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Stator Winding Faults Diagnosis of Three-Phase Induction Motor using Adaptive Centroid Defuzzification Based Fuzzy Inference System

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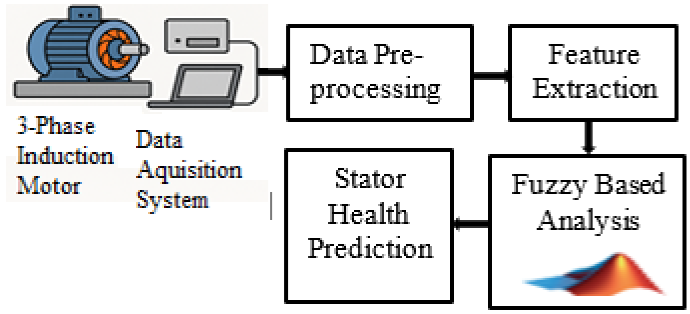
Abstract

Objective: To develop a reliable diagnostic approach for induction motors capable of identifying incipient stator winding faults under variable operating conditions, thereby enhancing predictive maintenance and minimizing downtime. **Method:** A laboratory setup was established to simulate both healthy and faulty stator conditions in a three-phase induction motor. Voltage and current signals were acquired and preprocessed to extract significant features. A Mamdani fuzzy inference system integrated with an adaptive centroid defuzzification approach was implemented in a MATLAB-based GUI for incipient fault monitoring. **Findings:** The proposed diagnostic framework achieved an accuracy of 99.2%, precision of 98.7%, and fault tolerance of 95.6% in detecting stator winding defects. These results demonstrate the method's robustness and reliability under variable and noisy operating conditions. **Novelty:** This manuscript introduces an optimized fuzzy-based diagnostic model combining adaptive centroid defuzzification with enhanced feature preprocessing. This integration significantly improves classification accuracy, decision sensitivity, and fault tolerance, establishing a powerful tool for intelligent predictive maintenance of induction motors.

Keywords: Induction motor; Mamdani fuzzy inference system; Adaptive centroid defuzzification; MATLAB GUI; Stator winding fault diagnosis; Predictive maintenance

Graphical Abstract



1 Introduction

Induction motors (IMs) have become the backbone of modern industries because of their robust structure, higher energy efficiency, and cost-effective operating conditions. However, their reliability of operation is mainly affected by electrical and mechanical faults due to harsh operating and environmental conditions [1,2]. The electrical faults are related to stator winding and rotor bars, while mechanical faults are related to mainly bearings, and rotor shaft. The studies have shown that bearing and stator winding defects accumulately ocuur nearly 70–80% of overall induction motor faults, with stator winding failures alone contributing about 30–40% [2–4]. The open-circuit and inter-turn faults are common stator winding failure in induction motor. In particular, an unbalanced voltage supply is also a common cause that accelerates stator insulation degradation through localized heating, hence increases the probability of winding failure [5,6]. The stator winding faults mainly stimulated high stator current consumption, heating of winding, and excessive vibration [7]. Such failures not only reduce the machine lifespan but also lead to unplanned shutdown of associated plant and enhanced maintenance cost. These issues greatly motivated reserachers for a reliable and incipient fault diagnostic approach to stator winding of induction motor.

In past decade, significant progress has been made using machine learning and AI based approach for fault diagnosis of induction motor [8,9]. Nakamura et al., have demonstrated an effective diagnostic approach using particle swarm optimization for feature extraction and a support vector machine based fault classification to identify inter turn short-circuit faults in induction motor [10]. The SVM, and ANN based method provides reliable fault diagnosis approach to identify stator defects, however these requires a large training dataset and having computationally complex structure [11]. Further, hybrid diagnostic approach offers a high classification accuracy and robustness even under unbalanced and noisy conditions to identify stator defects, however, its performance depends on parameter estimation [12,13].

Compared to these data-driven techniques, fuzzy logic System (FLS) provides distinct advantages due to its easeness of implementation and human skill intervention [14,15]. The FLS is inherently capable of handling uncertain and imprecise real-world data, while maintaining transparent and rule-based decision-making that can easily be interpreted by industrial engineers [16,17]. Unlike machine learning algorithms like neural networks (NN) or support vector machine (SVMs), fuzzy inference systems (FIS) do not require huge training datasets and can be tuned to provide robust and reliable output using human reasoning and expert knowledge [18]. Researchers also utilised ANFIS model to diagnose stator winding defects due to its acapability to learn complex fault patterns from data. However, its real time implementation in diagnosing stator defects is complex due to requirement of large training datasets [19]. Type-2 fuzzy system utilises genetic algorithm (GA) to optimise FIS parameters for handling complex features, however, this enhances the model's complication and makes it computationally intensive [20].

Thus, a FIS provides a simple and efficient approach to deal with uncentain datasets when properly trained and implemented. However, it cannot effectively mitigate the influence of noise and overlapping membership functions, which limits the accuracy of incipient fault detection. To address this, the present study develops an adaptive centroid defuzzification based FIS (ACD-FIS) in a MATLAB GUI to handle complex patterns of dataset. The proposed method enhances the discrimination capability of conventional FIS for detecting stator faults under unbalanced supply conditions.

2 Methodology

This section presents the detailed methodology employed for diagnosing stator winding faults under unbalanced voltage conditions using an Adaptive Centroid Defuzzification-based Fuzzy Inference System (ACD-FIS). The proposed method involves data acquisition related to healthy and faulty IM, data preprocessing, feature computation, and processing of input features to identify stator defects using proposed method ACD-FIS in MATLAB. The details of the proposed methodology to diagnose stator winding defects are illustrated using the block diagram shown in the Figure 1.

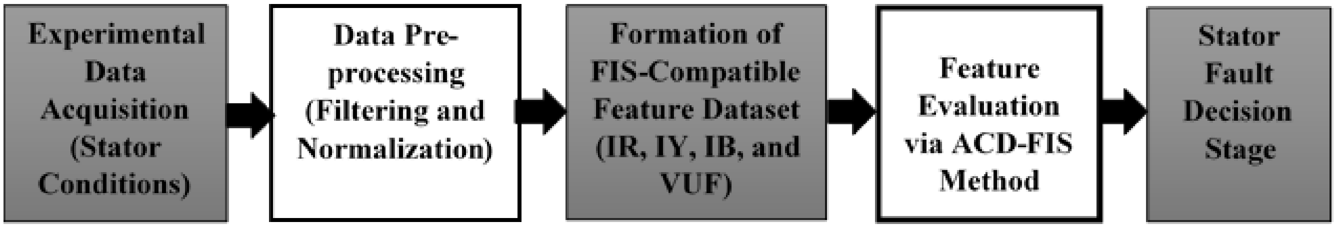


Fig 1. Block Diagram of the Proposed ACDFIS-based Diagnostic Approach for Stator Winding Fault Detection

2.1 Experimental Setup and Data Acquisition

The experimental setup involves a 2.2-kW (3HP), 230 V, 8.6 A, 50-Hz, 1440rpm and 4 pole squirrel-cage induction motor, connected with a separately excited dc generator (power 1.75kW, 1421rpm, 220V, 8A) to feed as variable load. The stator currents (IR, IY, IB) and voltages (VR, VY, and VB) were collected to analyze stator faults under voltage unbalanced condition using Fluke 435-II Power Quality and Energy Analyzer[(21)]. An 80Ω, 3A rheostat was connected in series to each supply phase to introduce unbalanced supply. The open circuit and shorted inter-turn faults in stator winding were simulated under rheostat operation. Figure 2 depicts the experimental setup used to extract fault features for diagnosing stator winding defects. Figure 3 presents the sample dataset of three-phase stator currents (IR, IY, IB) and phase voltages (VR, VY, VB). The variations in the amplitude of voltage and current waveforms clearly indicate the presence of faults in the stator winding. The collected dataset was processed and filtered to remove the redundancy and noise in the signal.

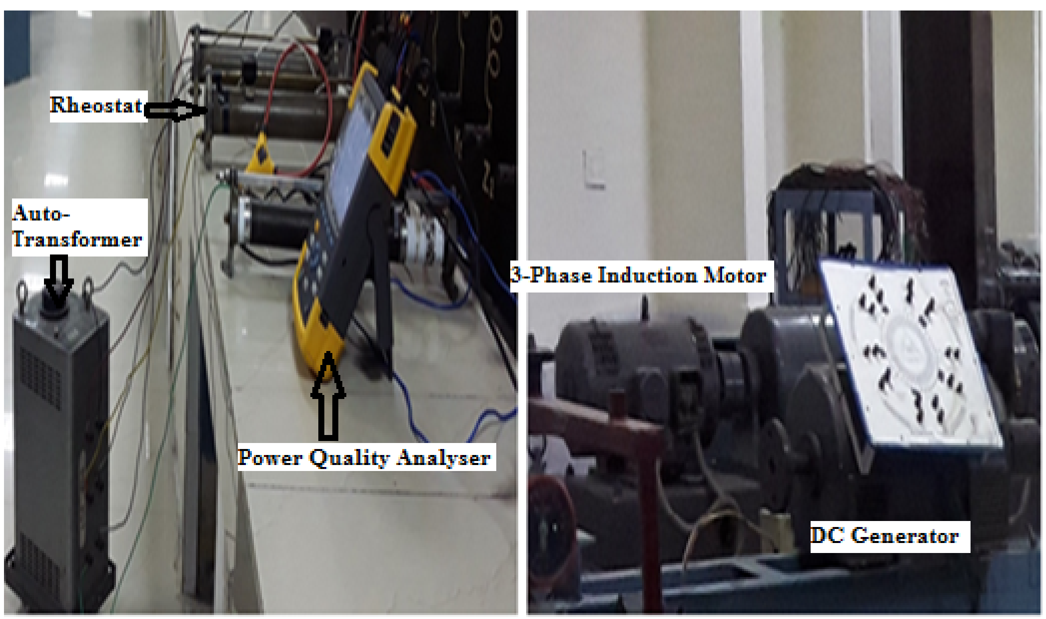


Fig 2. Experimental Setup used to Extract Fault Features for Diagnosing Stator Winding Defects

2.2 Data Preprocessing and Normalization of Features

In proposed work, data feaures were processed to minimize the effect of noise and redundancy. This analysis improves the quality and consistency of the input features like stator current and voltage unbalance signals before fuzzy analysis. During preprocessing, a moving average filtering method was employed to suppress high-frequency noise components caused by

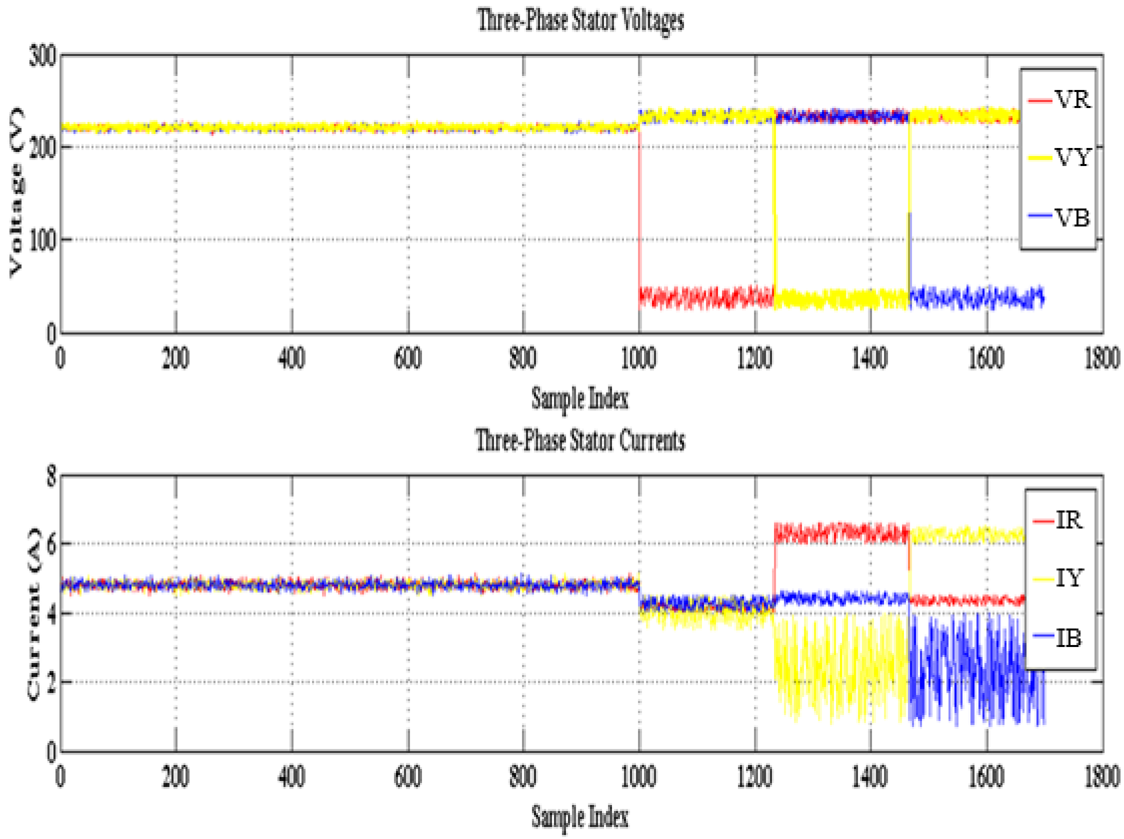


Fig 3. Three-phase voltage and current waveforms under stator winding fault conditions

measurement fluctuations and electrical interference to smooth the collected datasets from experiment. This facilitated in conserving the crucial features related to fault conditions while rejecting unwanted disturbances. For normalization of features, the min–max normalization technique was employed to scale all input parameters to a range between 0 and 1 using the mathematical equation:

$$x_{norm} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

Thus, each input signal (stator current and voltage unbalance) was processed to ensure equal contribution during the FIS process, thereby enhancing data uniformity, reducing computational errors, and improving the overall diagnostic accuracy and stability of the proposed ACD-FIS method.

2.3 Computation of Voltage Unbalance Factor

Voltage unbalance is one of the most frequent and harmful power quality problems in three-phase induction motors. Even a minor difference in different phase voltages lead to unequal current flow, causing in localized heating, torque fluctuations, vibration, and degradation in insulation of winding. Thus, voltage unbalance can vary the electrical characteristics of the motor, making fault identification in induction motors (IMs) more complex. Assessing and analyzing voltage unbalance enables the proposed diagnostic system to distinguish between normal supply variations and real fault indicators, thereby enhancing the system's accuracy and reliability in detecting incipient stator faults under varying supply conditions. Thus, voltage unbalance factor (VUF) alongwith other features serve as a crucial indicator of stator winding condition and it is determined using the following expression [5,6]:

$$Voltage\ Unbalance\ Factor\ (VUF) = \frac{Max(|VR - Vav|, |VY - Vav|, |(VB - Vav)|}{Vav} x100$$

$$Vav = \frac{VR + VY + VB}{3}$$

2.4 Implementation of ACD-FIS to Diagnose Stator Defects

Fuzzy logic is an extension of the binary logic system that is employed to classify the output states using fuzzy rules in linguistic terms. It utilizes expert knowledge to predict the outpcomes using a defined set of rule base. Fuzzy logic technique performs the classification through four main stages as fuzzification of variables, rule base construction, aggregation of fuzzy rules to get fuzzified output, and defuzzification to produce crisp result. The implementation of the proposed ACD-FIS method for diagnosing stator winding defects is described below.

2.4.1. Fuzzification of Input and Output Variables:

Fuzzy Inference system is a rule-based reasoning having fuzzy inputs to describe the health condition of an induction motor as eighther "healthy [1]" or "faulty [0]". In this study, stator currents IR, IY, and IB, and voltage unbalance factor (VUF) are considered as input variables. Linguistic terms such as *low (centre 0.2), medium (centre 0.5),* and *high (centre 0.8),* are assigned for stator current, while *zero (centre 0.05), medium (centre 0.2),* and *high (centre 0.6)* are allocated to VUF. The Gaussian membership function was employed for input variables, whereas a triangular membership function is used for the output variable. For better separation and improved classification accuracy, the centers of the Gaussian membership functions were determined using a statistical approach. The membership functions (MFs) of stator current and VUF are shown below using Figure 4 and Figure 5.

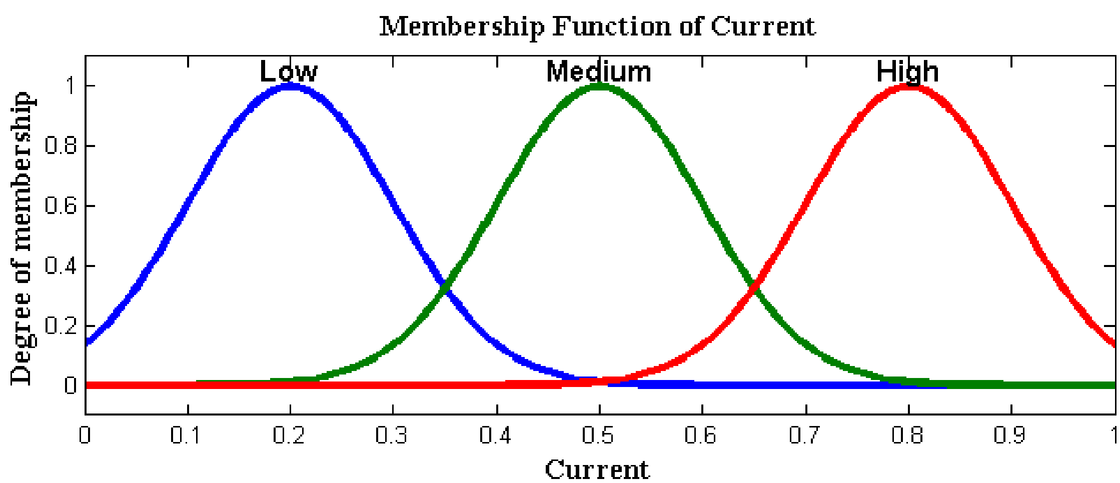


Fig 4. Gaussian shaped membership function of stator current

2.4.2. Fuzzy Rule Base Formation and Inference:

In this work, Mamdani fuzzy inference system was employed for its simplified approach and enhanced outcome. This inference system works on a set of expert defined fuzzy rules to predict output utilizing even uncertain or imprecise input dataset. The rule base is a set of "if–then" statements, connects fuzzified inputs to the expected outcomes. In this work, a set of comprehensive if-then AND rule base was utilised for diagnosing stator winding defects. The 'AND' rule ensures that all input conditions are satisfied before confirming a fault, thereby enhancing reliability and accuracy of fault prediction compared to the 'OR' rule. The accuracy of FIS also depends on the number of rule sets utilised to infer the output. Finally, defuzzification process converts this fuzzy outcome into a crisp value for better interpretation. The Mamdani FIS is widely employed due to its simplicity, transparency, and ability to imitate human reasoning, making it suitable for fault detection and decision-making in uncertain environments.

The sample if–then fuzzy rule set with input variables as voltage unbalance factor (VUF) and stator phase currents (IR, IY, IB) and the output variable as healthy or faulty is presented in Table 1. The first rule can be stated as:

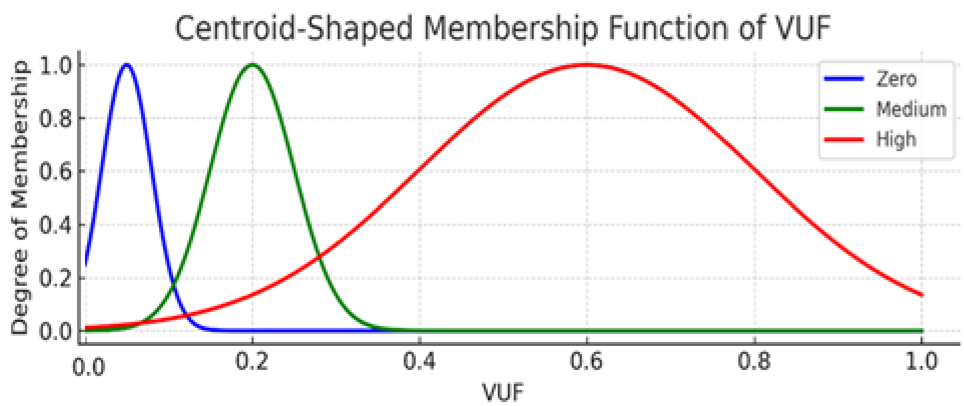


Fig 5. Gaussian shaped membership function of input variable VUF

"If VUF is zero and IR, IY, and IB are medium, then the induction motor (IM) is healthy."

Table 1. If-Then Fuzzy Rule Matrix for Stator Fault Diagnosis

VUF Level	Current Combination (IR, IY, IB)	Output (Motor Health Condition)
Zero	Med–Med–Med Low–Med–Med Med-Med-Low Med-Low-Med	Healthy
Medium	High–Med–Med Med–Low–High High–Low–Low	Faulty
High	High–High–High Med–High–High High–Low–High	

2.4.3. Adaptive Centroid Defuzzification Process:

The centroid method, also known as the center of gravity (COG) or center of area (COA) method, is the most commonly used defuzzification technique compared to methods such as bisector, mean of maximum, largest of maximum, and smallest of maximum. This preference arises from its ability to consider the entire shape of the output fuzzy set rather than peak or boundary, resulting in smoother, more balanced, and accurate outcomes. It also provides better stability and continuity in the system's response, making it highly suitable for precise control and diagnostic applications. However, its process becomes computationally expensive when operating on a fuzzified output with a complex membership function. The mathematical expression of general centroid defuzzification process is given as

$$h^* = \frac{\int_b \mu_{ag}(h) * h dh}{\int_b \mu_{ag}(h) * dh}$$

Where, $\mu_{ag}(h)$ is aggregated output membership function, h^* is crisp value of health condition and is the b domain of output variable.

To enhance sensitivity in detecting incipient faults under unbalanced supply conditions, an adaptive weighting function $w(x)$ is introduced into the standard centroid function. Thus, it is an improved form of the conventional centroid approach. It incorporates adaptive weighting factors that modify the influence of each membership function according to system dynamics or data variations, resulting in improved accuracy and greater resistance to noise in fault diagnosis applications.The mathematical expression of adaptive centroid defuzzification process is given as

$$h_a^* = \frac{\sum_{i=1}^{n} w_i \int_{bi} \mu_{agi}(h) * h dh}{\sum_{i=1}^{n} w_i \int_{bi} \mu_{agi}(h) * dh}$$

Where, h_a^* is adaptive defuzzified output, w_i is the adaptive weighting factor for the ith rule, $\mu_{agi}(h)$ is membership function of the ith fuzzy output set, bi is support to the ith fuzzy output. The adaptive weighting function w_i is expressed as

$$w_i = \frac{\mu_{Ai}(h)}{\sum_{j=1}^{n} \mu_{Aj}(h)}$$

Here, $\mu_{Ai}(h)$ represents the firing strength of the ith fuzzy rule, and μ_{Aj} denotes the firing strength of jth fuzzy rule.

Thus, this adaptive mechanism shifts the centroid position slightly toward the rule with the highest weight, thereby enhancing sensitivity and robustness under noisy or uncertain operating conditions.

2.4.4. Performance Analysis of Proposed Methodology:

The six performance indicators as accuracy, precision, recall, F1-score, noise sensitivity and fault tolerance are used in this work to evaluate the effectiveness and reliability of proposed ACD-FIS method in indentifying stator winding defects. These parameters depict at what percentage the proposed method correctly predict the stator defects without making false prediction during testing of model.

Let N_p be the number of true positive, N_n be the number of true negative, N_{fp} be the number of false positive and N_{fn} be the number of false negative prediction during the testing of model. Then, accuracy, precision, recall, and F1- score parameters can be expressed using mathematical equation as given below.

$$Accuracy = \frac{N_p + N_n}{N_p + N_n + N_{fp} + N_{fn}}$$

$$Precision = \frac{N_p}{N_p + N_{fp}}$$

$$Recall = \frac{N_p}{N_p + N_{fn}}$$

$$F1 - Score \ = 2 * \frac{Precision * Recall}{Precision + Recall}$$

The other two factors computed to assess the robustness of the ACD-FIS method are noise sensitivity and fault tolerance.The noise sensitivity evaluates the model response to variations or disturbance in input dataset. While the fault tolerance determines the ability of FIS model to maintain performance even with missing or faulty input variables.

3 Result and Discussion

The proposed diagnostic scheme comprises input features as three phase stator current components as IR, IY, and IB and voltage unbalance factor (VUF) and output variable as health condition of stator winding. The inpuit variables were extracted using an experimental setup for real time fault diagnosis. The adaptive centroid defuzzification process was employed to Mamdani FIS editor to process the fuzzified input variables to identify stator winding defects. The performance of introduced method in diagnosing stator defects was compared with the traditional FIS. The percentage value of various performance indicators are illustrated in Figure 6 using a bar chart. The results of Figure 6 depict that the proposed method significantly enhances diagnostic performance compared to the conventional FIS method. The conventional FIS achieves 90.0% classification accuracy, whereas the introduced FIS method attains an improved accuracy of approximately 99.2%. This improvement was achieved by optimizing the defuzzification process by incorporating an adjustable weight function to shift the centroid to utilize effective rule base. Further, the other performance indices like precision (98.7%), recall (99%), and F1-score (99.1%)

shows consistent enhancement in introduced method compared to traditional FIS method, confirming its superior capability in accurate classification of healthy and faulty stator winding.

The noise tolerance index which reflects the robustness of the proposed method under distorted or unbalanced supply conditions, achieving 97.8% compared to 88.7% for the general FIS, thereby demonstrating improved immunity to the disturbances. Additionally, a notable enhancement in fault tolerance, with a value of 95.6% compared to 87.9% for the general FIS, indicates higher reliability in identifying stator winding defects even under varying load and unbalanced supply.

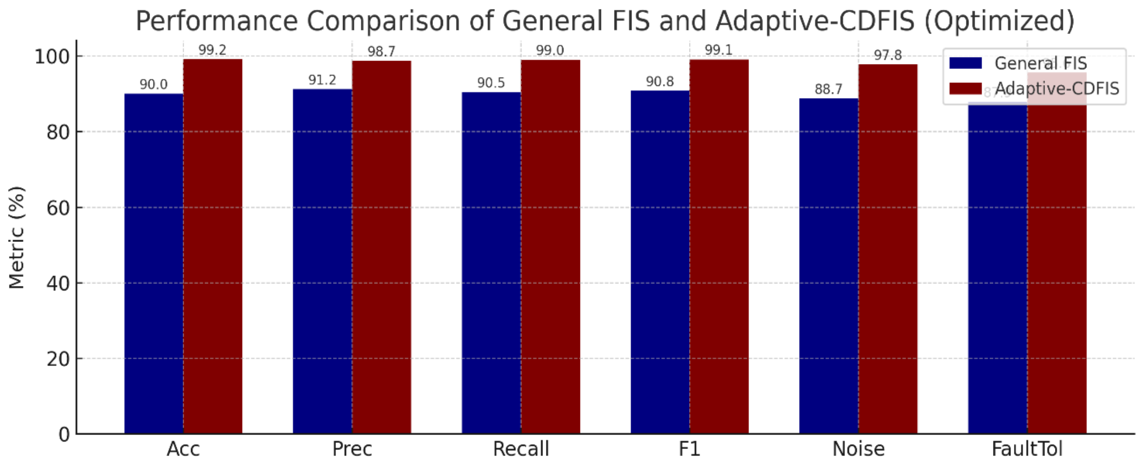


Fig 6. Comparative performance indices of the traditional FIS and the adaptive centroid-based defuzzification FIS in diagnosing stator winding related defects

To further validate the effectiveness of the proposed method in diagnosing stator defects of induction motors, a 3D fuzzy surface plot is shown in Figure 7. This plot illustrates how the fuzzy inference system responds to the relationship between the input variables and the output stator health condition. The traditional FIS surface plot is smoother, indicating limited fault sensitivity, whereas the adaptive centroid based FIS depicts sharper gradients. This confirms that the proposed method enhances input and output mapping, resulting in improved fault distinguishability and diagnostic accuracy.

The comparative analysis of the introduced method and existing fuzzy logic-based techniques for diagnosing stator winding defects is depicted in Table 2. The conventional FIS method (Type-1 FIS) employs fixed MFs and a static rule base, making it simple but effective only for stator defects with stable conditions. The Type-2 FIS incorporates graded MFs as fuzzy in fuzzy set to better track the uncertainties in the input signals. It provides better performance over Type-1 FIS under nonlinearity and fluctuating conditions, but at the cost of increased computational complexity. The hybrid ANFIS technique that combines the strength of fuzzy logic and neural networks to efficiently handle the uncertainties and varying conditions in dataset. However, it may suffer from overfitting and requires larger datasets for training. In contrast, the proposed methodology upgrades the defuzzification process through adaptive weighting led by rule activation strength. This mechanism significantly enhances accuracy, noise tolerance, and robustness in identifying incipient stator faults under unbalanced and uncertain operating conditions.

These studies have shown that the introduced methodology reveals higher convergence characteristics and improved output stability over the traditional FIS method for nonlinear dataset. It also significantly enhances the precision of the fuzzy diagnostic system, thereby providing more reliable fault detection, higher noise resistance, and improved fault classification accuracy in the presence of unbalanced voltage condition. These findings validate that the introduced method is better than the traditional defuzzification based FIS in identifying stator defects in presence of unbalanced voltage condition. The main limitation of the introduced method is the slightly increased computational effort required for adaptive weighting calculations during the defuzzification process. Overall, the introduced method significancly enhances the reliability and lifespan of industrial motors, thereby reducing maintenance costs, and preventing unexpected equipment failures that could disrupt production and safety in industrial process.

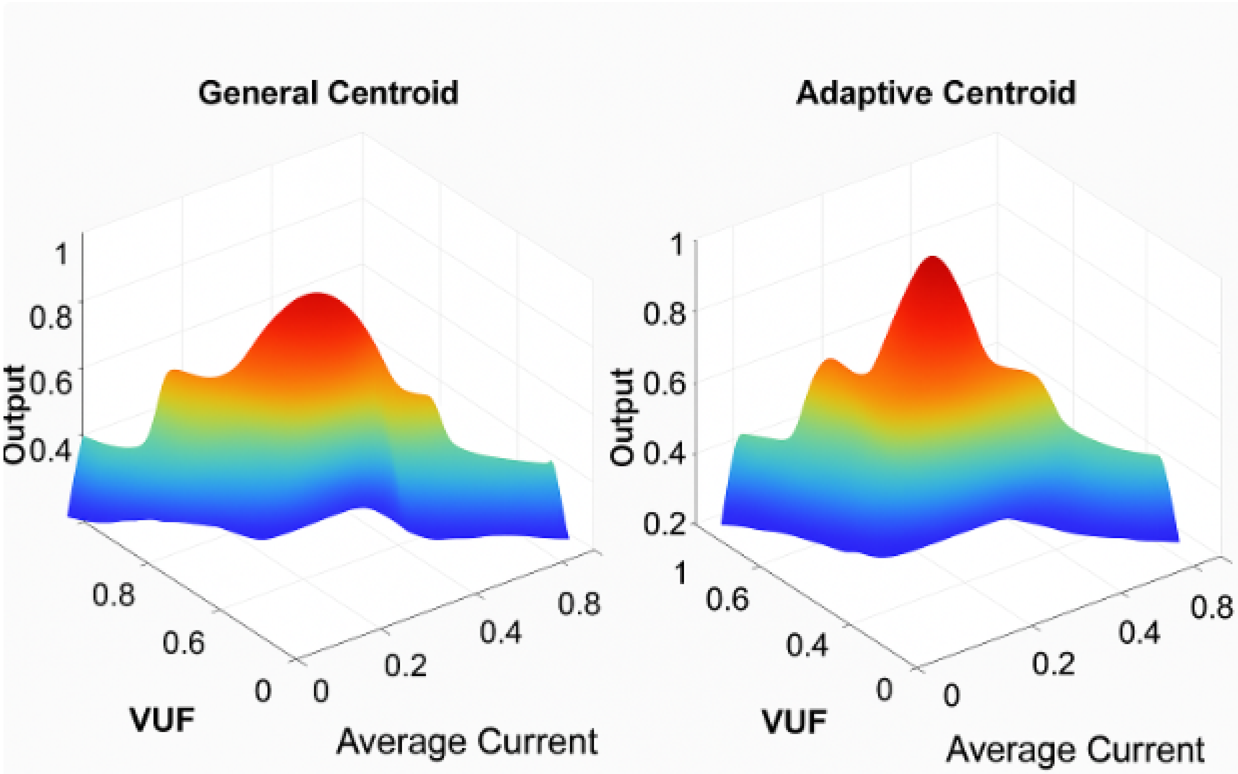


Fig 7. Fuzzy surface plot showing the effect of input variables on output

Table 2. Comparison of Various FIS-based Methods for Stator Fault Diagnosis

Method	Mechanism/ Learning Method Opted	Suitability for Stator Faults Diagnosis	Disadvantages	Reference
Conventional FIS (Type-1 FIS)	Employ fixed MFs and static rule base, no learning method opted	Suitable only for basic fault with low variable conditions	Sensitive to noise and parameter variation	(5,6,14–18)
ANFIS	Combines fuzzy logic with neural networks to learn membership and rule parameters, Gradient descent or hybrid learning	Effective for identifying defects under varying operating conditions	May overfit, requires large training dataset	(19)
Type-2 FIS	Employ fuzzy in MFs i.e. MFs grade itself , tuned via optimization (like GA, PSO)	Suitable for faults having highly uncertain or nonlinear datasets	Complex design, computationally intensive	(20)
ACD-FIS	adaptive weight function in centroid defuzzification process, Self-adjusting weight function based on rule activation strength	Highly suitable for incipient stator fault detection under uncertain and unbalanced conditions	Complex than Type-1 FIS	

4 Conclusion

The present work introduced an ACD-FIS based diagnostic approach for identifying stator winding defects in induction motors operating under unbalanced supply and varying load conditions. The integration of an adaptive centroid defuzzification strategy into the Mamdani FIS significantly enhanced the fault sensitivity, robustness, and interpretability compared to conventional FIS. To validate the proposed method, an experimental study was conducted to simulate the open circuit and inter-turn short circuit faults in the stator winding of a three phase induction motor. The extracted and normalized features as stator currents and voltage unbalance factor effectively presented the variations in behavior of IM caused by stator winding defects.

The presented methodology achieves fault classification accuracy of 99.2%, precision of 98.7%, recall of 99%, and F1-score of 99.1%, showing its ability to identify incipient stator winding defects with high level of reliability. The adaptive centroid mechanism dynamically modified the output centroid according to the degree of rule activation, enhancing the correlation between input features and the resulting health index. Consequently, the system exhibited strong performance even in the presence of voltage unbalance. The comparative study with the conventional FIS approach revealed that the adaptive model provides better classification accuracy, greater noise immunity, and improved fault tolerance.

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