# Voltage Unbalance Stifled Mamdani Fuzzy Logic Model for Stator Faults Analysis of Induction Motor

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## ABSTRACT

Stator winding related faults are second highest defect occurring in three phase induction motor. Motor current signature analysis (MCSA) based techniques are not reliable method to identify stator related defects for motor operating at low and fluctuating loads. The frequency spectrum of stator current acquired using elementary MCSA techniques are also affected by unbalance supply, low voltage and noise. In this context, this manuscript presents an automated system based on Mamdanifuzzy logic technique to identify voltage unbalance abnormalities, open winding and short circuit faults of stator winding. In this work, mean of three phase stator currents, voltage unbalance index and motor loads have been used as feature parameter for effective analysis of stator defects. The efficacy of proposed method has been verified using experimental work accomplished on 3hp three-phase induction motor. The results have shown that proposed method is capable to mitigate the complications caused by voltage unbalance and motor loads in identifying stator related defects.

**Keywords -** Fuzzy Logic System, Stator Defects, Three Phase Induction Motor, Voltage Unbalance Index

## 1. INTRODUCTION

Induction motor is the workhorse of most of manufacturing industry. Due to various adverse operating conditions like fluctuating and stressed loading, round the clock operation and antagonistic environmental conditions cause various defects in it. The major induction motor defects are related with stator winding and bearing (Liu *et al.,* 2017*)* .Electric Power Research Institute (EPRI) sponsored a survey to identify the share of various induction motor faults and the result shows that almost 41% failures are related with bearings, 37% are related with stator windings, 10% are due to rotor bars and remaining 12% are related with other parts of induction motor (Nandi et al., 2005; Gandhi et al., 2011). As per EPRI report, the percentage failures of various components of induction motor are given in figure 1. Stator currents are widely used characteristic parameter to diagnose stator related faults (Tallam *et al.*, 2003; Ukil *et al.*, 2011; Hegde *et al.*, 2017; Sarkar *et al*., 2013) . Previously many authors have worked on to detect stator defects using stator currents and other machine related parameters (Yadav *et al.*, 2013; Sawitri *et al.*, 2018; Gritli *et al.*, 2017). Many signal processing techniques have been used in literatures to detect stator related faults. However these techniques require diagnostic expert knowledge to interpret the result, these may sometimes provide false interpretation interpretation (Devi *et al.*, 2016; Sarkar *et al.*, 2013; Yaghobi *et al.*, 2017; Su *et al.*, 2007; Yadav *et al.*, 2019). To overcome the problems encountered in spectrum analysis techniques, artificial intelligent techniques may play important role in providing automatic decision making in prediction of result. Fuzzy logic method is the basic AI technique that may help to diagnose stator related faults (Allaoua *et al.*, 2013). There are a number of literatures available to diagnose IM faults using fuzzy logic technique. A major difficulty is the lack of a well processing of fuzzy input data. Mini et al. have used stator current, rotor speed and torque as feature inputs to detect stator faults (Mini *et al*., 2011). (Romero-Troncoso *et al*., 2011) have proposed a fuzzy logic based system to diagnose IM faults (Verma *et al*., 2014)have used stator current spectra and fuzzy logic technique to diagnose short circuit faults of stator winding of IM

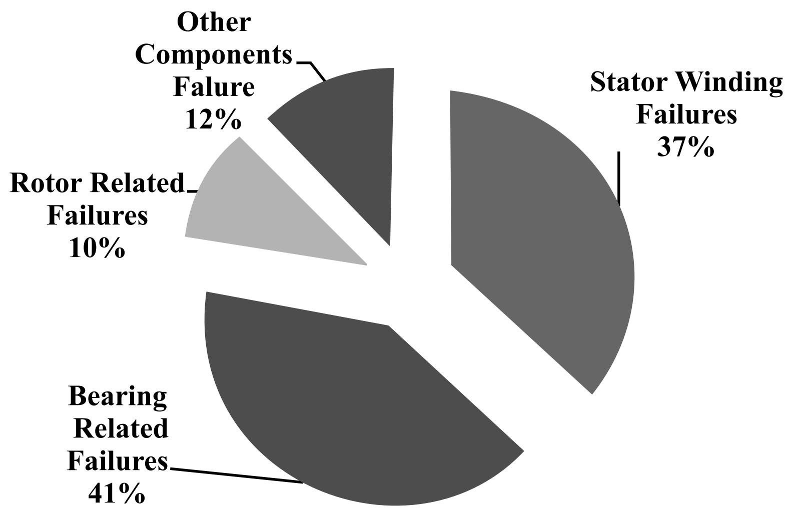



**Figure 1:** Percentage failure of components of 3-Phase induction motor (As per EPRI survey)

In this work, mean of stator current, voltage unbalance index (VUI) and IM load have been used as input features to diagnose stator related defects of induction motor. Motor load also affects the stator current of induction motor so motor load also considered in this analysis. In this work, stator faults diagnosis is performed based on fuzzy logic system using three phase stator currents and voltage unbalance index. Mamdani fuzzy inference machine is used to map the input to output for its various advantages. The simulation work is performed using fuzzy logic toolbox of MATLAB 2017. The fuzzy logic model used to diagnose the stator fault is shown by figure 2. The remaining part of this manuscript is organized as experimental setup and data collection, Fuzzy Logic System based Model to identify Stator Faults, results and discussion followed by conclusion and references.

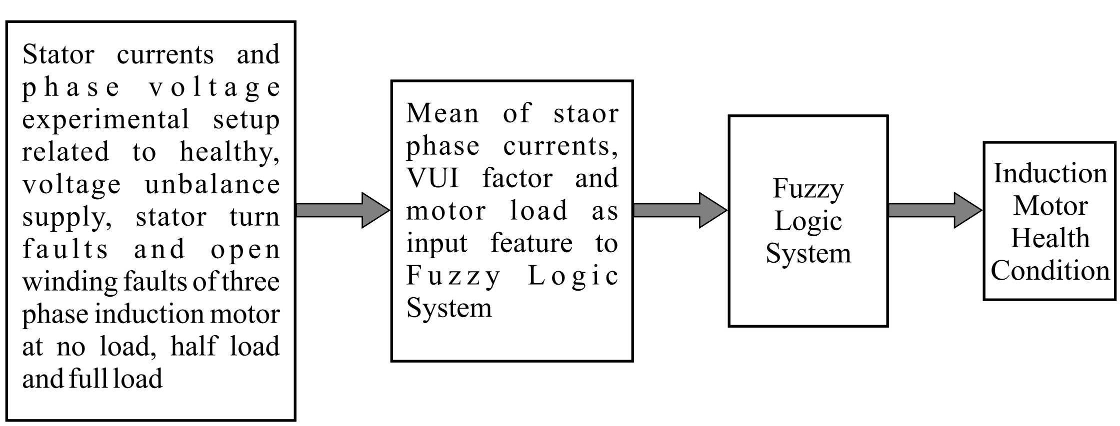



**Figure 2:** flowchart of procedure used to detect stator related faults using FLS

## 2. EXPERIMENTAL SETUP AND DATA COLLECTION

Experimental analysis is very important in order to verify the theoretical aspects of study. Without experimental setup, it is difficult to analyze the faults related to induction motor. For this, an experimental setup has been accomplished using 3hp induction motor. A number of parameters such as terminal voltages, stator currents and rotor speed have been measured and compared with different operating and health conditions of induction motor. A series of repeated experimental tests were carried out at different balanced and unbalanced supply voltages, operating loads and health conditions of stator winding. The details of experimental setup are shown by figure3. The experimental setup was consists of a 2.2-kW (3HP), 230 V, 8.6 A, 50-Hz, 1440rpm and 4 pole squirrel-cage induction motor. A mechanical load was provided on induction motor by separately excited dc generator (power 1.75kW, 1421rpm, 220V, 8A) feeding a variable resistor as a load. To investigate the effect of unbalance supply on its performance three rheostat with rating 0-80Ω, 3A were connected in series between power source and induction motor supply terminal.

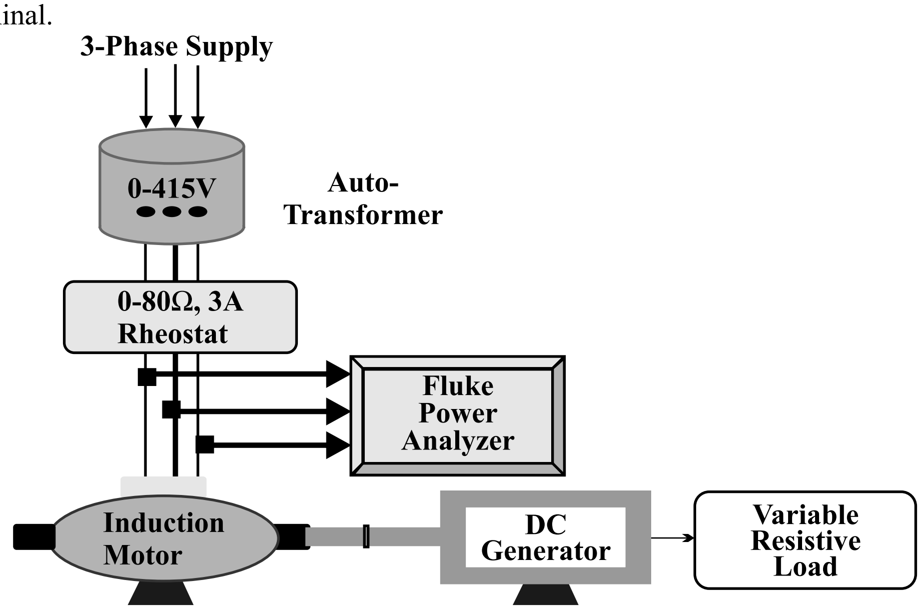



**Figure 3:** Schematic of experimental setup

The machine parameters were measured with the help of Fluke 435-II Power Quality and Energy Analyzer. The input supply was unbalanced by adjusting the resistance value of rheostat. A number of tests were performed at different levels of unbalance voltage and operating loads and parameters like stator current, input terminal voltage and rotor speed were measures. In further analysis open winding and short circuit faults were created and series of repeated tests were performed to log the terminal voltage, stator current and rotor speed with the help of power analyzer. During the experimental work, all precautions have taken to avoid any mishap. The schematic of experimental setup is shown by figure 3 and test rig is shown by figure 4.

For better analysis, voltage unbalance index (VUI) was calculated from three motor terminals voltage due to its inherent property to show voltage variation. The mathematical expression of VUI is given by equation (1). Where $V_R$, $V_Y$ and $V_B$ represents motor terminal phase voltage.

$$VUI = \frac{\max(V_R,V_Y,V_B)-\text{mean}(V_R,V_Y,V_B)}{V_{rated}} \times 100 \qquad (1)$$

The radar plot of three phase stator currents and voltage unbalance index (VUI) parameters for healthy and inter turn shorts circuited stator winding is shown by figure 5 and figure 6. Radar plot provides way to find the relative approach to targets. The figures of radar plot show that in healthy IM, the three phase stator currents are evenly distributed while these stator currents are asymmetrically distributed in IM having inter-turn short circuited stator winding.

**Figure 4:** Experimental setup to identify stator related faults of induction motor

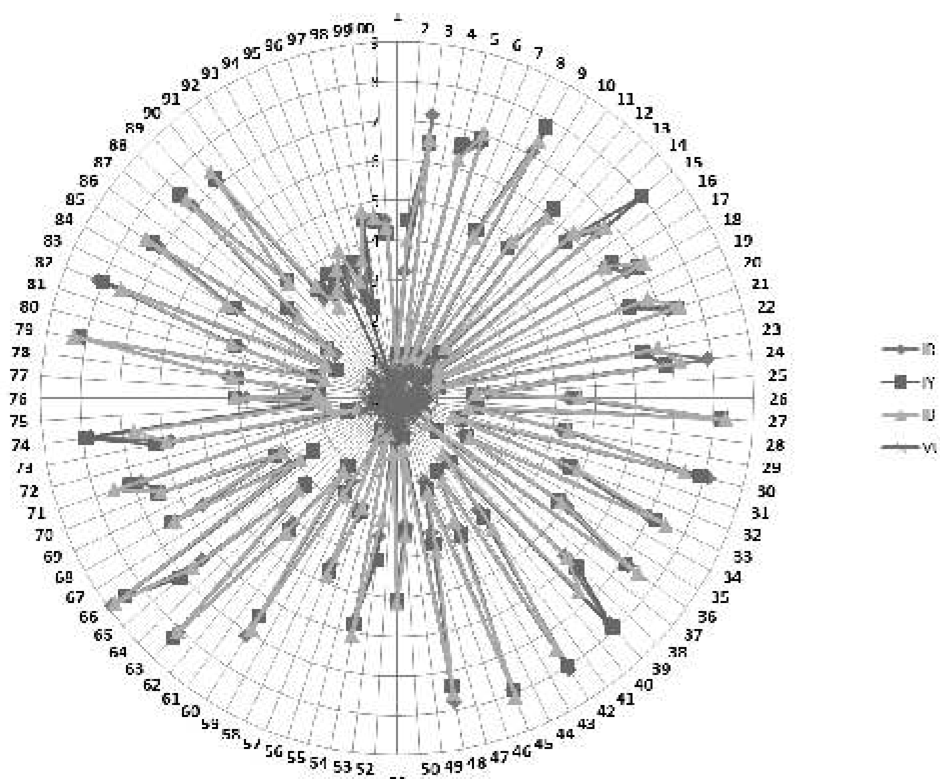


**Figure 5:** Radar plot of three phase stator currents and voltage unbalance index (VUI) for healthy IM

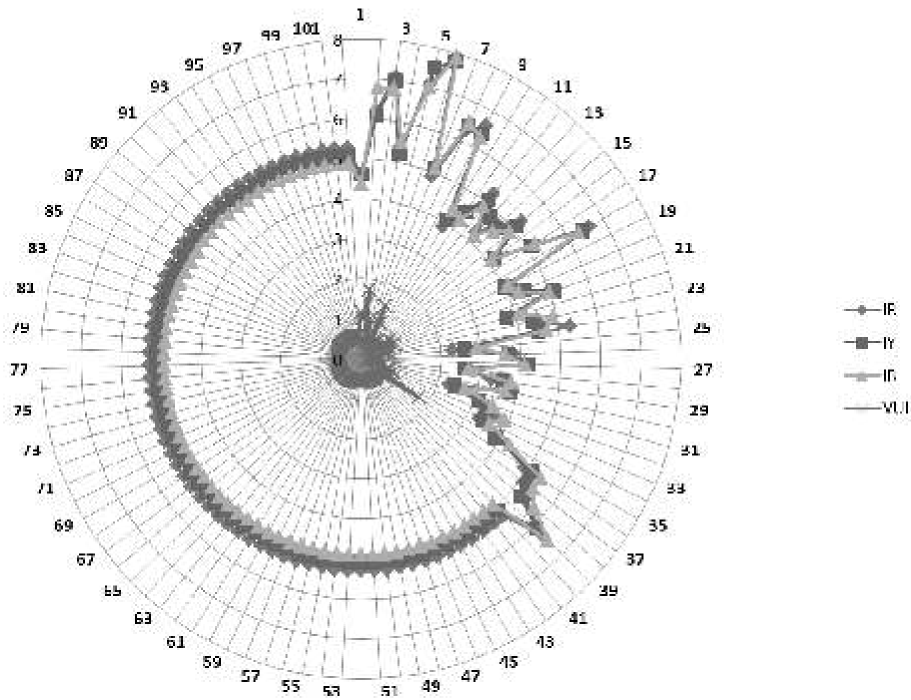



**Figure 6:** Radar plot of three phase stator currents and voltage unbalance index (VUI) for IM having inter turn shorts

## 3. FUZZY LOGIC SYSTEM BASED MODEL TO IDENTIFY STATOR FAULTS

The concept of Fuzzy set was first developed by Zadeh in 1965 to represent ambiguous and vague understanding. The term fuzzy is related with not clear or uncertain information. Fuzzy logic is based on fuzzy set theory used to represent a system by graded statement rather than binary i.e. true and false. On utilizing human expert knowledge and natural language it provides simpler solution to a complex and imprecise nonlinear problem. Thus, it provides better result when the data denoting features are having vague information.In this work, mean of stator currents, voltage unbalance index (VUI) and motor loads are used as features to diagnose stator related defects. As relationship between the unbalance motor conditions, the stator current amplitudes and IM fault conditions are vague so elucidation of results is difficult by using spectrum analysis techniques. In this condition, the role of fuzzy logic technique may be valuable to construe the fault conditions as it deals the problems in linguistic variables. The components of fuzzy logic systems (FLS) are shown below by figure 7.

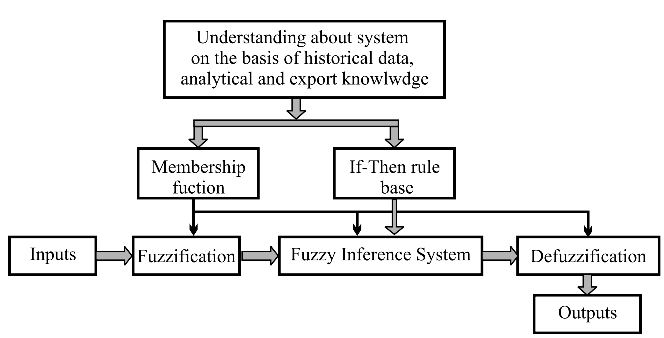



**Figure 7:** Basic structure of Fuzzy logic system (FLS)

### 3.1 INPUT-OUTPUT VARIABLES OF FUZZY SYSTEM

The proposed algorithm has three inputs variables namely mean of stator currents (I), voltage unbalance index (VUI) and motor loads and stator fault conditions (FC) as output variable.
All the system inputs and outputs are defined using fuzzy set theory as

$$I= \{\mu I(i_j)/ i_j Є I\} \tag{1}$$

$$VUI = \{\mu_{VUI} (vui_j)/ vui_j Є VUI \tag{2}$$

$$L= \{\mu L(l_j)/ l_j Є L\} \tag{3}$$

$$FC=\{\mu FC(fc_j)/ fc_j Є FC\} \tag{4}$$

Where I, VUI, L and FC are, respectively, the elements of the discrete universe of discourse mean current (I), voltage unbalance index (VUI), motor load (L) and fault condition (FC). $\mu I(i_j)$, $\mu_{VUI}$ $(vui_j)$, $\mu L(l_j)$ and $\mu FC(fc_j)$ are the corresponding membership functions and j represents members of input.

### 3.2 LINGUISTIC VARIABLES CORRESPONDING TO INPUT AND OUTPUT FUZZY SET

Linguistic variables are the elementary tools of FLS used to represent uncertain information into real world applications. Linguistic variables corresponding to each input and output are selected on the basis of datasets and expertise knowledge about the system. These variables are very effective in solving the problems having no mathematical relationship between inputs and outputs. The linguistic variable corresponding to inputs and outputs Mean of stator current T (I), voltage unbalance index T (VUI), Motor Load T (L) and fault condition T (FC) are represented as:

T (I) = {Normal, Medium (M), High (H), Very High (VH), Extreme (E)}

T (VUI) = {No Unbalance (NU), Low Unbalance (LU), High Unbalance (HU), Extreme Unbalance (EU)}

T (L) = {No Load (NL), Half Load (HL), Full Load (FL)}

T (FC) = {Healthy, less Healthy (LH), Faulty (F), Serious Faulty (SF)}

For mean stator current the linguistic variables are characterized as Normal (up to 20% of full load current), Medium (18-40% of full load current), High (38-55% of full load current), Very High (50-82% of full load current), and Extreme as (80-100% of full load current). The linguistic variables of VUI factor are NU (0-5%), L (5-10%), HU (9-30%) and EU (25-100%). In this study 10% VUI is considered as reference value. In the case of motor load, linguistic variables NL (0-20%), HL (18-50%) and FL (48-100%) areconsidered corresponding to full load. While in case of motor fault conditions, 0-20% is Healthy, 15-30% LH, 28-50% as F and 48-100% of reference values are considered as SF.

### 3.3 FUZZY MEMBERSHIP FUNCTIONS AND RULE BASE CONSTRUCTION

Fuzzy rules and membership functions are constructed by observing the data set collected from experimental analysis. It requires a deep analysis of datasets collected from experimental study. The membership function of mean stator current is shown in figure 8. Figure 9 represents the membership function of VUI. The membership function of motor load is represented by figure 10 while the membership function of IM health conditions is represented by figure 11. In this analysis the shapes of membership function for all inputs and outputs are considered as triangular except motor load which are trapezoidal.

Once the practice over membership functions completed, the *fuzzy if-then* rules are constructed. The accuracy of fault prediction of FLS depends on the number of rule bases. More the number of rules, high will be prediction accuracy. Total 58 rules have been created on the basis of training datasets extracted from experimental analysis. The 10 rule sets are given as

If (Load is NL) and (VUI is NU) and (current is Normal) then (Health_Condition is Healthy).

If (Load is NL) and (VUI is NU) and (current is M) then (Health_Condition is Healthy).

If (Load is NL) and (VUI is LU) and (current is M) then (Health_Condition is LH).

If (Load is NL) and (VUI is HU) and (current is M) then (Health_Condition is F).

If (Load is HL) and (VUI is LU) and (current is M) then (Health_Condition is H).

If (Load is HL) and (VUI is LU) and (current is VH) then (Health_Condition is LH).

If (Load is HL) and (VUI is LU) and (current is E) then (Health_Condition is F).

If (Load is FL) and (VUI is LU) and (current is E) then (Health_Condition is LH).

If (Load is FL) and (VUI is HU) and (current is E) then (Health_Condition is F).

If (Load is FL) and (VUI is HU) and (current is E) then (Health_Condition is SF).

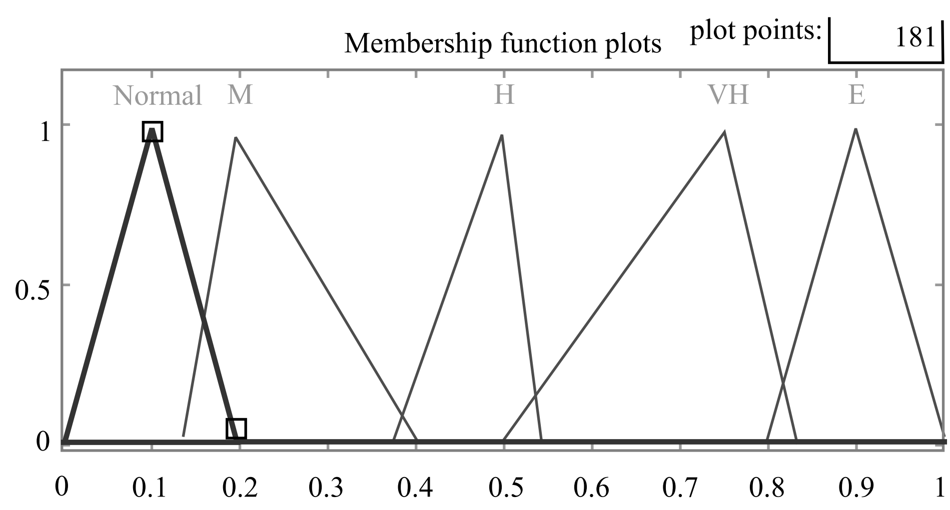



**Figure 8:** Membership function corresponding to mean of stator currents

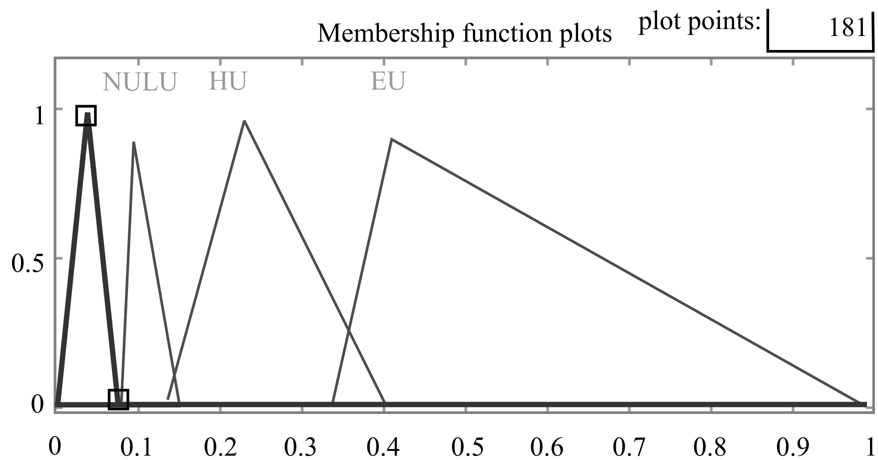



**Figure 9:** Membership function of voltage unbalance index (VUI)

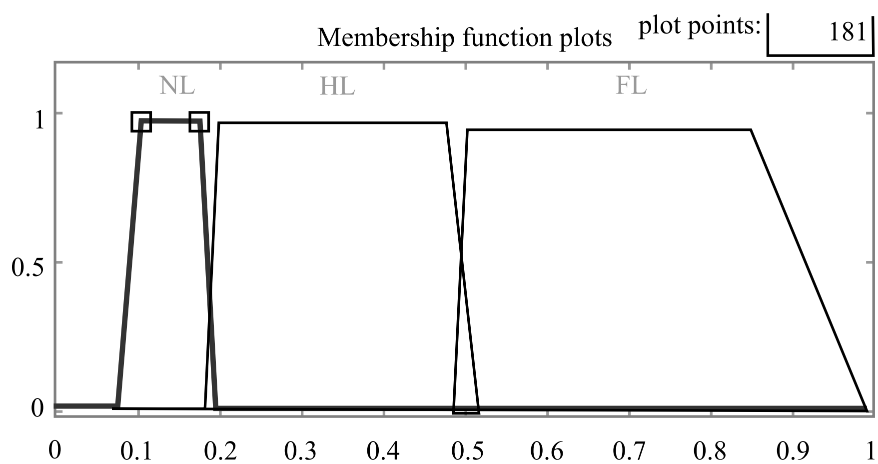



**Figure 10:** Membership function corresponding to motor load

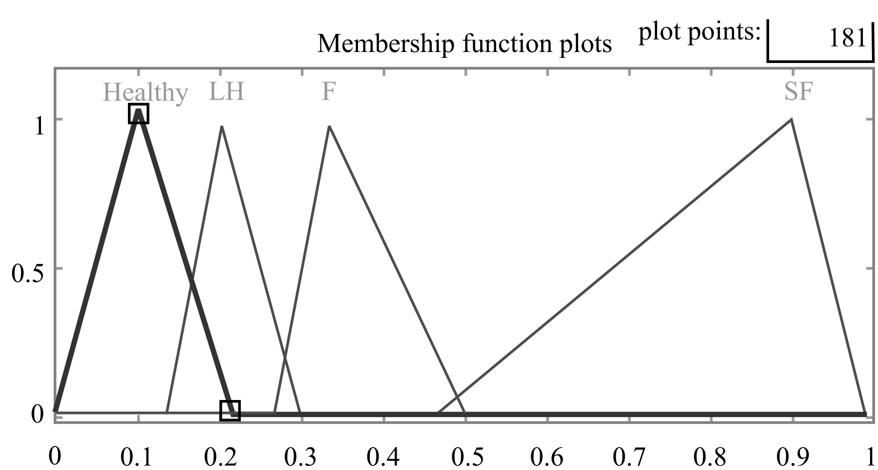
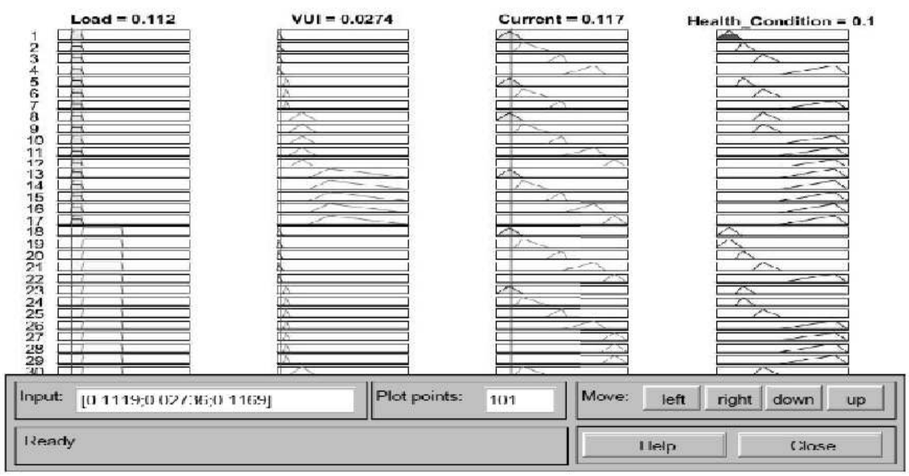


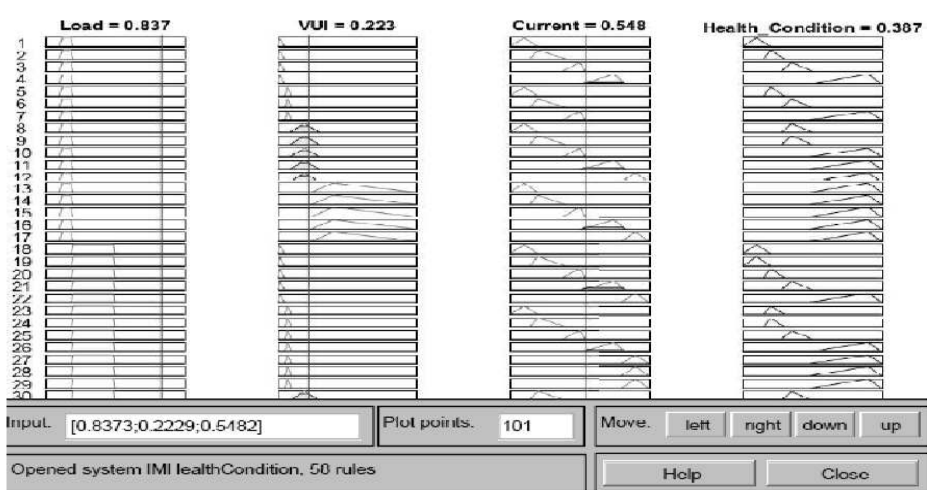

**Figure 11:** Membership function of health condition of induction motor

## 4. RESULTS AND DISCUSSION

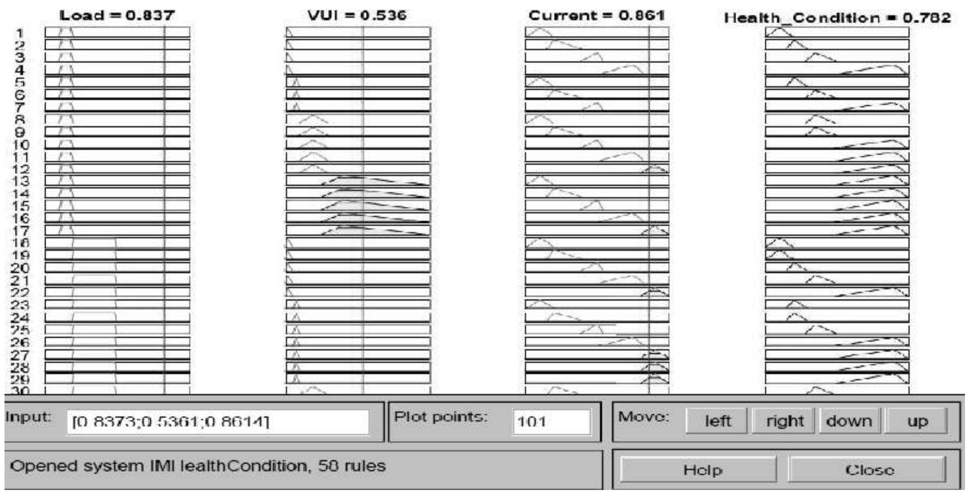
Mean of stator current, VUI and motor loads are considered as features to detect the fault severities of IM. Mamdani fuzzy inference system (MFIS) is used to predict the fault severities for its simplicity and better result prediction. The stator current of induction motor affected by various factors and fault types, mechanical load applied to it is also one of the factors. Therefore mechanical load is also considered with stator current and voltage parameters. The collected datasets are related to healthy, unbalanced stator supply, open stator winding and inter-turn short circuit faults of stator winding. Initially, the collected datasets were analyzed manually, after that linguistic variables as well as membership functions were created for improved results. The simulated results were compared and analyzed with experimental data. The three simulated results are shown by figure 12 (a), (b) and (c). The results of figure 12(a) illustrate that if motor is half loaded and VUI is extreme and mean of stator current is very high then motor is seriously faulty. The figure 12(b) demonstrates that if motor is fully loaded and voltage unbalance index is high unbalance and mean of stator current is high then motor is faulty. The results of figure 12(c) reveal that if motor is fully loaded and VUI is extreme and mean of stator current is extreme then motor is serious faulty. The surface view of rule base is also shown by figure 13. In this figure, load is denoted on x axis, the VUI is represented at y axis and fault conditions of motor are represented at z axis.




(a)




(b)




(c)

**Figure 12:**(a) (b) and (c) represent the simulated results of IM health conditions using FLS

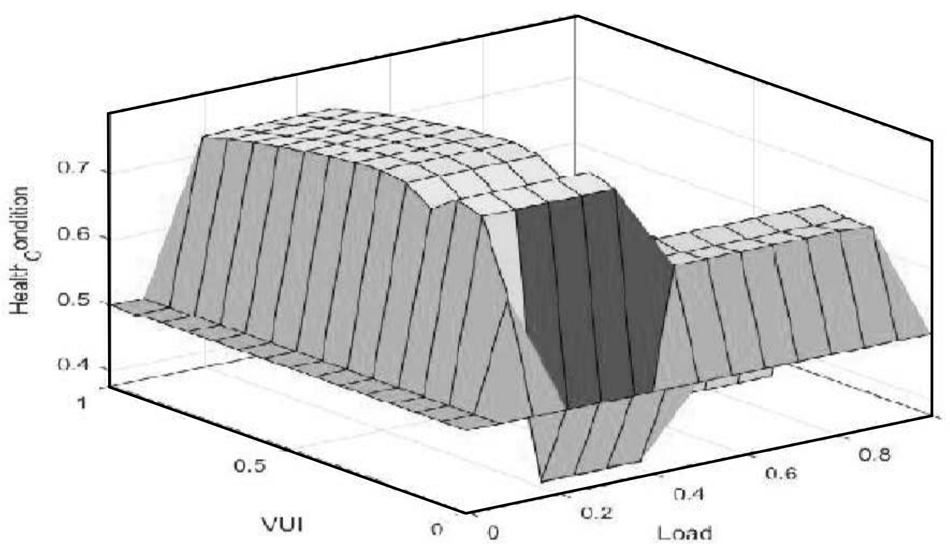



**Figure 13:** The surface view of rule bases used to diagnose health conditions of induction motor

The simulated results obtained using proposed method is shown by table 1. The results of table shows that when load is half and voltage unbalance index is extreme and mean of stator current is very high the IM is serious faulted. In this case the simulated and experimental results are same. the results of table also show that if motor is fully loaded and VUI is high unbalance and I is very high then simulated result show that IM is faulty but experimental result show that IM is serious faulty. The table show thirteen results, out of these four results were not matched with experimental results. Thus table show that approximately 70% results are accurate. In this simulation work more than hundred samples were calculated using simulation work and compared with experimental work and approximate 84% results were found true. Thus with proper training to FLS by selecting appropriate number of features and rule bases, the fault prediction can be improved.

**Table 1:** Simulated and experimental results of stator winding fault conditions of three phase induction motor

| L | VUI (Normalized value) | I (Normalized value) | FC (Experimental) | FC (Simulated) |
|---|---|---|---|---|
| 0.5 | 0.5 | 0.548 | SF | 0.755 (SF) |
| 0.837 | 0.223 | 0.548 | SF | 0.387 (F) |
| 0.216 | 0.0512 | 0.216 | H | 0.221(LH) |
| 0.837 | 0.536 | 0.861 | SF | 0.782 (SF) |
| 0.102 | 0.042 | 0.067 | H | 0.1 (H) |
| 0.102 | 0.042 | 0.157 | H | 0.15(H) |
| 0.929 | 0.858 | 0.682 | SF | 0.758(SF) |
| 0.608 | 0.858 | 0.466 | SF | 0.386(F) |
| 0.366 | 0.0871 | 0.157 | LH | 0.22(LH) |
| 0.732 | 0.288 | 0.918 | SF | 0.706(SF) |
| 0.5 | 0.5 | 0.5 | F | 0.377(F) |
| 0.069 | 0.162 | 0.037 | LH | 0.5(F) |
| 0.112 | 0.0274 | 0.117 | H | 0.1(H) |

## 5. CONCLUSION

In this work, Mamdani inference based fuzzy logic system has been used to detect stator fault severities of IM. The proposed algorithm applies the concept of fuzzy logic to diagnose the health conditions of three phase induction motor using mean of three phase stator currents, voltage unbalance index (VUI) and motor load. In this manuscript, the uncertainty of result prediction due to unbalance supply and motor load variations of spectrum analysis were tried to mitigate by selecting proper feature variables. The validation of proposed algorithm has been verified using experimental setup and result shows tremendous improvement in diagnosing stator health conditions.

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