

A Hybrid TSA-Fuzzy Logic Approach to Detect Induction Motor Rotor Faults

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Abstract—This paper treats the broken rotor bar fault detection and diagnosis in induction motors. Indeed, the broken rotor bar fault do not have an initial effect can lead an induction motor to fail, there can be serious secondary effects. In this context, a new fault detection and diagnosis approach, namely the TSA-Fuzzy are presented. This technique uses the residual current, obtained by the TSA method. In fact, this current enables to detect faults that cannot be detected by analyzing the stator current, especially in the low load motor case. The RMS of residual current and the load will be used as inputs for the fuzzy logic bloc, where the decision about the state of the rotor is made. The results show the reliability and the efficiency of the proposed approach.

Index Terms—Broken Rotor Bar, Condition Monitoring, Fuzzy Logic, Induction Motors, Time Synchronous Averaging (TSA).

I. INTRODUCTION

Because of their advantages such as simplicity, robustness, low cost and adaptation with many applications in different fields, induction machines have a crucial importance in industry. Some of these machines are a squirrel cage type, this kind is considered to be a robust, reliable and easily adapted at several load conditions [2]. Despite these encouraging features, induction machines can present some electrical faults, such as, short-circuit between phases, Interruption of a phase and magnetic circuit fault, and some mechanical faults, such as break up of rotor bars, breaking up of end-rings and unbalanced rotor [1]. These defects are all a source of damages to the motor itself as well as the associated motor equipment. Therefore, there is a strong necessity to develop condition-monitoring techniques to address these matters and to allow earlier detection of rotor faults [3].

The investigations on different failure modes in induction machines prove that the rotor related faults are around 10% including broken rotor bar fault, which is the subject of this paper [4], [5]. These faults can lead the motor to interruption, causing unexpected shutdowns of the industrial process, resulting in considerable economic losses [6].

There are a great number of researchers developing many diagnostic methods used to detect rotor faults in induction motors. Temperature measurements [7], infrared recognition [8], noise and vibration monitoring [9], motor-current signature analysis (MCSA) [10], neural network and fuzzy systems

[11], [12]. The objective of these techniques is the detection and identify the state of the motor in the current instant. These methods provide high reliability with a good database for diagnosis. In the last years, several diagnosis techniques were used to supervise the broken rotor bar faults, such as vibration analysis and stator current analysis [13], [9]. Most of these conventional techniques are able to detect and indicate faults but could not provide detailed information about location and severity of the fault because they were not suitable for non-stationary signal.

Stator current signals from induction motor are usually noisy and with the properties of non-stationary [14]. As a result, it is difficult to find a potential early failure without appropriate analysis tools.

A new method exploiting stator current signals is developed for the motor condition monitoring. Many researchers have investigated the TSA method for rotor fault detection, in which TSA resamples the stator current data synchronously. This helps to obtain a definite periodic signal and reduce the noise influence [15], [16].

There are many studies using the stator current and fuzzy logic to detect broken rotor bar faults [17]. Furthermore, a broken rotor bar fault at a premature phase, which can lead to a larger failure or even be catastrophic, may not be detectable even under full load conditions. Therefore, there is a strong necessity to develop condition-monitoring techniques to address these matters to allow earlier detection of rotor faults.

The aim of this paper is to monitor the condition of an induction machine by analysis of the residual current obtained from the TSA method, based on fuzzy logic. This approach consists in modeling data extracted from the current and approaching it to a certain extent of flexibility of human reasoning in order to avoid using input/output model, which is still insufficient to detect defects in the machine. In this work, a modeling presentation of changes in residual current by fuzzy way is established. The obtained models are formulated in linguistic form and treated with a form to provide fuzzy conclusions on the engine condition. This helps to make the right decision to determine the degree of membership of the value measured at a fuzzy set. The model of this approach is

simulated by using software MATLAB/SIMULINK. To verify the efficiency of this method, a special 3 kW industrial three-phase induction motor has been designed in order to create a broken-rotor-bar fault at several levels. Experimental results exhibit the good performances of the proposed diagnosis approach.

The rest of the paper is structured as follows: Section II presents a theoretical study of fuzzy logic. Section III depicts the architecture of “Time Synchronous Averaging” approach. Section IV describes the details of the process, followed by a presentation of the results and discussion. Section V finally gives the conclusions.

II. ARCHITECTURE OF THE COMBINED TSA – FUZZY LOGIC APPROACH

A. Time Synchronous Averaging (TSA)

In this work, only key points of the TSA analysis are presented, for more details are referred in this paper [18]. Time synchronous averaging is a signal processing technique that extracts periodic waveforms from noisy data. The TSA is well suited for induction motor diagnosis, where it allows the separation between the excitation sources and, consequently, fault identification.

Formally the stator current can be decomposed as follows :

$$I_s(t) = I_{s_h}(t) + I_{s_{mec}} + n(t) \quad (1)$$

where $I_{s_h}(t)$, $I_{s_{mec}}$ and $n(t)$ are respectively the harmonic stator current harmonic component, the mechanical-structure-related stator current, and the noise.

In order to detect broken bar faults, Researchers have established sideband components around the fundamental frequency. In fact, if the rotor is damaged, a set of new components at frequencies $f_b = (1 \pm 2k \cdot s)f_0$ appears in the spectrum of the stator currents, where f_b is the Sideband components, f_0 is Fundamental frequency, s is Motor slip and $k = 0, 1, 2, \dots, n$. [19].

Therefore, the fundamental frequency which is related to electrical phenomena must be separated from mechanical-structure-related frequency must be separated.

To eliminate those unwanted in the analysis, the TSA method will be applied to the stator current. The following relation, as established in (2) does T_h -period TSA of stator current:

$$\langle I_s \rangle_{T_h}(t) = \lim_{K \rightarrow +\infty} \frac{1}{K} \sum_{k=1}^K I_s(t + k \cdot T_h) = I_{s_h}(t) \quad (2)$$

where $\langle I_s \rangle_{T_h}(t)$ is a train of K impulses of amplitude $\frac{1}{K}$ and $T_h = 1/f_s$ is the harmonic period and $f_s = 50Hz$ the harmonic frequency corresponding to supply frequency. Once the harmonic part of the stator current $I_{s_h}(t)$ corresponding to 50Hz frequency have been identified. The synchronous averaging allows an effective separation between electrical-related and mechanical-related components. The subtraction

between the stator current and its TSA gives the residual current where only mechanical-related frequencies remain, as shown in (3):

$$I_{res}(t) = I_s - \langle I_s \rangle_{T_h} \quad (3)$$

B. Condition Monitoring of Induction Motor Based Fuzzy Logic

A scheme of the fuzzy system diagnosis is shown in Fig. 1. The value of K and the load will be used as inputs for the fuzzy system. The numerical inputs data are converted as linguistic information. By fuzzy inference, using a knowledge base, compressing a rule and data base, the condition monitoring of the rotor, is then obtained as output.

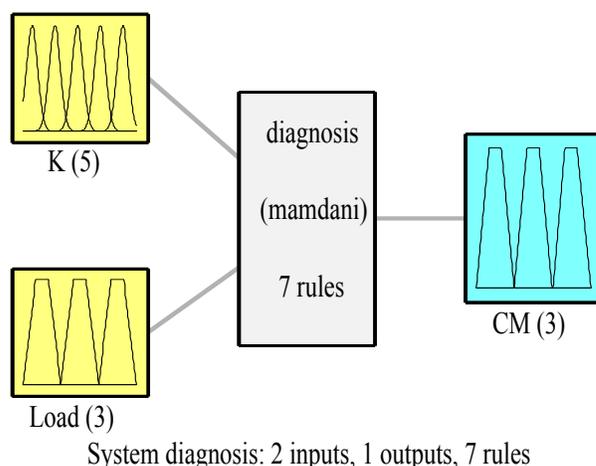


Fig. 1. System diagnosis using fuzzy logic

Fuzzy set theory is based on the notion of partial membership: each element partially or gradually up to the fuzzy sets that have been defined already. A system based on fuzzy logic allows the transformation of linguistic terms into numerical values via fuzzy rules and membership functions and is able to approximate the complex relationships related to the diagnostic task. Fuzzy logic has been applied to condition monitoring and fault diagnosis for electric motors [20], [21]. A membership function allows a quantity, such as a residual current, to be associated with a linguistic variable with some degree of truth. For example, the same figure shows the membership functions for the ratio of the residual current in defective condition and healthy state of an induction motor. In Fig.2, the vertical axis is the residual measured current normalized to the residual current of the supposed healthy state of the motor. The horizontal axis indicates how residual current is associated to five linguistic variables denoted as “Very Small” (VS) “small” (S) “means” (M), “large” (L) or “Very Large” (VL).

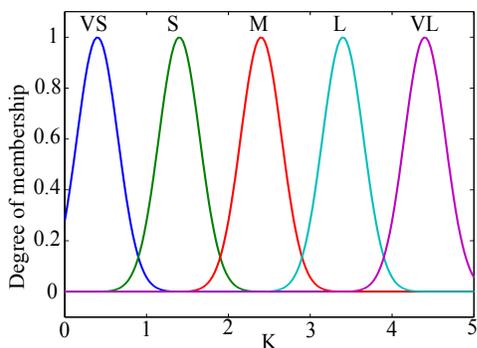


Fig. 2. Membership functions for K.

In Fig.3, the vertical axis is the load condition. The horizontal axis indicates how residual current is associated to three linguistic variables denoted as “Low Load”, “Half Load” and “Full Load” .

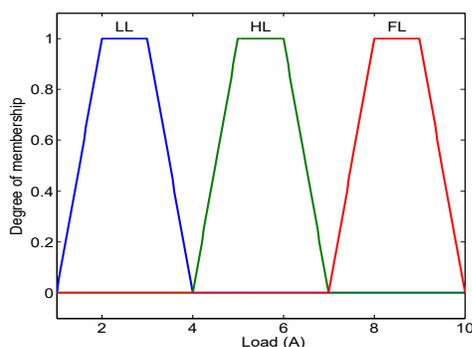


Fig. 3. Membership functions for Load.

Fig.4 formulates the status of the linguistic term monitoring of "Good", "Damaged" and "Severely Damaged". This provides the membership function of the output variables:

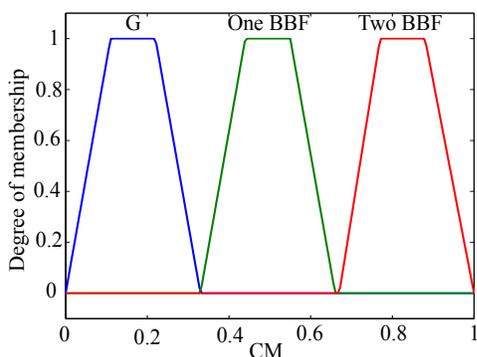


Fig. 4. Membership functions for CM.

To cover all healthy and defective cases of this study, the following rules are used:

- 1) Rule (01): “If K is VS then CM is G”.

- 2) Rule (02): “If K is S and Load is LL then CM is One BBF”.
- 3) Rule (03): “If K is S and Load is HL then CM is Two BBF”.
- 4) Rule (04): “If K is M then Load is HL is One BBF”.
- 5) Rule (05): “If K is M and Load is FL then CM is Two BBF”.
- 6) Rule (06): “If K is L and Load is FL then CM is Two BBF”.
- 7) Rule (07): “If K is VL then CM is Two BBF”.

where K is the ratio between the Root Mean Square (RMS) value of residual current measured and the RMS value of residual current healthy state and CM is the condition monitoring.

C. The Proposed hybrid “TSA-Fuzzy Logic” motor fault algorithm

The algorithm illustrated by Fig. 5 shows the proposed induction-motor condition monitoring method, based on the combination of TSA and fuzzy logic.

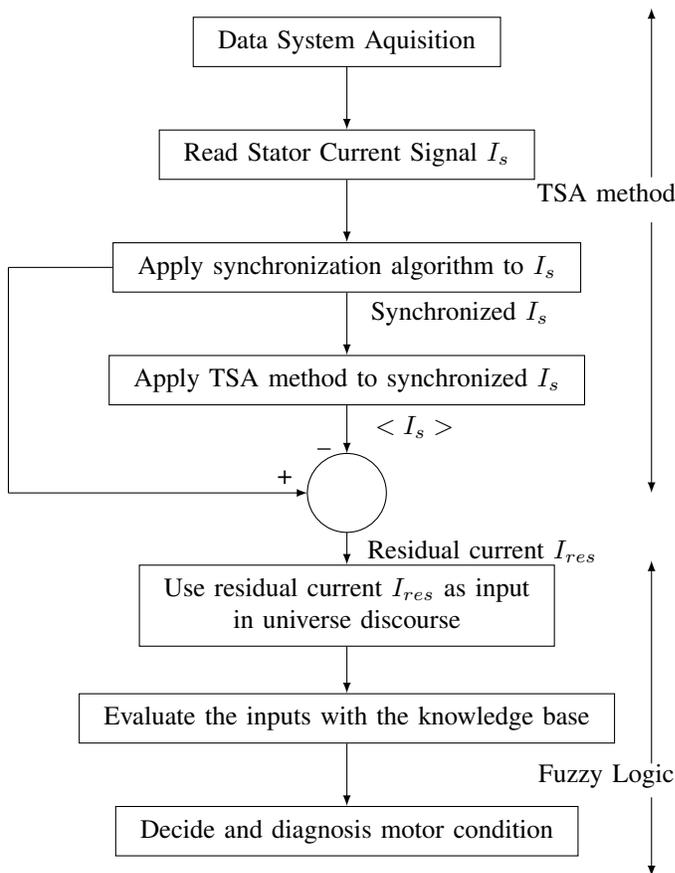


Fig. 5. Flowchart of the proposed hybrid “TSA_Fuzzy Logic” technique diagnosis.

III. RESULTS AND DISCUSSION

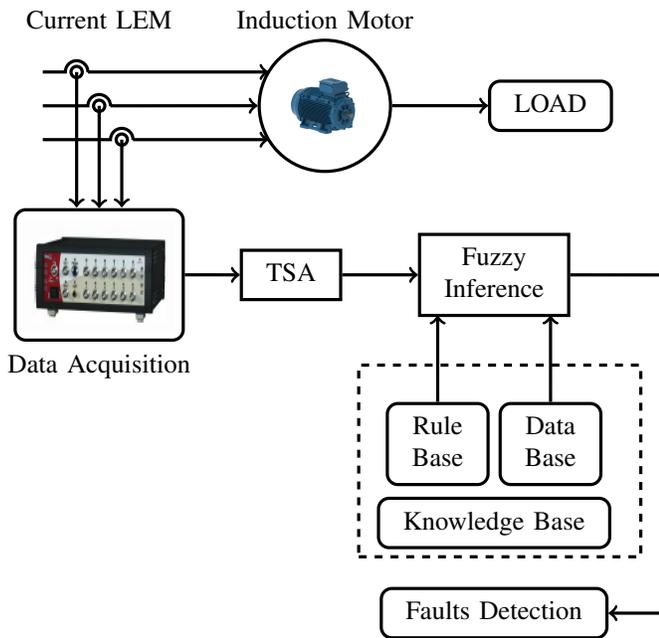


Fig. 6. Block Diagram of the implementation for diagnosis system

Initially, the induction motor is tested in absence of faults to determine its healthy state. Afterwards, the same experiment is carried out with a defective motor.

A. results

A simple comparison between the oscillogram of the stator current in the healthy and defective modes of machine under different load conditions does not allow us to detect the failure as shown in figure 7. 8 and 9. The stator current cannot thus be used as a sensitive rotor defect indicator. By application of the TSA, we obtain by subtraction the residue related to the machine mechanics. After using the oscillograms of the residual currents, these oscillograms will allow the easy distinction of the healthy and defective cases as shown In Fig.10, Fig. 11 and Fig. 12.

The objective of this work is to conceive an efficient fuzzy system to diagnosis the induction motor rotor. To overcome this drawback, the TSA was applied to the stator current. When the TSA was applied the residual current was extracted then K was calculated as the ratio between the Root Mean Square (RMS) value of residual current measured and the RMS value of residual current healthy state. The value of K were transferred into the corresponding discourse universe at the input. The fuzzy logic inference engine evaluates the inputs with the knowledge base and then diagnoses the motor condition. The value of K and the stator current will be used as inputs in the fuzzy system, and the condition monitoring of the rotor is obtained as output.

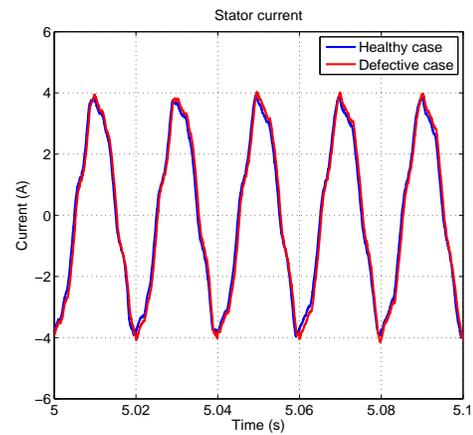


Fig. 7. Stator current in time domain in low load motor.

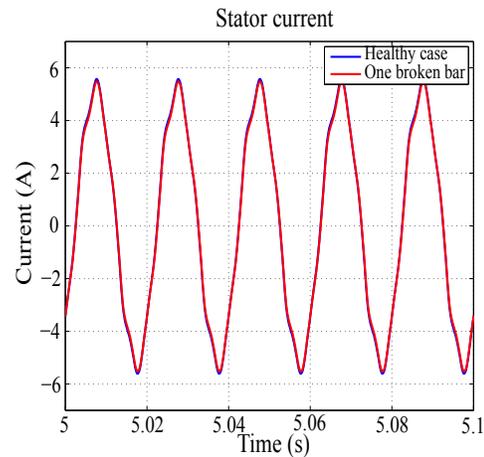


Fig. 8. Stator current in time domain in half load motor.

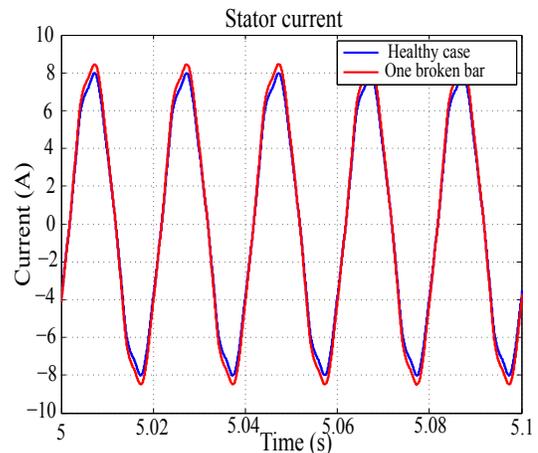


Fig. 9. Stator current in time domain in full load motor.

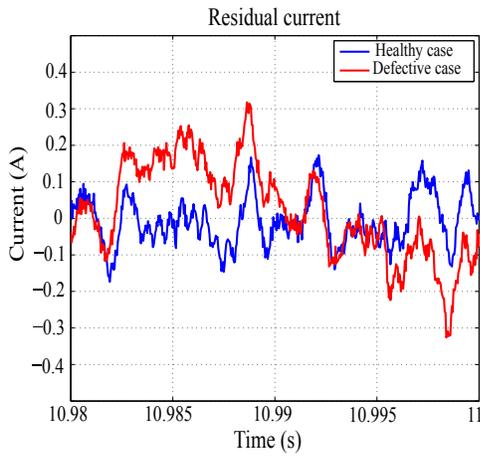


Fig. 10. Residual current in low load motor.

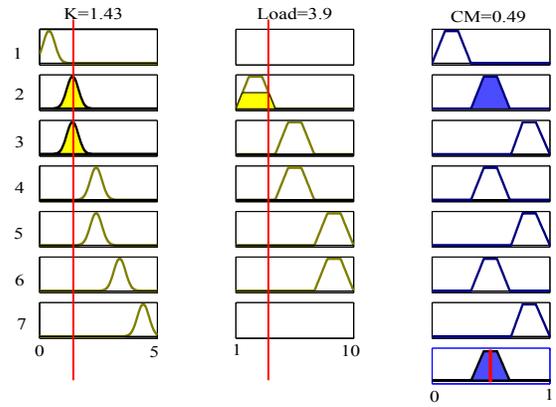


Fig. 13. Rule view for low loaded motor.

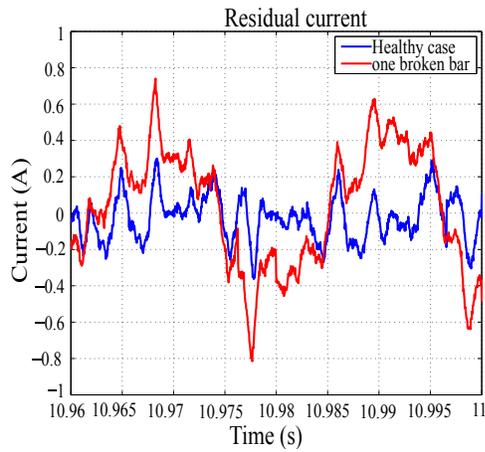


Fig. 11. Residual current in half load motor.

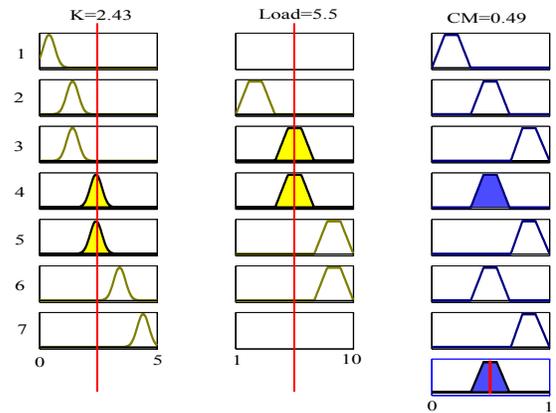


Fig. 14. Rule view for half load motor.

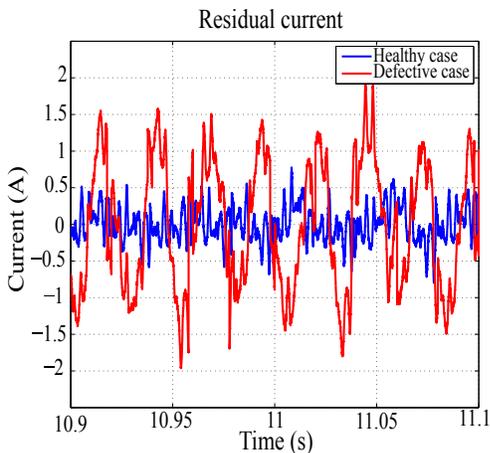


Fig. 12. Residual current in full load motor.

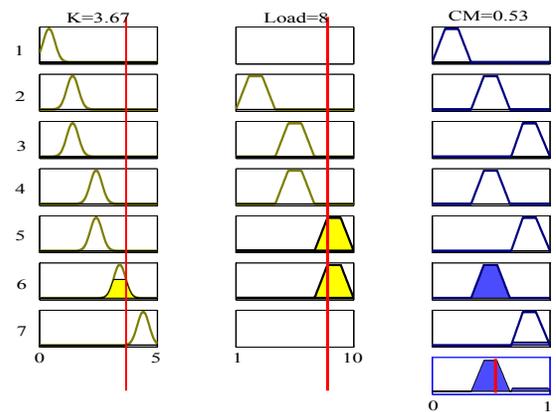


Fig. 15. Rule view for full load motor.

B. Discussion

The aim of this paper was to demonstrate the usefulness of combining residual current to fuzzy logic. Using the system

depicted in Fig. 6, stator current was measured, and residual current was calculated by the subtraction between the stator current and its TSA. Finally, fuzzy logic was applied to residual current in order to detect the induction-motor fault. In order to show the utility and efficiency of the combination of the fuzzy logic with TSA approach, several tests were performed to obtain motor measurements under different loads (low load, half load and full load) using the healthy motor, then a motor with one broken bar. Fig. 13, Fig. 14 and Fig. 15 show the use of fuzzy system for diagnosis the induction motor rotor in different case of load. For example, for $K=1.43$ and Load is low, condition monitoring value is 0.49, which corresponds to the one broken bar in low load. For $K=2.43$ and Load is half load, condition monitoring value is 0.49, which corresponds to the one broken bar in half load. For $K=3.67$ and Load is full load, condition monitoring value is 0.53, which corresponds to the one broken bar in full load. The experimental test proves the performances of the proposed fuzzy logic with TSA approach. The technique is capable to ensure highly accurate diagnosis.

IV. CONCLUSION

This paper applies a new method to monitoring the motor conditions using Time Synchronous Averaging (TSA) and fuzzy logic in order to make an effective and reliable diagnosis. The method is based on the extraction of the residual current by the TSA method and calculating the value of their root mean square (RMS). The processing of this current is then done using fuzzy logic. The ratio between the RMS value of residual current measured and the RMS value of residual current healthy state are employed as input in the fuzzy logic block, the obtained result in output of the fuzzy logic block provides a diagnosis of the healthy state or faults of the induction machine. This method enables to make an accurate judgment of the motor's operating status. It also gives the right decision to rectify or take precautions. Therefore, we can avoid the motor failure and increases its availability, reliability, and performance.

APPENDIX

TABLE I
ELECTROMECHANICAL CHARACTERISTICS OF INDUCTION MOTOR

Motor parameters	Values
Nominal power	3kW
Nominal voltage RMS value	400 V
Nominal stator frequency	50 Hz
Stator resistance	1.9Ω
Stator leakage inductance	11.5 mH
Rotor resistance	4.0Ω
Rotor leakage inductance	11.5 mH
Mutual inductance	239.7 mH
Number of pole pairs	2

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