A Hybrid Monitoring Technique for Diagnosis of Mechanical Faults in Induction Motor

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Abstract

The paper aims to engineer an efficient technique for the condition monitoring of induction motor that not only provides the detection and identification of the faults but also assesses the operational condition of the motor. Induction motors possess one of the most important roles industrially and commercially. The developing faults in the motors can become catastrophic, if remain unanalyzed. The paper presents an effective novel solution to diagnose the major mechanical faults at the early possible stage by utilizing two efficient condition monitoring techniques to effectively deploy the strategies for the predictive maintenance. Primarily it employs the MCSA (Motor Current Signature Analysis), in which the faults are located by the spectral analysis of the particular harmonic components in the line current at specific characteristic frequencies generated by specific faults as the unique rotating flux. Fuzzy logic system has also been utilized, which assesses severity of the fault and operating condition of machine. The induction machine's modular Simulink implementation has been presented that unlike other approaches provides the access to almost all parameters of the machine for analysis and control purposes. The mechanical faults specially bearing and eccentricity faults are simulated and successfully detected and localized in the results along with the severity assessment of the operational condition due to simulated faults.

Keywords: Bearing faults, Condition Monitoring, Eccentricity, Fault Diagnosis, Fuzzy Logic, MCSA

1. Introduction

Fault diagnosis and Online condition monitoring has emerged extensively because of the wide applications of automation and subsequent depletion in the man machine interfacing to administer the motor drive operation[1,2]. Induction motors are the Ninety percent of the Electric motors in industry[3] and are responsible for forty to fifty percent of the consumption of energy, in an industrialized country[4]. However, they possess the vulnerability to certain faults, which may result the catastrophe if left unanalyzed and may even lead to the shutdowns and extensive human as well as economic losses. Condition monitoring would be the most feasible solution in that case as most of these failures do not cause all of a sudden but slowly degrade[5]. So there is the provision to detect these faults, their location and the severities at early so that predictive maintenance strategies can be planned to tolerate the development of any major failure that would ultimately lead to the substantial cost savings, improved reliability increased and industrial efficiency.

Condition monitoring of induction motor has been remained one of the challenging tasks for the researchers. In the[6,7] model based approach is employed that uses a parallel dynamic model along with the real process but the major demerit is the requirement of the dynamic accurate model and the continuous latter simulation. Numerous methods have been introduced over the years like vibration, temperature, acoustic emission monitoring but they require additional sensors and can only be used for analysis of specific faults[8–10]. Vibrations of the motor for monitoring the operational condition have been used

in[3]. Vibration has traditionally been used to analyze the mechanical faults of the machine[10], however vibrations are from unique electromagnetic forces caused by the specific faults are comparatively second order effects as compared to the current components that are induced directly by the specific rotating flux. In majority of the cases, the severity of fault has to be severe before the detection by vibration[4]. MCSA has emerged as the most efficient and reliable method for the induction motors condition monitoring and can solely be used to analyze almost all major faults[11]. It is a non-invasive method, based on the spectral analysis and decomposition of the stator current that is acquired using simple measurement tools and under normal machine operation. MCSA can even detect the developing faults can at early possible stage[2]. One of the greater advantages of MCSA is the processing of an electric signal that possesses the current components that are the direct by-products of faults unique rotating flux components and it also curtails the usage of cost and maintenance of additional sensors and thereby empowers stability in the system.

Fuzzy logic has also been proven to be an efficient approach for the condition monitoring and prediction of complex, vague and nonlinear systems[3]. Fuzzy logic is also attractive because of its capability to diagnose problems even in the absence of mathematical models[12]. The paper applies fuzzy logic for induction motor monitoring depending on the amplitude features of stator currents. A hybrid Neuro-Fuzzy technique has also been used previously[13], but it can only be limited to analyze specific faults and would not be efficient to analyze the mechanical faults directly from the motor current. The presented approach using the combination of MCSA and Fuzzy logic can analyze almost all major induction motor faults.

Figure 1 illustrates the overview of the designed system. The hybrid monitoring techniques of MCSA and fuzzy logic have been used where MCSA is employed for the fault detection and localization whereas fuzzy logic system determines the fault severity and operational condition of the motor.

Mechanical faults especially bearing and eccentricity faults possess the major impact and collectively contribute more than 50% of all faults[8,14]. Therefore, these two faults are mainly considered for the analysis. Rough operation of bearings results the radial motion between the stator and rotor, upsetting the torque and speed of the motor[5]. Eccentricity is the misalignment of the rotor and stator axis that is caused due to of unbalanced load, elliptical stator inner cross-section, wrong placement bearing etc. The consequences are the unbalanced magnetic pull and radial forces and change in the air gap flux density distribution[14].

2. Proposed Methodology

2.1 Induction Motor Modeling
Paper presents the modular approach for simulation of the dynamic performance of induction motor model whose variables of rotor and stator are referred to an arbitrary reference frame. In modular approach, each block solving one of the model equations, provides almost all of major machine for verification and control purposes. Figure 2 presents the dq equivalent circuit of the induction motor in arbitrary reference frame[15]. One of the most efficient models derived from this circuit is krasue's model in[16].

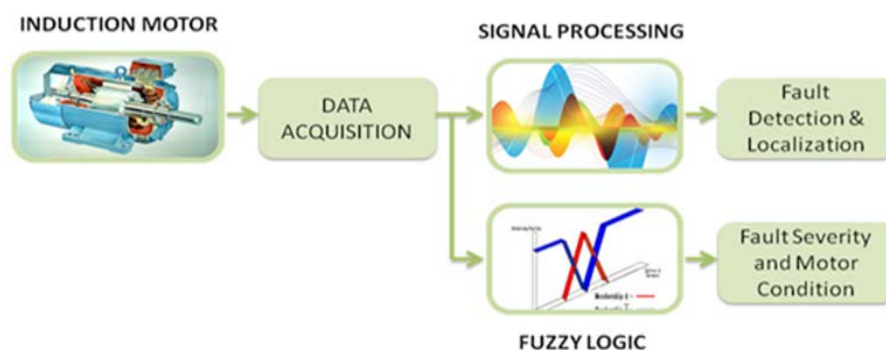The flux linkage equations for this model are as follows:

Figure 1. Overview of the designed system.

$$\frac{dF_{qs}}{dt} = \omega_b\left[v_{qs} - \frac{\omega_e}{\omega_b}F_{ds} + \frac{R_s}{x_{ls}}\left(\left(\frac{x_{ml}^{\bullet}}{x_{ls}} - 1\right)F_{qs} + \frac{x_{ml}^{\bullet}}{x_{lr}}F_{qr}\right)\right] \tag{1}$$

$$\frac{dF_{ds}}{dt} = \omega_b\left[v_{ds} - \frac{\omega_e'}{\omega_b}F_{qs} + \frac{R_s}{x_{ls}}\left(\left(\frac{x_{ml}^{\bullet}}{x_{ls}} - 1\right)F_{ds} + \frac{x_{ml}^{\bullet}}{x_{lr}}F_{dr}\right)\right] \tag{2}$$

$$\frac{dF_{qr}}{dt} = \omega_b\left[\frac{R_r}{x_{lr}}\left(\left(\frac{x_{ml}^{\bullet}}{x_{lr}} - 1\right)F_{qr} + \frac{x_{ml}^{\bullet}}{x_{ls}}F_{qs}\right) - \frac{[(\omega)]_{e-}\omega_r)}{\omega_b}F_{dr}\right] \tag{3}$$

$$\frac{dF_{dr}}{dt} = \omega_b\left[\frac{R_r}{x_{lr}}\left(\left(\frac{x_{ml}^{\bullet}}{x_{lr}} - 1\right)F_{dr} + \frac{x_{ml}^{\bullet}}{x_{ls}}F_{ds}\right) + \frac{[(\omega)]_{e-}\omega_r)}{\omega_b}F_{qr}\right] \tag{4}$$
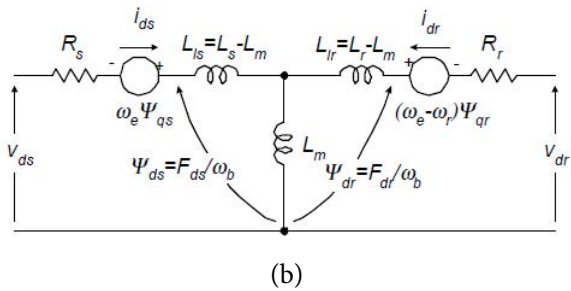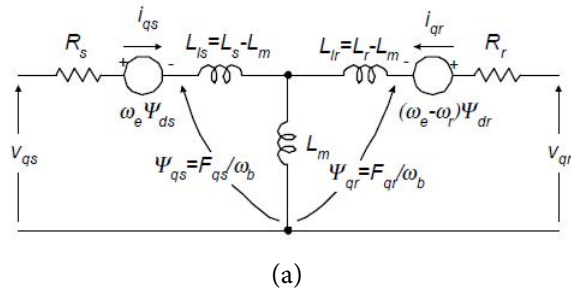

(a)

(b)

Figure 2. Dynamic dq equivalent circuit of induction machine. (a) d axis. (b) q axis.

The current Equations of the circuit based on the flux linkages would be as under:

$$i_{qr} = \frac{1}{x_{ls}\left(F_{qr} - F_{mq}\right)} \tag{5}$$

$$i_{qs} = \frac{1}{x_{ls}\left(F_{qs} - F_{mq}\right)} \tag{6}$$

$$i_{dr} = \frac{1}{x_{ls}\left(F_{dr} - F_{mq}\right)} \tag{7}$$

$$i_{ds} = \frac{1}{x_{ls}\left(F_{ds} - F_{md}\right)} \tag{8}$$

Where, $F_{md} = x_{ml}^{\bullet}\left[\frac{F_{ds}}{x_{ls}} + \frac{F_{dr}}{x_{lr}}\right]$ and

$$F_{mq} = x_{ml}^{\bullet}\left[\frac{F_{qs}}{x_{ls}} + \frac{F_{qr}}{x_{lr}}\right]$$

The electromagnetic torque and rotor speed equations would be written as:

$$T_e = \frac{3}{2}\left(\frac{p}{2}\right)\frac{1}{\omega_b}\left(F_{ds}i_{qs} - F_{qs}i_{ds}\right) \tag{9}$$

$$\frac{d\omega_r}{dt} = \frac{p}{2J}\left(T_e - T_L\right) \tag{10}$$

For the dq axis transformation, the three phase input voltages have been transferred to a synchronously rotating reference frame in the two phases by implementing the following three Equations

$$\begin{bmatrix} v_{qs}^{s} \\ v_{ds}^{s} \end{bmatrix} = \frac{2}{3}\begin{bmatrix} 1 & \frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix}\begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} \tag{11}$$

$$v_{ds} = v_{qs}^{s}\sin\theta_e + v_{ds}^{s}\cos\theta_e \tag{12}$$

$$v_{qs} = v_{qs}^{s}\cos\theta_e - v_{ds}^{s}\sin\theta_e \tag{13}$$

Where, $\theta_e = \int\omega_e dt$ \tag{14}

Finally, the values of the rotor currents and stator currents in three phase system are then calculated from the dq axis using the following transformation

$$i_{ds}^{s} = -i_{qs}\sin\theta_e + i_{ds}\cos\theta_e \tag{15}$$

$$i_{qs}^{s} = i_{qs}\cos\theta_e + i_{ds}\sin\theta_e \tag{16}$$

$$\begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} = \frac{2}{3}\begin{bmatrix} 1 & 0 \\ -\frac{1}{2} & -\frac{\sqrt{3}}{2} \\ -\frac{1}{2} & \frac{\sqrt{3}}{2} \end{bmatrix}\begin{bmatrix} i_{qs}^{s} \\ i_{ds}^{s} \end{bmatrix} \tag{17}$$

Simulink implementation of the presented induction motor model is shown in the Figure 5.

Where, i_{ds}, i_{qs}, i_{dr}, i_{qr} : dq stator and rotor currents. v_{ds}, v_{qs} : dq stator voltage. F: flux linkage. R_s, R_r, x_{ls}, x_{lr} : stator and rotor resistance and reactance, ω_b, ω_e, ω_r : motor angular electrical base frequency, stator angular electrical frequency, rotor angular electrical speed,

$$x_{ml}^{\bullet} = 1 \div \left(\frac{1}{x_m} + \frac{1}{x_{ls}} + \frac{1}{x_{lr}}\right)$$

2.2 Fault Diagnosis and Condition Monitoring Techniques

MCSA has proved to be one of the most efficient techniques over the years for the detection and identification of the faults. However, it lacks to assess the overall operational condition of the motor. Therefore, Fuzzy Logic is used in conjunction with MCSA to assess the operational state of the motor and to determine the overall damage caused by the occurred faults.

2.2.1 Motor Current Signature Analysis

Implementation of a suitable signal analysis algorithm can provide feasibility to inquire the signals changes produced by faulty components. FFT is used for the signal processing that provides more insight regarding the components of signal and is efficient for decomposition of the signal into the harmonic components, thus presents productive frequency spectrum of the stator current of the motor that leads to the accurate motor current signature analysis[2,11]. The fact which must be taken into account here is that the load conditions of the motors are not the same always; this may also alter the characteristics of fault signature as well[1,11]. The main objective of the technique described in this paper, is the identification of the frequency components associated with the types of failures, independently from the motors' operating conditions. Therefore, to overcome this phenomenon and the masking effect, Hanning window has been used with the FFT to reduce the discontinuity.

Each specific fault results the harmonics at a specific characteristic frequencies in the stator current. Those frequencies are the functions of motor's characteristics data and operating conditions and represent the signatures of specific fault.

The frequency for the bearing fault signatures in the stator current can be given by[17,18]:

$$f_{bf} = |f_s \pm k f_c| \tag{18}$$

Where, f_s is the supply frequency, f_c is the fault characteristic frequency and k = 1,2,3…

For most of the bearings having rolling elements between 6 and 12, these frequencies can also be approximated as[17] :

$$f_o = 0.4 N_b f_r \tag{19}$$

$$f_i = 0.6 N_b f_r \tag{20}$$

Where, f_i and f_o are the inner and outer raceway fault frequencies while N_b is number of rolling elements and f_r is the mechanical rotor frequency.

For the eccentricity fault indicators, the simplified equation can be represented as the rotor frequency sidebands of the supply frequency[14]:

$$f_{ec} = f_s \pm k f_r \tag{21}$$

2.2.2 Fuzzy Inference System

Fuzzy inference system uses inferential engines on the linguistic variables and employs fuzzy if-then rules to build the data bases[19]. Magnitudes of the stator currents have been employed as the inputs to the fuzzy system. The operating condition of the motor, "condition" is set as the fuzzy output. All the inputs and output are defined by the Fuzzy set theory. Stator currents (i_a, i_b and i_c) are represented linguistically as t(Q) = {very-small, small, medium, big}. Similarly, the set t(condition) represents the motor operational condition linguistically as t(condition) = {good, damaged, severely-damaged}.

The input current values are categorized by the membership functions using the linguistics forms as shown in Figure 3(a), where the horizontal axis presents the numerical value that are related with the categories, i.e., 'very small', 'small', 'medium' and 'large' and vertical axis presents the degree of truth between 0 and 1. Similar procedure is utilized for the configuration of the output 'condition' membership function. The membership functions for the 'condition' output in linguistic forms are 'Good', 'Damaged' and 'Severely Damaged' as seen Figure 3(b).

Finally, the *if-then* rules shown in Figure 4 have been implemented to cover all the faulty and healthy cases of motor.

(a)

(b)

Figure 3. Fuzzy membership functions. (a) Stator currents. (b) Stator condition.
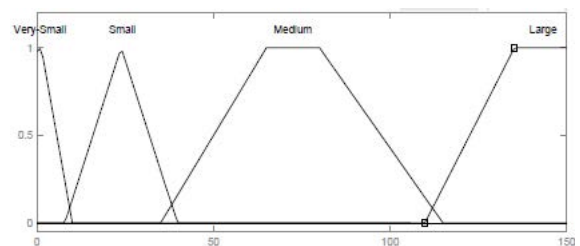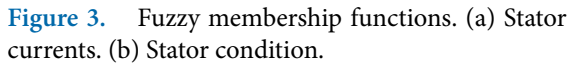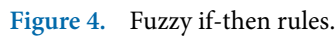
3. Simulation

Figure 5 shows the complete system model simulated in the SIMULINK. The motor that is simulated is a 30 kW three phase squirrel cage induction motor, operating at 220 V, 50 Hz supply. Table 1 presents the parameters for the selected motor. The overall operation of the system is graphically described by the flow chart shown in Figure 6.

3.1 Simulation of faults

One of the most challenging tasks is to introduce the

1. If (Ia is very_small) then (Condition is Severly_Damaged) (1)
2. If (Ib is very_small) then (Condition is Severly_Damaged) (1)
3. If (Ic is very_small) then (Condition is Severly_Damaged) (1)
4. If (Ia is large) then (Condition is Severly_Damaged) (1)
5. If (Ib is large) then (Condition is Severly_Damaged) (1)
6. If (Ic is large) then (Condition is Severly_Damaged) (1)
7. If (Ia is small) and (Ib is small) and (Ic is medium) then (Condition is Damaged) (1)
8. If (Ia is small) and (Ib is medium) and (Ic is small) then (Condition is Damaged) (1)
9. If (Ia is medium) and (Ib is small) and (Ic is small) then (Condition is Damaged) (1)
10. If (Ia is medium) and (Ib is medium) and (Ic is medium) then (Condition is Good) (1)
11. If (Ia is medium) and (Ib is medium) and (Ic is small) then (Condition is Good) (1)
12. If (Ia is medium) and (Ib is small) and (Ic is medium) then (Condition is Good) (1)
13. If (Ia is small) and (Ib is medium) and (Ic is medium) then (Condition is Good) (1)

Figure 4. Fuzzy if-then rules.
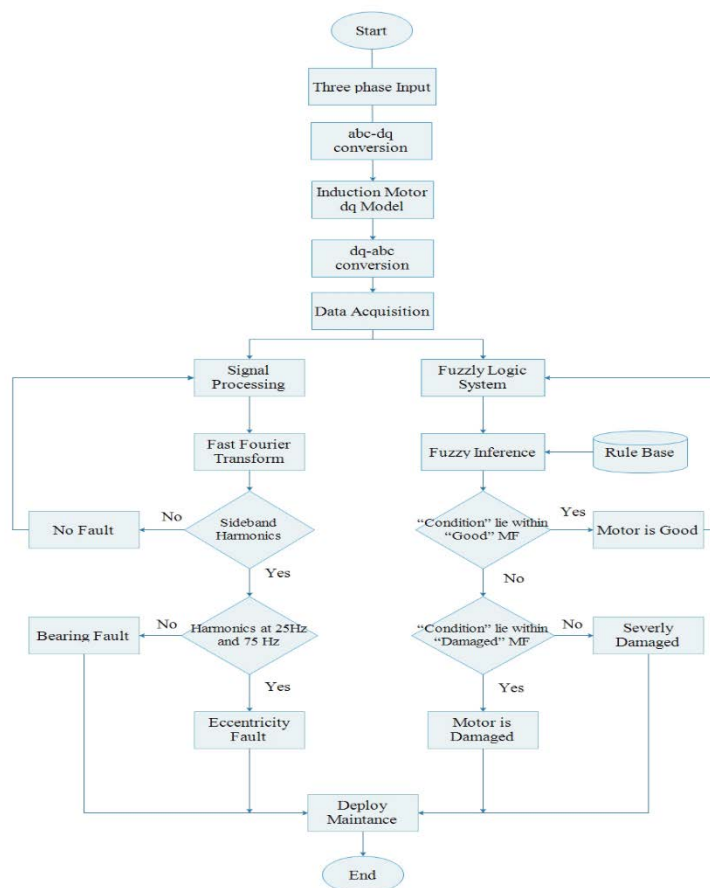

Figure 5. Complete system model.

Figure 6. System flow chart.

mechanical faults in the simulation model as these faults are the mainly the functions of the mechanical characteristics of the motor that are difficult to simulate. The presented model presents the versatility to simulate the bearing and eccentricity faults. It has been analytically and experimentally validated that inductances of the induction motor are directly affected by the eccentricity faults[20]. Bearing faults causes the load torque oscillations and have the direct impact on the torque of the machine[17,18]. Therefore, these faults are simulated by means of the load torque variations and mutual inductance of the machine presented in the proposed model.

Table 1. Parameters of Induction motor

Parameter	Value
Rotor resistance	0.40 Ω
Stator resistance	0.20 Ω
Rotor inductance	0.60 mH
Stator inductance	0.21 mH
Mutual Inductance	4 mH
Number of poles	4
Moment of inertia	0.0226 kgm²

4. Results and Discussion

Figure 7 is representing the MCSA of the healthy machine, with no side bands across the supply frequency component. Introduction of any fault causes the variation in the spectrum of the stator current. Experiments have been performed by simulating the faults for analysis of the designed system. Eccentricity faults generate the characteristic components at 25 Hz and 75Hz as the supply frequency sidebands, corresponding to Equation (21). Figures 8 show the location of the eccentricity faults in the stator current spectrum.
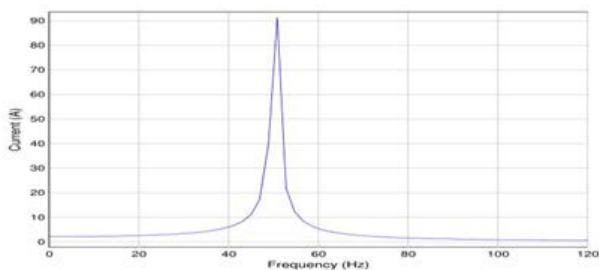
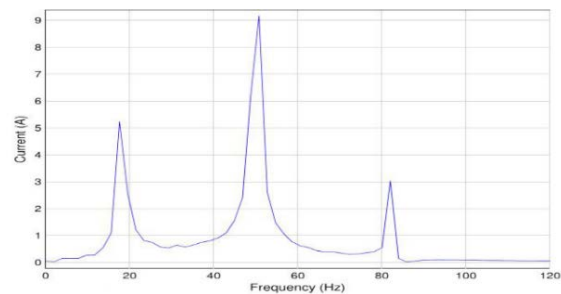**Figure 7.** Healthy induction motor.
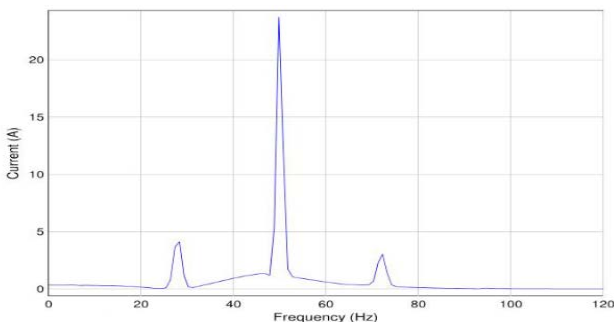
(a)
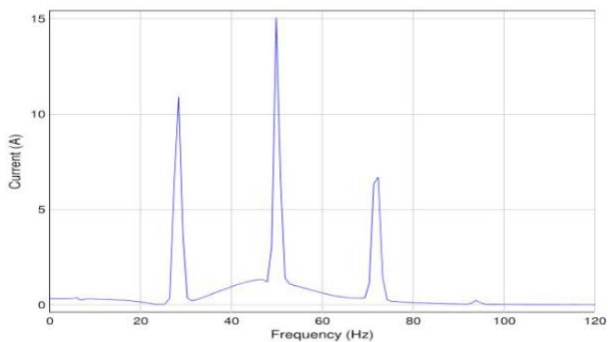
(b)

Figure 8. (a), (b) Eccentricity faults.

Bearing faults generates the characteristic components

at around 17 Hz and 83 Hz, corresponding to Equations (18) to (20). Figures 9 show the location of the bearing faults in the spectrum of stator.
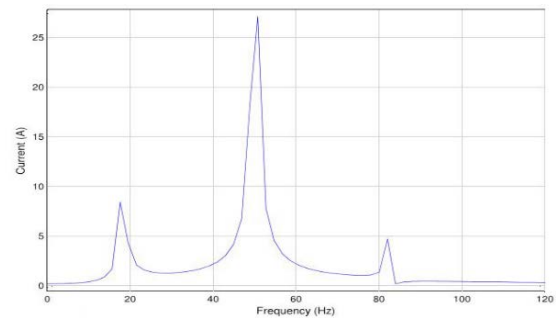

(a)

(b)

Figure 9. Bearing faults.

Finally fuzzy logic determines the state of operational condition of motor and the severity of the occurred fault. Figure 10 (a) employs the rule 10 of the fuzzy inference. All the three currents lie in the medium member function and the condition of the motor lie within the good operational condition. The fuzzy controller output of this condition is shown in figure 10 (b). Initially the fuzzy value is high due to the high starting currents and then settles at low value of 0.132.
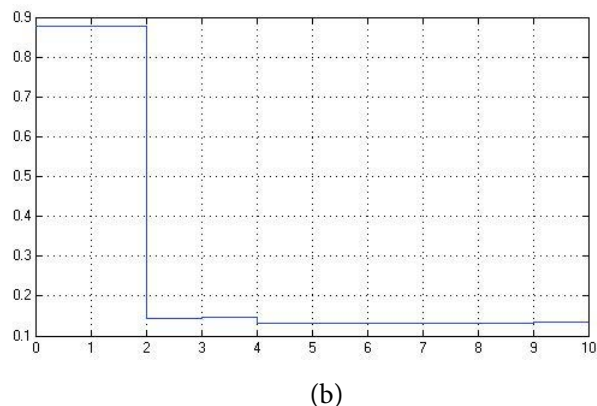

(a)

(b)
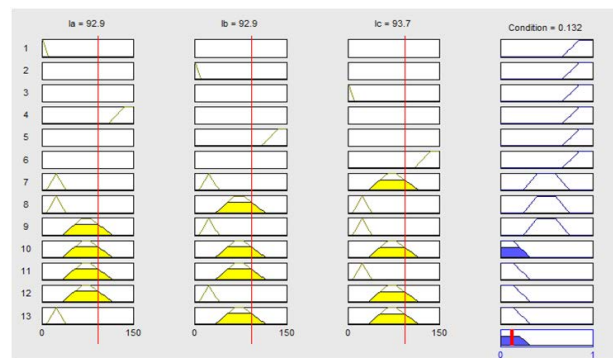
Figure 10. Healthy motor. (a) Fuzzy rule viewer. (b) Fuzzy controller output.

Figure 11 (a) represents the faulty case, employing the fuzzy rules 1, 2 and 3. The three currents lie in very small member function and the condition of motor lie within the severely damaged operational condition with the high severity of the occurred fault. The fuzzy controller output of this condition is shown in Figure 11 (b) where the fuzzy value is 0.87, the high value represent the severely damaged condition of the motor.
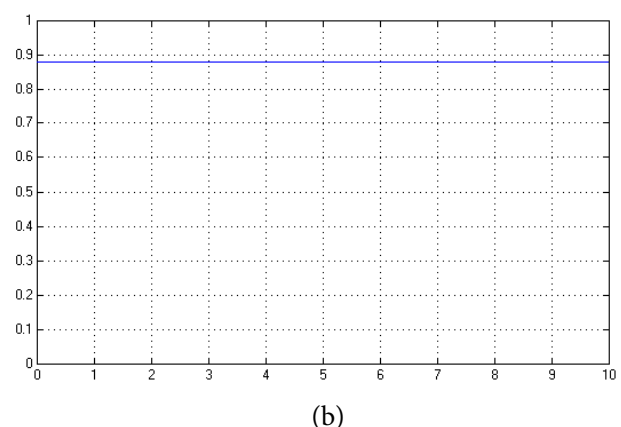

(a)

(b)

Figure 11. Severely damaged Motor. (a) Fuzzy rule viewer. (b) Fuzzy controller output.

Figure 11 (a) represents the faulty case, employing the fuzzy rules 1, 2 and 3. The three currents lie in very small member function and the condition of motor lie within the severely damaged operational condition with the high severity of the occurred fault. The fuzzy controller output of this condition is shown in Figure 11 (b) where the fuzzy value is 0.87, the high value represent the severely damaged condition of the motor.
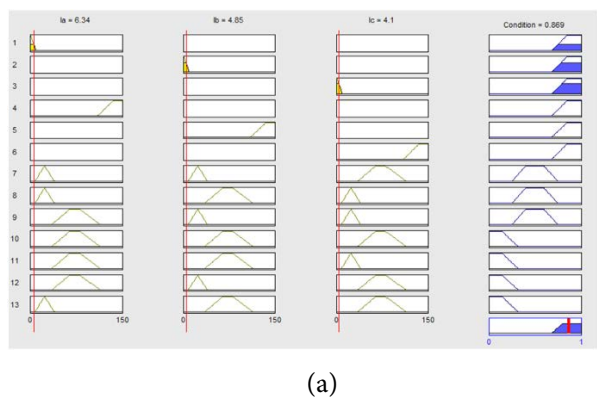
5. Conclusion

The paper has presented the hybrid condition monitoring approach for analysis of the mechanical faults (Bearing and Eccentricity) of the induction motor. The proposed approach offers the potential for not only detecting and locating the faults at an early stage but also the assessment of the motor condition and severity of fault. It conjunctives the features of both MCSA and fuzzy logic, where MCSA identifies the faults and fuzzy logic monitors the severity of the fault and to assesses the operating condition of the motor. Proposed approach can also be used to analyze almost all major motor faults. Hence, the approach provides more features than most of the available techniques. The presented results also successfully demonstrate the potential of the idea.

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