Machine Learning based Fault daignosis in Electric Drives

1[st]Bachu Naga sri Harini
Department of Artificial Intelligence
Amrita vishwa vidyapeetam
Coimbatore, India
cb.sc.u4aie24010@cb.students.amrita.edu

2[nd] Bhavanam Siva Sai Yogeswar Reddy
Department of Artificial Intelligence
Amrita vishwa vidyapeetam
Coimbatore, India
cb.sc.u4aie24011@cb.students.amrita.edu

3[rd] kallam Pratheep Reddy
Department of Artificial Intelligence
Amrita vishwa vidyapeetam
Coimbatore, India
cb.sc.u4aie24021@cb.students.amrita.edu

4[th] Bhavesh Reddy
Department of Artificial Intelligence
Amrita vishwa vidyapeetam
Coimbatore, India
cb.sc.u4aie24034@cb.students.amrita.edu

***Abstract*—In this particular study we focused on preparing a modern approach to detect the faults in electric drives in the prior and prevent them from happening in real.And the elctric drives are one of the crucial industrial components. In this study,we used a matlab simulink model to prepare a electric drive. We implemented different faults in the electric drive. We collected a dataset which includes voltage, current, speed and torque changes time to time at different faults conditions in the elctric drive. A supervised model(KNN - K- Nearest Neighbours) which would get trained and can predict a fault when we give the model required values. The proposed method provides a scalable and real-time solution for predictive maintenance in industrial motor drive systems**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

In the present day world, there is a huge demand for the use of intelligent monitoring systems in the application of electric drives, as industries are opening day by day with their continuous growth. Industrial automation, transport systems, and domestic appliances are witnessing greater use of electric drives. et al, prior fault detection and correcting them plays a vital role. Manual inspection or expertise has been a normal method which in most cases lacks in insuuficient for real time anomalies. Through the progress of data-driven methods, machine learning based methods would the probelm easy which came out as a very strong tool to learn the patterns and identify the same patterns in today's technology.We can implement these machine learning models by collecting the data under various fault conditions and make the model learn the patterns and should be capable of identifying fault for the new as well In this paper, we aimed at developing a matlab simulink model of three phase induction motor's electric drive. This simulink model will act as a actual electric drive of three phase induction motor. We created data at various fault conditions whcih would nearly equal to actual world scenerios. We identified four faults in the electric drives. They are

1) Phase to phase short circuit
2) Phase to ground short circuit
3) Over voltage fault
4) Under voltage fault

We employed KNN - K Nearest Neighbour for model training which is efficient for classification based on provided by identifying recurring patterns. We employed this model and were able to predict the faults. We are testing the model with Accuracy, Precision, Recall and F-1 score.

II. Literature Review

Schoen et al. [1] pioneered an unsupervised system for induction motor fault detection using stator current monitoring, demonstrating neural networks' capability to identify anomalous patterns without prior labeling. Building on this foundation, Murphey et al. [2] developed a model-based fault diagnosis approach using machine learning for electric drives, which integrated domain knowledge with data-driven techniques.

For classification methodologies, Zhang et al. [3] implemented fuzzy neural networks for fault diagnosis in rotary machines, combining fuzzy logic reasoning with neural network learning capabilities. This hybrid approach showed improved accuracy over single-method implementations. Bazzi and Krein [4] contributed significantly by utilizing median filters in power electronics for traction drive applications, which enhanced signal processing prior to fault classification.

While previous approaches demonstrated high classification accuracy in controlled environments, they typically required extensive computational resources and struggled with real-time implementation in dynamic load conditions. Additionally, most studies focused on single fault detection rather than diagnosing multiple simultaneous faults under varying operational conditions

III. Proposed Methodology

The proposed system aims to diagnose multiple types of faults in three-phase electric drives using machine learning models trained on simulated current and voltage data. The methodology consists of five primary stages: understanding electric drives, understanding faults ocuurred, preparation of matlab simulink model, extraction of data at different fault conditions, training the machine learning model, classification of faults.

A. A.Electric drives

Electric drives refer to control systems for manipulating the movement of electrical machines through regulation of speed, torque, and position. They are made up of an electric motor, power electronic converter, controller, and sensors for feedback. Examples of common motors are induction motors, BLDC, and PMSM, powered by converters such as inverters or choppers. Drives are ubiquitous in the field of automation, transport, and energy systems. Precise control is obtained with the help of real-time feedback and sophisticated control techniques like vector control. Electric drive faults like under/over voltage and short circuits can reduce performance or lead to failure, and hence fault detection and diagnosis are critical for system reliability and safety.

B. Matlab simulation creation

To design and build an integrated model that efficiently simulates an electric drive system, we employed a direct current (DC) power supply, which was then converted to alternating current (AC) by the help of an Inverter that employs Insulated Gate Bipolar Transistors (IGBTs) as its core components. The inverter was controlled and regulated by a process called Pulse Width Modulation (PWM), through which we were able to design three-phase sinusoidal voltage waveforms of desired specifications. Having designed these sources of voltage, they were then directed and supplied to an asynchronous three-phase motor, with a power rating of 50 horsepower, and was made to function efficiently at a frequency of 60 Hertz (Hz) and a speed of rotation of 1760 revolutions per minute (RPM).

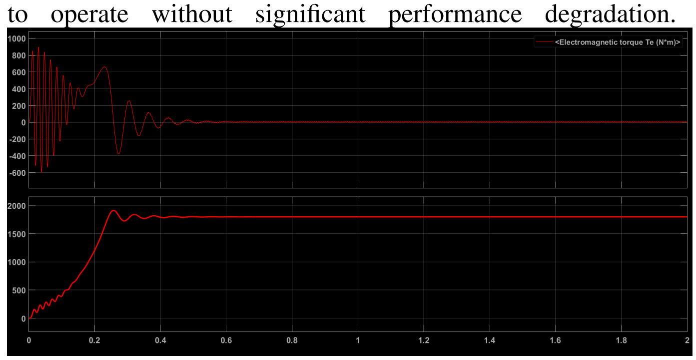
In order to successfully implement performance monitoring and enable fault diagnosis with accuracy, we recorded a sequence of key motor parameters with utmost care. These were phase currents, also known as Iab, Ibc, and Ica, and key motor parameters like motor speed and torque. The information provided by these readings gives a complete set of information that is key to complete system analysis. In addition, this information is at the core of the different fault detection and diagnostic processes, which have been implemented methodically in the drive model.

C. Data Extraction

We implemented each and every fault and their observations are here.

1) Over-Voltage and Under-Voltage Faults: Speed Behavior: In both **over-voltage** and **under-voltage** scenarios, the motor speed remained relatively stable, with minimal to no disturbance. This suggests that the motor's speed regulation system, likely controlled by the inverter, is able to compensate for voltage variations within fault limits.

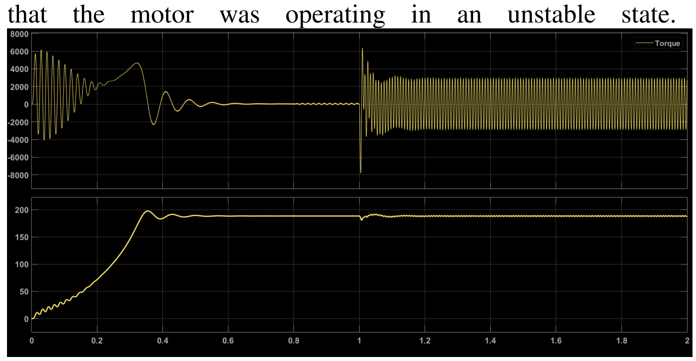
Torque Behavior: However, slight fluctuations in the motor's torque were observed in both cases. These fluctuations are attributed to transient behavior resulting from the voltage changes, as the torque output is sensitive to variations in the voltage supply. Although the torque experienced slight variations, it did not show any major deviations, indicating that the motor was still able to operate without significant performance degradation.



Graph Observation: The graph for both over-voltage and under-voltage faults shows minor torque variations, while speed remained unaffected.

2) Phase-to-Phase Fault: Speed Behavior: During a **phase-to-phase fault**, the motor experienced noticeable small or minor speed fluctuations. This fault directly affects the power supply to the motor, causing a voltage imbalance between two phases. As a result, the motor speed fluctuated more significantly compared to the over-voltage and under-voltage faults.

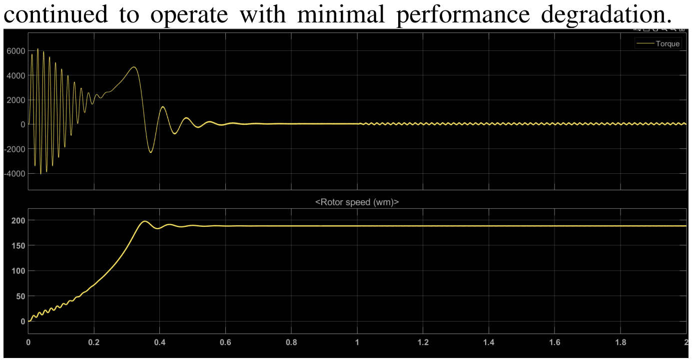
Torque Behavior: Alongside speed changes, the torque also exhibited greater fluctuations in comparison to the previous faults. The imbalance between the two phases caused a disruption in the motor's torque production, leading to larger variations in torque output. This fault caused more pronounced performance degradation, and the torque became less predictable, indicating that the motor was operating in an unstable state.



Graph Observation: The graph shows significant fluctuations in both speed and torque, with torque exhibiting greater variations than speed.

3) Phase-to-Ground Fault: Speed Behavior In the case of a **phase-to-ground fault**, no significant fluctuations in speed were observed. However, the speed change was less significant compared to the phase-to-phase fault. A phase-to-ground fault causes one of the motor's phases to short to ground, which leads to some disruption in the power supply. Despite this, the motor was able to maintain its operation with minor fluctuations in speed.

Torque Behavior Similarly, the torque fluctuations were mild compared to the phase-to-phase fault. This indicates that the motor experienced only a minor impact in terms of torque output. Despite the fault, the motor continued to operate with minimal performance degradation.



Graph Observation: The graph reflects minor fluctuations in both speed and torque, with torque showing only slight variations.

Fault Type	Speed Behavior	Torque Behavior
Over-Voltage	No significant change	Minor fluctuations
Under-Voltage	No significant change	Minor fluctuations
Phase-to-Phase	Minor fluctuations	Significant fluctuations
Phase-to-Ground	No significant fluctuations	Minor fluctuations

TABLE I
SUMMARY OF FAULT BEHAVIORS IN TERMS OF SPEED AND TORQUE

D. Model Training Using K-Nearest Neighbors (KNN) and Classification of faults

In this study, the machine learning model for fault diagnosis was trained using the **K-Nearest Neighbors (KNN)** algorithm. KNN is a *non-parametric, instance-based learning algorithm* that classifies a data point based on the majority class of its nearest neighbors. It assumes that similar data points exist in close proximity within the feature space.

The algorithm calculates the *distance metric*, commonly Euclidean distance, between a given sample and all other points in the training set. Classification is performed by identifying the most frequent class among the k closest training examples in the feature space.

To enhance model performance, various values of **k** (the number of neighbors) were evaluated. The hyperparameter tuning process involved testing values such as **k = 5**, **23**, and other intermediate values to assess the impact on the model's accuracy and generalization.

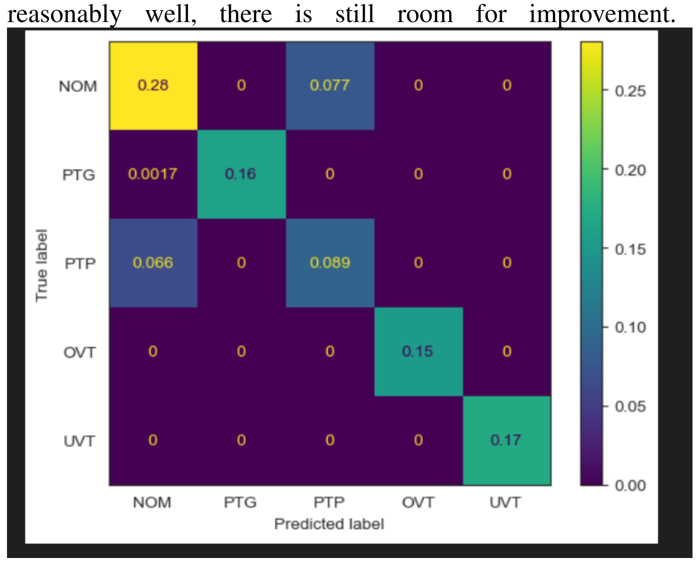
Hyperparameter Tuning:

- **k = 5**: Provided an effective trade-off between bias and variance. It yielded high accuracy with relatively low overfitting.
- **k = 23**: Offered smoother classification boundaries and better generalization, although it slightly reduced the sensitivity in detecting certain fault conditions.

The final model configuration was selected based on performance metrics derived from **cross-validation** and **confusion matrix analysis**. The results demonstrate that with an appropriately chosen k, KNN effectively classified various fault scenarios in electric drives with notable accuracy and stability.

IV. RESULTS

The machine learning model was tested on various fault types including Over-Voltage, Under-Voltage, Phase-to-Phase, and Phase-to-Ground faults. From the confusion matrix, it is clear that the model is able to correctly classify a majority of the cases, especially for Normal Operation, Over-Voltage, and Under-Voltage conditions. However, some misclassifications occurred between faults that show similar characteristics, such as Phase-to-Ground and Normal Operation, or Phase-to-Phase and Normal Operation. These results indicate that while the model is functioning reasonably well, there is still room for improvement.



The model shows promising performance in detecting faults in electric drives. It is able to classify most conditions effectively, but its accuracy can be improved with a larger and more diverse dataset. Further work is needed to collect more data, fine-tune the model, and enhance its ability to distinguish between closely related fault types for more accurate real-time fault diagnosis.

REFERENCES

[1] R. Schoen, B. Lin, T. Habetler, J. Schlag, and S. Farag, "An unsupervised, on-line system for induction motor fault detection using stator current monitoring," IEEE Transactions on Industry Applications, vol. 31, no. 6, pp. 1280–1286, Nov/Dec 1995.

[2] Y. Murphey, M. Masrur, Z. Chen, and B. Zhang, "Model-based fault diagnosis in electric drives using machine learning," IEEE/ASME Transactions on Mechatronics, vol. 11, no. 3, pp. 290–303, June 2006.

[3] S. Zhang, T. Asakura, X. Xu, and B. Xu, "Fault diagnosis system for rotary machines based on fuzzy neural networks," in IEEE/ASME International Conference on Advanced Intelligent Mechatronic, vol. 1, July 2003, pp. 199 – 204.

[4] A. Bazzi and P. Krein, "Utilization of median filters in power electronics: Traction drive applications," in Proc. IEEE Applied Power Electronics Conference, 2013, in Press.

IEEE conference templates contain guidance text for composing and formatting conference papers. Please ensure that all template text is removed from your conference paper prior to submission to the conference. Failure to remove the template text from your paper may result in your paper not being published.