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MODELING AND SIMULATION OF THREE PHASE INDUCTION MOTOR WITH BROKEN ROTOR BARS USING MACHINE LEARNING

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ABSTRACT

Three-phase induction motors are essential in industrial applications due to their durability, efficiency, and reliability. However, faults in rotor bars can degrade their performance, leading to operational inefficiencies, unplanned downtime, and increased maintenance costs. This study presents a comprehensive approach to modelling and simulating three-phase induction motors with rotor bars, utilizing machine learning techniques to improve fault detection, diagnostics, and predictive maintenance. A mathematical model is developed to represent the motor's electromagnetic and mechanical dynamics, including rotor bar characteristics. Simulations are conducted under varying operational conditions, generating data that includes both healthy and faulty motor states. This data is used to train machine learning models such as Support Vector Machines, Random Forest, and Neural Networks, focusing on identifying fault patterns, classifying motor conditions, and predicting the remaining lifespan of rotor bars. The performance of the machine learning models is evaluated using metrics like accuracy, precision, and computational efficiency. Results demonstrate the potential of these approaches to enable accurate fault diagnosis and support real-time predictive maintenance strategies. This research contributes to the advancement of intelligent motor diagnostics by integrating advanced simulation techniques with machine learning. The findings offer practical benefits for industries aiming to reduce downtime, optimize energy efficiency, and lower maintenance costs.

Keywords: Modelling, Simulation, Induction Motor, Rotor Bars, Machine Learning

I. INTRODUCTION

Three-phase induction motors (IMs) are the backbone of industrial operations due to their robustness, simplicity, and high efficiency. They are widely used in applications ranging from manufacturing processes to power generation and transportation systems. Despite their advantages, induction motors are prone to faults, with rotor bar damage being one of the most common issues. Rotor bar faults can result in decreased operational efficiency, excessive energy consumption, and unscheduled downtimes, making their early detection and diagnosis critical for maintaining system reliability and reducing maintenance costs, Yang et al., (2019).

Traditional fault detection techniques, such as vibration analysis, thermal imaging, and motor current signature analysis (MCSA), have been extensively used for diagnosing induction motor faults. While effective, these methods often require expert interpretation and can be time-consuming (Li et al., 2020). Furthermore, they may lack the ability to predict faults before their occurrence, limiting their usefulness for predictive maintenance. Advances in digital technologies, particularly machine learning (ML), have paved the way for more sophisticated fault detection and predictive maintenance systems, offering the potential for enhanced accuracy, automation, and reliability Karmakar et al., (2020).

Machine learning has emerged as a powerful tool in condition monitoring and fault diagnosis. By leveraging large datasets of operational and fault scenarios, ML algorithms can identify complex patterns and correlations that are difficult for traditional methods to capture (Yang et al., 2019). Studies have shown that techniques such as artificial neural networks (ANNs), support vector machines (SVMs), and random forests can effectively classify motor conditions and predict faults with high precision (Zhang et al., 2022). When integrated with physics-based modelling and simulation, ML can provide a robust framework for both diagnosing existing faults and predicting future failures, offering a transformative approach to motor reliability (Liu et al., 2020).

Modelling and simulation are critical components of this framework. They enable the detailed study of motor behaviour under different operational conditions, including fault scenarios. By simulating rotor bar faults, researchers can generate realistic datasets for training ML models. The integration of machine learning with simulation not only enhances the fault diagnosis process but also facilitates predictive analytics, allowing for early intervention and maintenance planning, Chen et al., (2021).

Despite significant progress, challenges remain. The complexity of induction motor systems, variability in operational conditions, and limited availability of labelled fault data pose barriers to developing universally applicable fault detection models (Zhang et al., 2021). Additionally, the computational demands of real-time ML-based diagnostics systems can be prohibitive in some industrial settings. Therefore, further research is needed to optimize ML algorithms, improve the accuracy of fault detection, and reduce computational overhead (Zhang and Zhang, 2021).

This study aims to address these challenges by combining advanced modelling techniques with machine learning to enhance the diagnosis of rotor bar faults in three-phase induction motors. By developing a detailed simulation model and training ML algorithms on the generated data, the study seeks to improve fault detection accuracy and enable predictive maintenance strategies. This approach has the potential to revolutionize motor condition monitoring, ensuring operational efficiency and reducing maintenance costs for industrial systems.

II. MATERIALS AND METHODS

The following materials were used for this work.
i.) Three Phase Induction Motor Rotor Bars, ii, Induction Motor Rotor Bars Data, iii) MATLAB/Simulink Apps, iv) Ansys Maxwell 2D tools

A. Model Equations

Electrical Model

$$\bar{V}_s = R_s\bar{\imath}_s + d\bar{\lambda}_s/dt + jwe\bar{\lambda}_s$$

$$O = R_{r1}\bar{\imath}_{r1} + d\bar{\lambda}_{r1}/dt$$

(3.1)

$$O = R_{r2}\bar{\imath}_{r2} + d\bar{\lambda}_{r2}/dt$$

$$\bar{\lambda}_s = L_s i_s + L_{m1}\bar{\imath}_{r1} + L_{m2} i_{r2}$$

$$\bar{\lambda}_{r1} = L_{m1}\bar{\imath}_s + L_{r1} i_{r2} + M_{rr}\bar{\imath}_{r2}$$

$$\bar{\lambda}_{r2} = L_{m2}\bar{\imath}_2 + L_{r2} i_{r2} + M_{rr} i_{r2}$$

$$T = PL_{m1}(\bar{\imath}_{r1} \times \bar{\imath}_s) + PL_{m2}(\bar{\imath}_{rr} \times \bar{\imath}_s)$$

- - - - (3.3)

Where

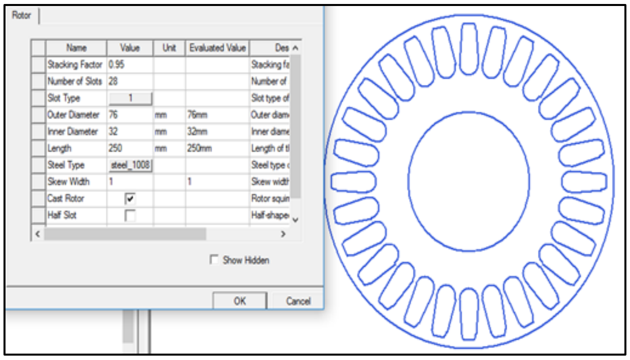
$$\begin{bmatrix} \lambda d_s \\ \lambda q_s \\ \lambda dr_1 \\ \lambda qr_1 \\ \lambda dr_2 \\ \lambda qr_2 \end{bmatrix} = \begin{bmatrix} Ll_s + L_m & 0 & L_m & 0 & L_m & 0 \\ 0 & Ll_s + L_m & 0 & L_m & 0 & L_m \\ L_m & 0 & Ll_{r1} & 0 & L_{mr} + L_m & 0 \\ 0 & L_m & 0 & Ll_{r1} + L_m & 0 & L_{mr} + L_m \\ L_m & 0 & L_{mr} + L_m & 0 & Ll_{r2} + L_m & 0 \\ 0 & L_m & 0 & L_{mr} + L_m & 0 & Ll_{r2} + L_m \end{bmatrix} \begin{bmatrix} id_s \\ iq_s \\ idr_1 \\ iqr_1 \\ idr_2 \\ iqr_2 \end{bmatrix} \quad (3.4)$$

Equation (1) represents the voltage performance in the rotor and stator of induction motor.

B. Machine Learning Model

Regression models for performance prediction: 2Y=f(X) ……………………. Equation. 1
Classification models for fault detection: Y=g(X)……………. Equation 2
Where X is the feature vector and Y is the predicted output

C. Simulation Interfaces



	Name	Value	Unit	Evaluated Value	Des
	Stacking Factor	0.95			Stacking fa
	Number of Slots	28			Number of
	Slot Type	1			Slot type of
	Outer Diameter	76	mm	76mm	Outer diam
	Inner Diameter	32	mm	32mm	Inner diame
	Length	250	mm	250mm	Length of t
	Steel Type	steel_1008			Steel type
	Skew Width	1		1	Skew widt
	Cast Rotor	☑			Rotor squir
	Half Slot	☐			Half-shape

☐ Show Hidden

FIGURE 1. ROTOR BARS MODELLED IN ANSYS MAXWELL 2D TOOLS

The Figure 1. shows a cross-sectional view of the rotor bars modelling during the three-phase induction motor design process. The dimensions are all in millimetres. This process could be hectic and error prone, hence using the machine learning tools to harness it becomes very imperative.

FIGURE 2. ORIGINAL MACHINE LEARNING ROTOR BARS DATA INTERFACE

This shows the originating dataset for the rotor bars taken with respect to months. It allows the easy comparison between original data and trained data.

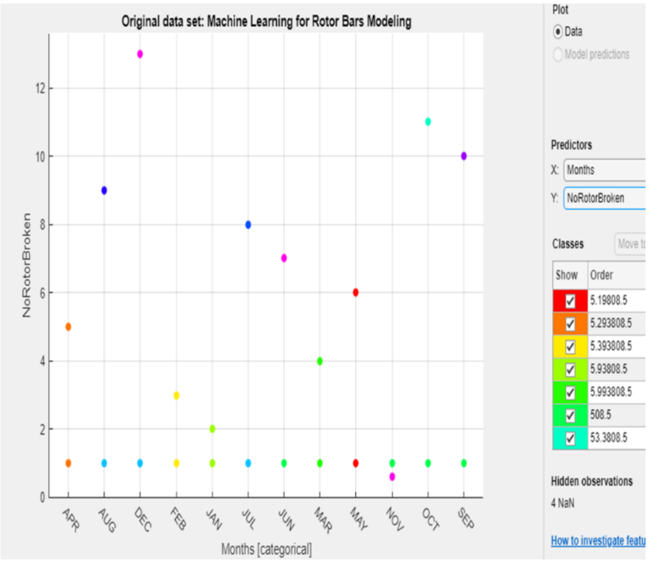


FIGURE 3. ROTOR DATA SAMPLING IN MACHINE LEARNING INTERFACE

This shows the rotor data interface for the processing of the original data for the purpose of training and validation.

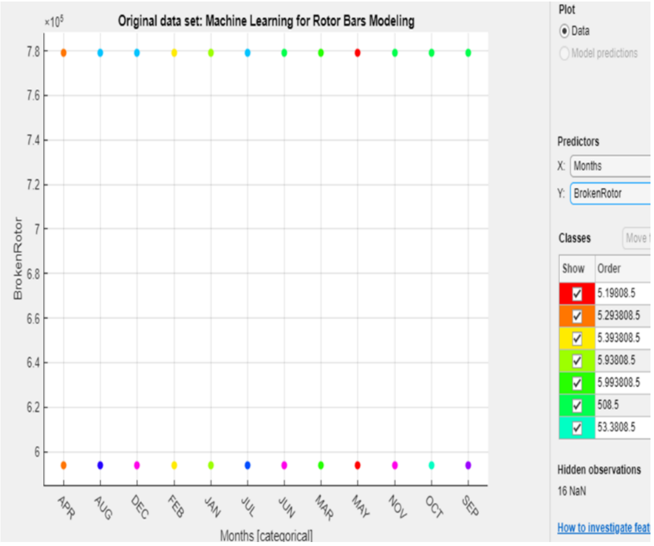


FIGURE 4. ORIGINAL MACHINE LEARNING ROTOR BARS DATA INTERFACE

III. RESULTS AND DISCUSSION

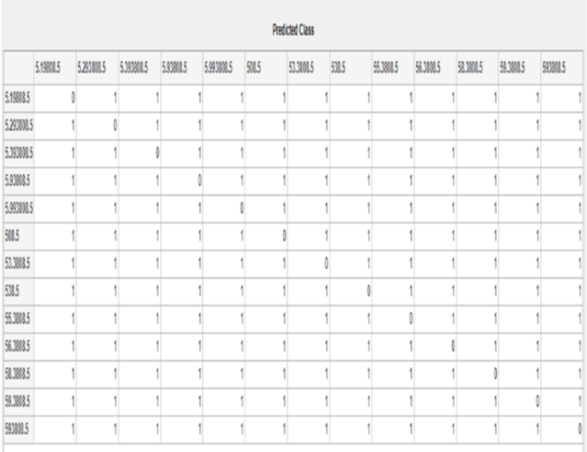
A. Prediction Outcome

The overall simulated results for the selected motor in question and its discussion are presented below.

Each component being detailed to validate the outcome.

TABLE I

PREDICTION OUTCOME MATRIX TABLE



Predicted Class

	5.19808.5	5.293808.5	5.393808.5	5.93808.5	5.993808.5	508.5	53.3808.5	538.5	55.3808.5	56.3808.5	58.3808.5	59.3808.5	593808.5
5.19808.5	0	1	1	1	1	1	1	1	1	1	1	1	1
5.293808.5	1	0	1	1	1	1	1	1	1	1	1	1	1
5.393808.5	1	1	0	1	1	1	1	1	1	1	1	1	1
5.93808.5	1	1	1	0	1	1	1	1	1	1	1	1	1
5.993808.5	1	1	1	1	0	1	1	1	1	1	1	1	1
508.5	1	1	1	1	1	0	1	1	1	1	1	1	1
53.3808.5	1	1	1	1	1	1	0	1	1	1	1	1	1
538.5	1	1	1	1	1	1	1	0	1	1	1	1	1
55.3808.5	1	1	1	1	1	1	1	1	0	1	1	1	1
56.3808.5	1	1	1	1	1	1	1	1	1	0	1	1	1
58.3808.5	1	1	1	1	1	1	1	1	1	1	0	1	1
59.3808.5	1	1	1	1	1	1	1	1	1	1	1	0	1
593808.5	1	1	1	1	1	1	1	1	1	1	1	1	0

Figure 5 presents result of trained rotor data 1. The oval shaped dots represent the correct data after being trained while the crossed shaped signifies the incorrect data after the data training. In the process of modelling rotor bars of three phase induction motor, there are certain errors in the process which may not be physically detected by experts but by machine learning using classification learner algorithm, this is easily detected to avoid waste of resources and time.

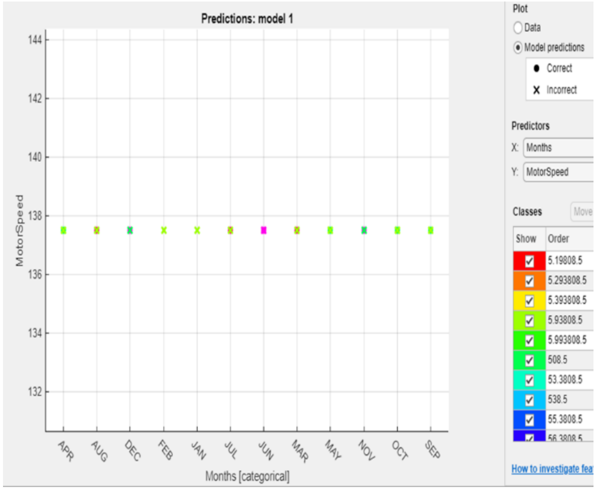


FIGURE 5. TRAINED ROTOR DATA 1

Figure 6 presents trained rotor data 2, which indicates the prediction model 1 for the rotor bars model and faulty operation of the induction motor. The oval shaped dots represent the correct data after being trained while the crossed shaped signifies the incorrect data after the data training. Using machine learning to address this case makes it easy to detect possible errors in the process.

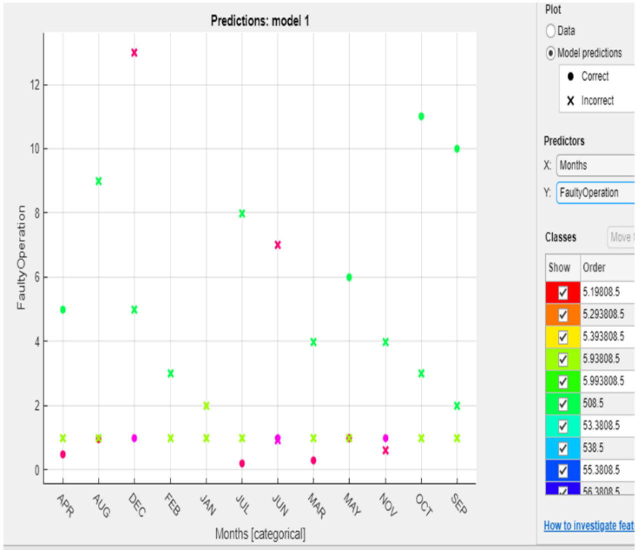


FIGURE 6. TRAINED ROTOR DATA 2

Figure 7 presents simulated results of trained rotor data 3. This represents the trained data for no rotor broken with respect to the months within a year. The oval shapes indicate correct predictions while the crossed shapes represent the affected rotor bars within the selected months of the year.

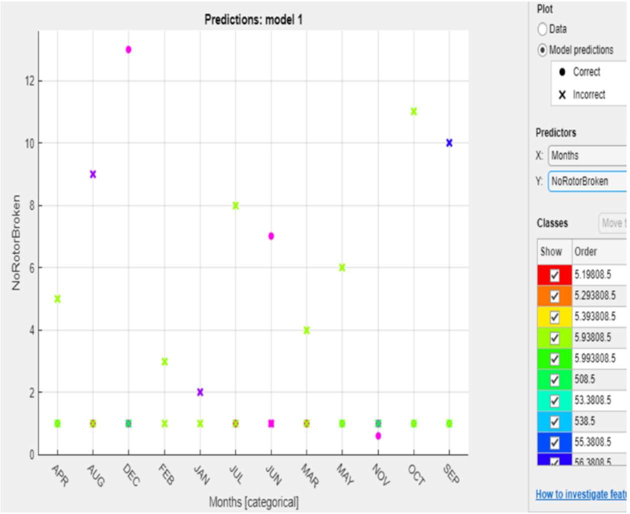
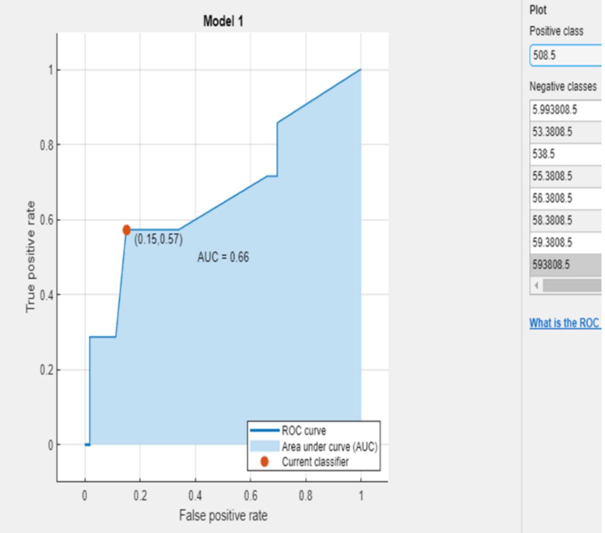


FIGURE 7. TRAINED ROTOR DATA 3

In Figure 8, the region of convergence for trained rotor data is presented. It shows the relationship between the true positive rate and the false positive rate of the trained data. At Points 0.3%, 0.59%, 0.78%, 0.89% and 1.00% the data shows true positive rate. At points 0.1%, 0.2%, 0.4%, 0.7%, 0.8% and 1.0% the data trained was false positive rate. This indicates a good trained output.



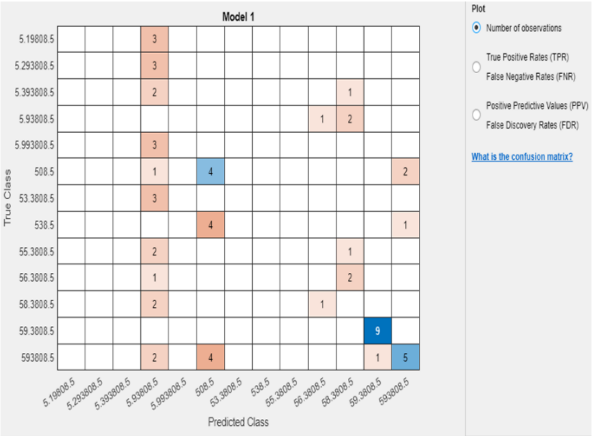
Plot

Positive class: 508.5

Negative classes:
- 5.993808.5
- 53.3808.5
- 538.5
- 55.3808.5
- 56.3808.5
- 58.3808.5
- 59.3808.5
- 593808.5

FIGURE 8. REGION OF CONVERGENCE FOR TRAINED ROTOR DATA

In Figure 8, outcome observation chart for trained rotor bars is presented, the distribution of tallies in the chart indicates the percentage of true class related to the prediction class. The region with highest repeated value indicates the true response from the trained data and region with lowest repeated values indicates false value from the trained data.

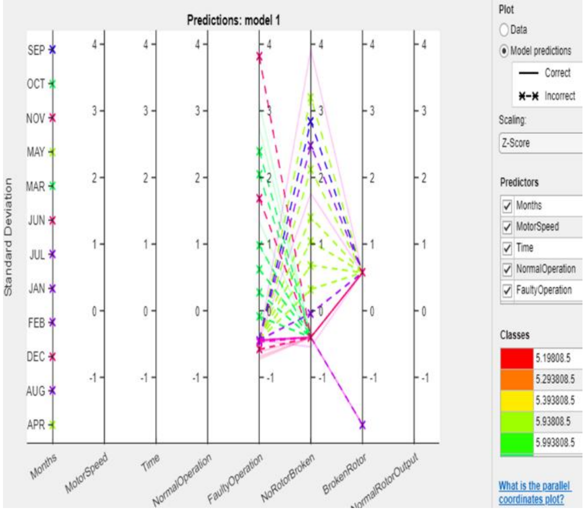


	5.19808.5	5.293808.5	5.393808.5	5.93808.5	5.993808.5	508.5	53.3808.5	538.5	55.3808.5	56.3808.5	58.3808.5	59.3808.5	593808.5
5.19808.5				3									
5.293808.5				3									
5.393808.5				2							1		
5.93808.5										1	2		
5.993808.5				3									
508.5				1		4							2
53.3808.5				3									
538.5						4							1
55.3808.5				2							1		
56.3808.5				1							2		
58.3808.5				2						1			
59.3808.5												9	
593808.5				2		4						1	5

Plot
- ● Number of observations
- ○ True Positive Rates (TPR) False Negative Rates (FNR)
- ○ Positive Predictive Values (PPV) False Discovery Rates (FDR)

FIGURE 9. OUTCOME OBSERVATION CHART FOR TRAINED ROTOR BARS

Figure 10. presents the class deviation for trained rotor bars data at Z-Score predictions. The model prediction shows two regions. Region, one carries a dash sign which indicates correct predictions of the model while the double crosses indicate the incorrect predictions. This prediction is made realistic using the Z-Score derivatives.



Plot
- ○ Data
- ● Model predictions
  - — Correct
  - ✕-✕ Incorrect

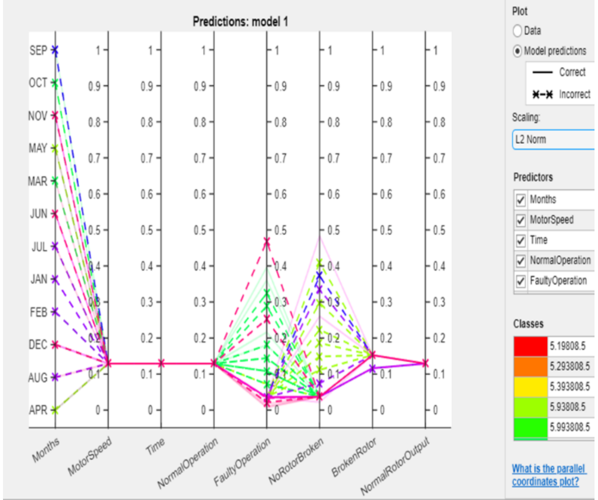
Scaling: Z-Score

Predictors
- ☑ Months
- ☑ MotorSpeed
- ☑ Time
- ☑ NormalOperation
- ☑ FaultyOperation

Classes
- 🟥 5.19808.5
- 🟧 5.293808.5
- 🟨 5.393808.5
- 🟩 5.93808.5
- 🟩 5.993808.5

FIGURE 10. CLASS DEVIATION FOR TRAINED ROTOR BARS DATA AT Z-SCORE PREDICTIONS

Figure 11. presents trained rotor bars data at L2 Norm predictions, the trained model shows two regions which are region one and region two. Region is a dash sign which indicates correct predictions of the model while the double stars indicate the incorrect predictions. This was done using the L2 Norm scaling derivatives.



Plot
- ○ Data
- ● Model predictions
  - — Correct
  - ✕-✕ Incorrect

Scaling: L2 Norm

Predictors
- ☑ Months
- ☑ MotorSpeed
- ☑ Time
- ☑ NormalOperation
- ☑ FaultyOperation

Classes
- 🟥 5.19808.5
- 🟧 5.293808.5
- 🟨 5.393808.5
- 🟩 5.93808.5
- 🟩 5.993808.5

FIGURE 11. TRAINED ROTOR BARS DATA AT L2 NORM PREDICTIONS

Figure 12. presents trained rotor bars data at unit variance predictions, presents the model prediction using the unit variance derivatives. Predictions with correct tallies are represented with dash signs while the incorrect are represented with double stars. This is ideal in determining the best possible outcome from the rotor bars modelled data.

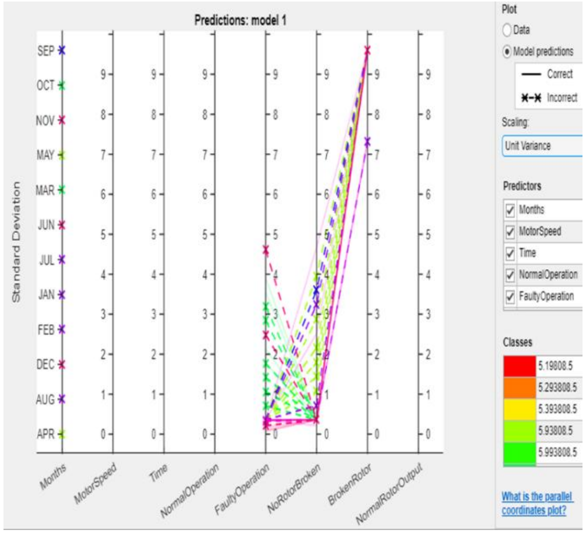


FIGURE 12. TRAINED ROTOR BARS DATA AT UNIT VARIANCE PREDICTIONS

Figure 13. presents results of trained rotor bars data at range predictions, it showed the trained data range predictions. The difference between the maximum value and minimum value makes this prediction more compliance and reliable than any other. This helps to model the rotor bars with high level of precisions.

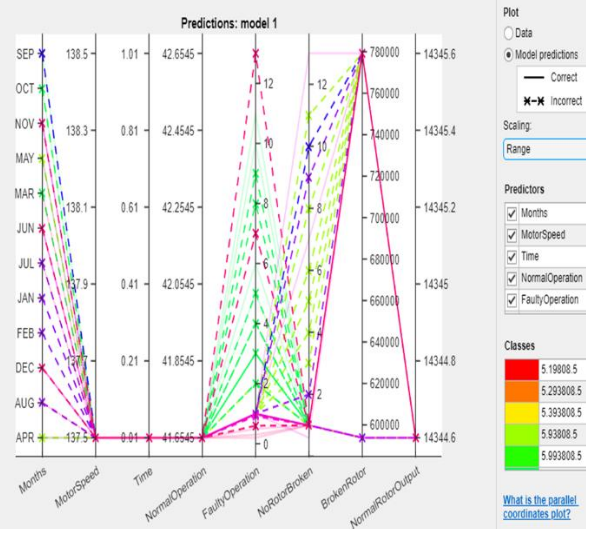


FIGURE 13 . TRAINED ROTOR BARS DATA AT RANGE PREDICTIONS

Figure 14. presents results of trained rotor bars data at Zero Mean predictions, the simulated results showed that the correct and incorrect regions are indicated as dash and star-crossed signals. The model predictions used the Zero Mean prediction derivatives. This gives a wide range of data trained for the rotor bars modelling.

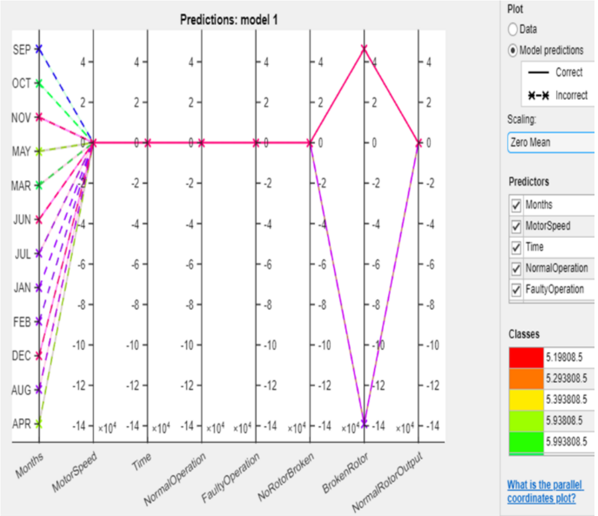


FIGURE 14. TRAINED ROTOR BARS DATA AT ZERO MEAN PREDICTIONS

Figure 15 presents result of region of convergence for trained model predictions, the region of convergence between the true positive rate and the false positive rate. The model predictions started from point 0 and progressed to point 1. The entire area under curve was 1.00 representing a perfect model prediction for the rotor bars model using machine learning tools.

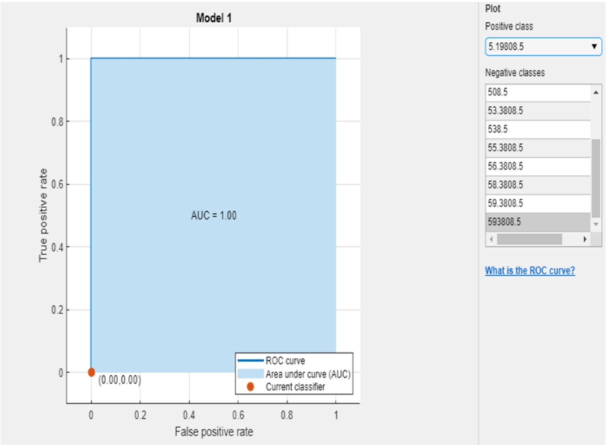


FIGURE 15. REGION OF CONVERGENCE FOR TRAINED MODEL PREDICTIONS

IV. CONCLUSIONS

This study investigates the modelling and simulation of three-phase induction motors with rotor bar faults using machine learning techniques to develop an efficient fault detection and predictive maintenance framework. The research begins by developing a comprehensive simulation model that accurately represents the dynamics of induction motors and the impact of rotor bar faults. Machine learning algorithms, including neural networks, support vector machines (SVMs), and decision trees, were employed to detect faults based on simulation data. The study integrates MATLAB and Simulink simulation tools with machine learning models to create a unified fault diagnosis system, which can be applied in real-time monitoring and predictive maintenance scenarios. A key innovation of the study is the development of a predictive maintenance framework that predicts the remaining useful life (RUL) of motors, helping prevent unplanned downtime and improving overall system reliability. By focusing on real-world applicability, this research provides a foundation for more advanced, data-driven fault detection systems in

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