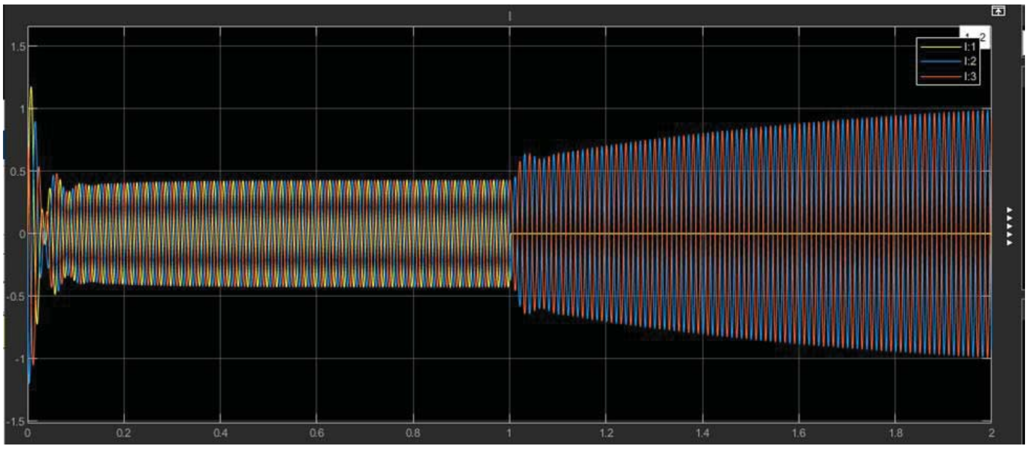

Figure 5: Cutting of Phase A (Single Phasing)

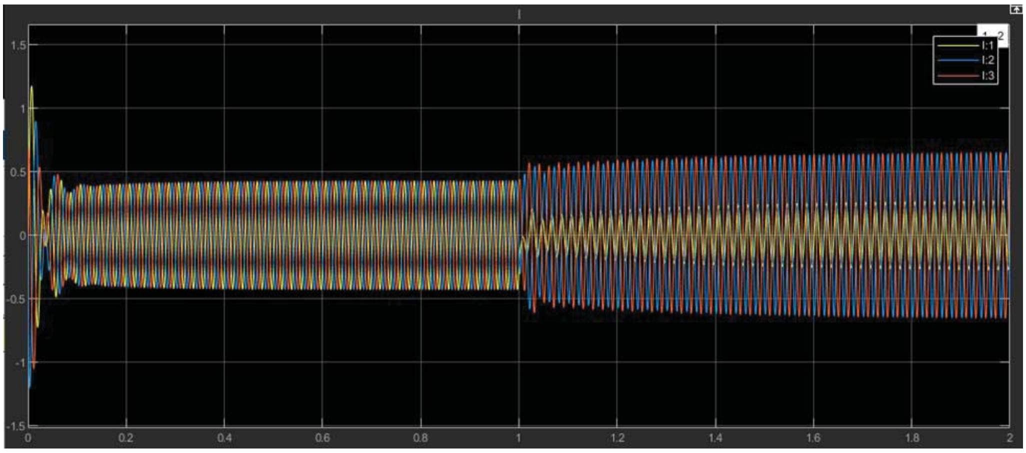

Figure 6: Decreasing the amplitude of Phase A

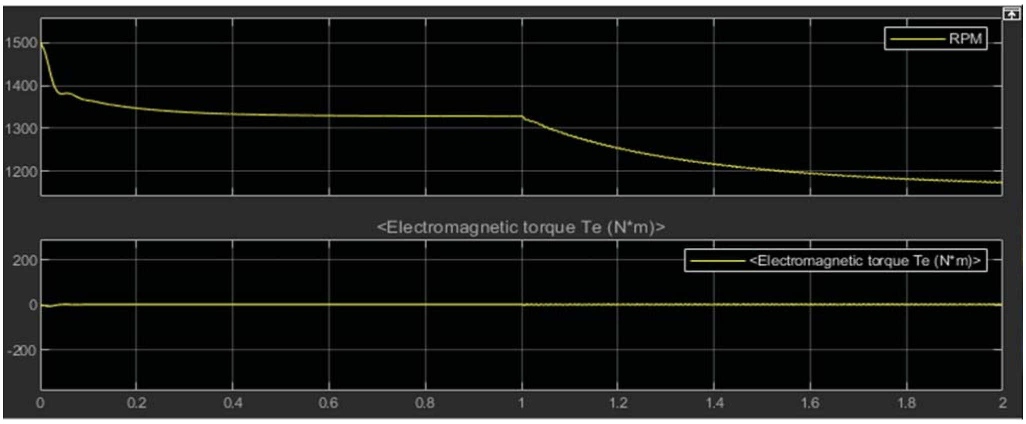

Figure 7: The RPM and Torque curves

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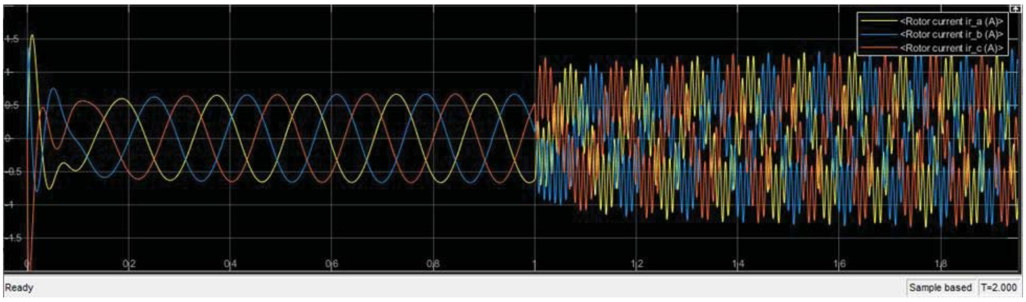

Figure 8: Rotor currents when Phase A fluctuates after 1 sec.

Voltage imbalance is also an important factor to consider when analysing the performance of an induction motor. It is defined by the Line Voltage Unbalance Rate (LVUR), which measures the deviation of the maximum voltage from the average line voltage as a percentage of the average line voltage. This can affect the motor's performance and efficiency and should be monitored to ensure optimal operation.

We Try simulating Voltage Imbalance and classify those using an LSTM based model. We also try to predict RPM using current signals because that factor is usually measured using an accelerometer to calculate the fault frequencies. All these models had variables which were controlled by an underlying MATLAB script which also played a part in data collection and storage. We have simulated single phasing by shorting each phase (fig. 5). Unbalance in phase A was introduced by decreasing the amplitude of that phase (fig. 6).

The effects can be seen in Rotor currents as well (fig. 8)

VII. MODELS

a. Voltage Fault Classifier

Analyzing current waveforms will help detect faults in the motor. [6] We used a machine learning model called LSTM to analyze the current waveforms and classify the health of the motor (healthy, single phasing, unbalanced voltage) and the phase of the fault. Due to limitations in MATLAB Simulink's that particular block-set and our understanding of it, we are only able to simulate unbalanced voltage in phase A. We have collected a dataset of current waveforms under different load conditions and simulated motor conditions. The dataset consists of 64 files for each class. Each file is representing a simulation of 2s where faults were introduced between 1s and 2s (in case of faulty data). The sampling frequency is

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5460 as is in the case of our IRL sensors. This will keep the data consistent with the real readings. The faults are named as 'normal', 'phase_1_unbal','single_phase_fault_A'-,'single_phase_fault_B','single-phase_fault_C'.

We did the cleaning of data as mentioned in the Data Cleaning section of the paper. The faulty data was generated using MATLAB as previously mentioned. Each of the files were labelled accordingly. After labelling, the data was used to fit an LSTM based model.

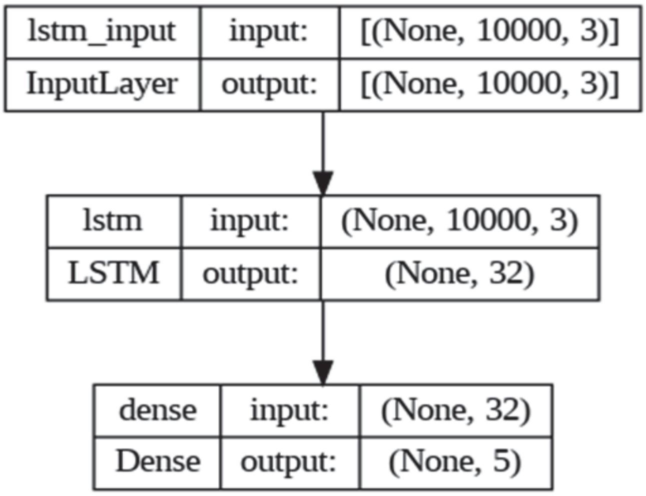

Figure 9: Volage Imbalance Classifier Model

b. RPM and Load Predictor

RPM plays and important role in calculation of features such as slip, which in turn helps identify fault frequencies in the FFT of the current signals. Since, we were limited in resources, we were unable to install an accelerometer to the motor. Also, this defeats the purpose of MCSA since it's done to monitor the current signals remotely away from the motor where it won't be possible to reach the motor such as submersed-pumps. Data was generated similar to when simulating voltage fault's health data mentioned in previous section. But in this case, we measured more data (128 files) for healthy condition along with each file's corresponding RPM and Load values. After pre-processing and labelling it was used to fit an LSTM model. Each file had 10921 rows of 3 phase current readings. Hyper-Parameters where about the same for both models.

Google Collab was used to train these models.

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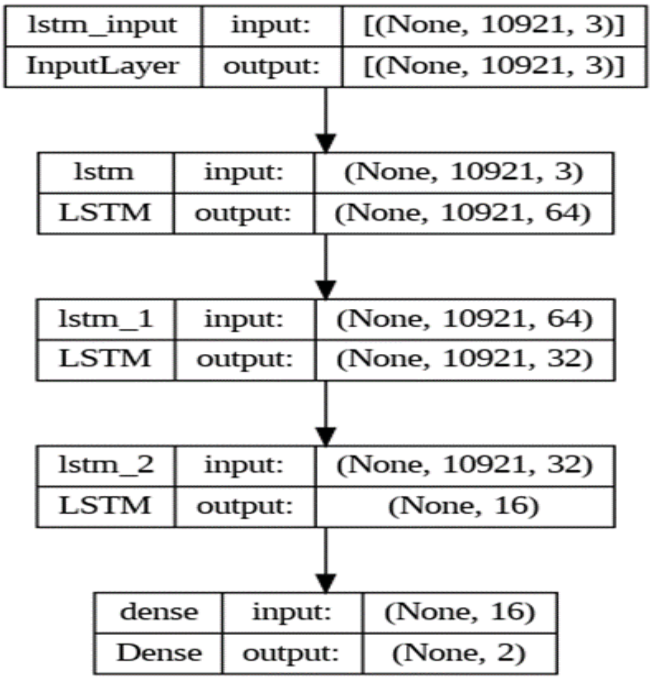

Figure 10: RPM and Load Predictor Model

VII. RESULTS

Due to ideal nature of the current without noise that naturally occurs in the real world, fitting the model was easier but at the same time it has its own drawback.

The model for classifying voltage faults is not that complex as can be seen from the figure. However, despite being simple, it accurately classified all the given data. It gave an accuracy of 1.

Each fault was accurately classified by the model proving LSTM's capability in classify voltage faults, which is more than [6]. Accuracy = Precision = recall = 1

This accuracy suggests that voltage imbalances can easily be detected using this method even if there is noise in the signals. Our next focus would be to induce artificial noise to simulate more real world like signals, close to what we are receiving from the conveyor motor.

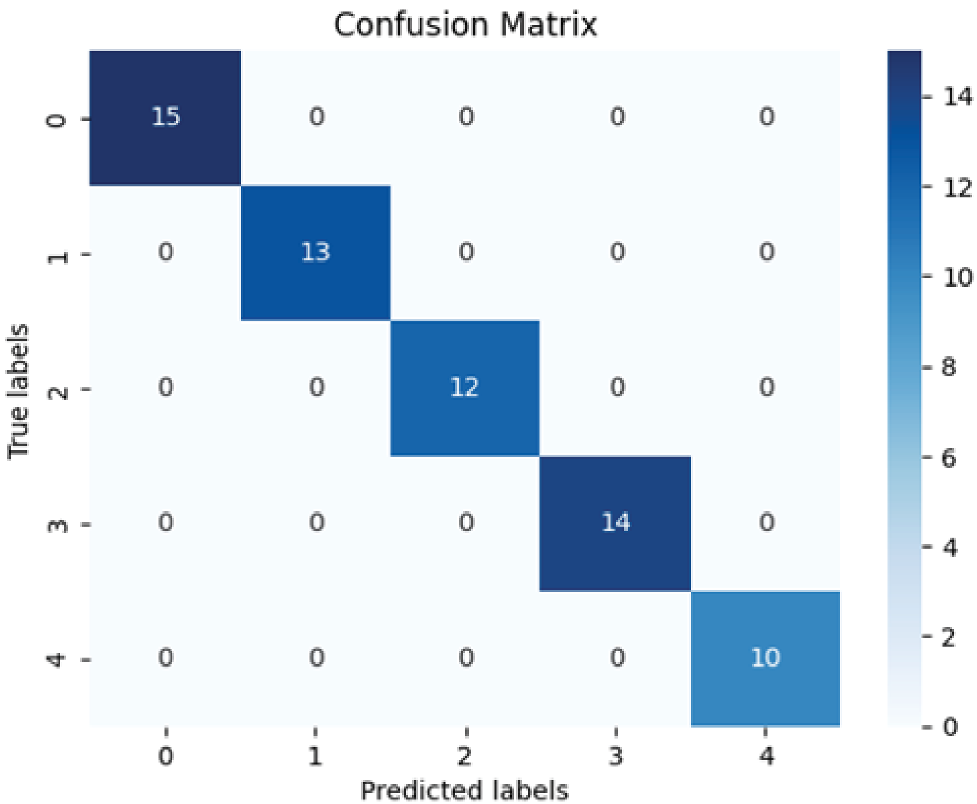

Figure 11: 0: 'normal',1: 'phase-1-unbal', 2: 'single-phase-fault-A', 3: 'single-phase-fault-B', 4:'single-phase-fault-C'

The RPM and load predictor model weren't so great at predicting accurately but were close to the actual

values. It gave MAE as 673 and MSE as 90000 approx. which isn't great but given the size of data it performed well.

An example: Pred_RPM: 1299.5647 Pred_load: 2.895188,

Actual_RPM: 1308, Actual_load: 2.8121.

These may not be accurate but still can be useful in approximating slip of the motor which is used to calculate the fault frequencies of the motor in frequency domain and monitor them. Considering we don't have any other means of measuring load and RPM; this is acceptable result and we are confident that with more data and the model will be able to accurately predict these values.

XI. CONCLUSION

Voltage fault detection by using LSTM works exceptionally well. RPM prediction through current doesn't work as well since Current is not the only factor responsible for it. But the research was greatly limited by the lack of real-world fault data which had to be simulated through Simulink which gives ideal results without any noise or modulation. This research is only a small part of a larger ongoing research regarding condition monitoring of induction motor only through current. The purpose of this paper was to prove that Deep Learning models can be well used in this domain and give better results even though the data is limited to only one degree which is current in our case.

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