Single Parameter Fault Identification Technique for Three Phase Induction Motor through Wavelet Analysis and Fuzzy Logic

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Abstract – Three phase squirrel cage induction motors are the major power consuming device in houses and small scale industries. So, fault identification is very much essential for three phase induction motors to increase its life time and also to reduce its power consumption. There are many conventional techniques and soft computing techniques available for fault identification in three phase squirrel cage induction motors. Recent work has been carried out to find the faults in three phase induction motors by entropy based wavelet analysis of startup transient current. The entropy based wavelet analysis has disadvantage compared to norm based wavelet analysis while quantifying the fault. In this paper, fuzzy logic and norm based wavelet analysis of startup transient current is proposed to identify and quantify the faults such as broken rotor bar and bearing fault in three phase induction motors. The proposed work identifies the fault using norm based discrete wavelet transform and quantifies the level of the fault with the help of fuzzy logic. The results are verified by doing simulation using MATLAB. Practical verification is also done using 2Hp three phase induction motor.

Keywords: Discrete Wavelet Transform, Fuzzy logic, Fault Identification, Three phase squirrel cage Induction Motor, Norm analysis.

1. INTRODUCTION

In India, conveyor motor load has 2% share, cooling motor has 7% share, air compressor motor has 18% share and other industrial motor has 36% share out of total motor load of a country [1-2]. Three phase induction motors are majorly used for conveyor, cooling, air compressor and other industrial applications. Fault identification in these motors leads to cost saving because of its increased life time and decreased power consumption. Recently single parameter based fault identification in induction motors using entropy based wavelet analysis of startup transient current is reported [3]. Before that various methods such as fault identification by three phase current monitoring [4-5], fault identification by current pattern recognition [6], fault identification by analyzing various parameters of induction motor [7-8], fault identification with the help of neural network, fuzzy logic and neuro fuzzy [9], [13-15],[17-18], fault identification by current fluctuations and zero crossing instants [10] and fault identification with the help of support vector machine [11] are used by industries. Fault identification in the machines which employs field oriented control is discussed in [12] and review of different fault classification techniques are discussed in [16]. Single parameter fault identification through entropy based wavelet analysis of startup transient currents is very simple to implement due to its one parameter identification of multiple faults and it also has good diagnosis certainty compared to other methods. Discrete wavelet transform is very useful to decompose a signal in to various frequency bands [19]. In this paper, norm based wavelet analysis of startup transient current is used to identify the faults in three phase induction motor and fuzzy logic is used to indicate the level of fault. The norm based analysis is very useful while quantifying the level of fault compared to entropy analysis [20]. The fuzzy logic approach may help to diagnose three phase induction motor faults. The concept of fuzzy logic was introduced by Professor Lofti A. Zadeh to present vagueness in linguistic terms and express human knowledge in a natural way [13]. It is well known that fuzzy logic can describe the characteristics of process with linguistic terms. The motor fault identification and quantification task requires the interpretation of data and makes decision from the data. Simulations are performed in MATLAB for the proposed technique to identify and quantify the faults such as broken rotor bars and bearing fault in three phase squirrel cage induction motor.

2. FREQUENCY EFFECTS ON FAULT SIGNAL

In induction motor, the energy content of different frequency regions in current waveform varies according to the fault during the startup period [3]. Thus the frequency spectrum of the current signal varies during the fault condition. This indicates that a faulty condition modifies the quantity of information in the signal providing higher or lower entropy and norm values in different frequency bands. Thus fault can be identified by analyzing the entropy or norm values of the particular frequency band corresponding to a fault. For decomposing the current signal, discrete wavelet transform is used.

3. DISCRETE WAVELET TRANSFORM (DWT)

The wavelet transform converts the distorted signal into different time-frequency scales. The wavelet transform uses the wavelet function φ and scaling function $\varnothing$ to perform simultaneously the decomposition and reconstruction of the measured signal. The wavelet function φ will generate the detailed version (high-frequency components) of the decomposed signal and the scaling function $\varnothing$ will generate the approximated version (low-frequency components) of the decomposed signal. The wavelet transform is a well-suited tool for analyzing high-frequency transients in the presence of low-frequency components such as non stationary and non periodic wideband signals.

4. MATHEMATICAL MODEL OF DWT

Before the WT is performed, the wavelet function $\varphi(t)$ and scaling function $\varnothing(t)$ must be defined. The wavelet function serving as a high pass filter can generate the detailed version of the distorted signal, while the scaling function can generate the approximated version of the distorted signal. In general, the discrete $\varphi(t)$ and $\varnothing(t)$ can be defined as follows [20]:

$$\varnothing_{j,n}[\mathbf{t}] = 2^{\mathbf{j}/2}\sum_{n} c_{j,n}\varnothing\left[2^{j}t-n\right] \tag{1}$$

$$\varphi_{j,n}[\mathbf{t}] = 2^{\mathbf{j}/2}\sum_{n} d_{j,n}\varphi\left[2^{j}t-n\right] \tag{2}$$

Where c_j is the scaling coefficient at scale j, and d_j is the wavelet coefficient at scale j. simultaneously, the two functions must be orthonormal and satisfy the properties as follows:

$$\begin{cases} \varnothing.\varnothing = \dfrac{1}{2^{j}} \\ \varphi.\varphi = \dfrac{1}{2^{j}} \\ \varnothing.\varphi = 0. \end{cases} \tag{3}$$

Assuming the original signal $x_j(t)$ at scale j is sampled at constant time intervals, thus $x_j(t) = (v_0, v_1 \dots v_{n-1})$ the sampling number is N = 2^J. J is an integer number. For $x_j(t)$, its DWT mathematical recursive equation is presented as follows:

$$\mathrm{DWT}x_j(t) = \sum_{K} x_j(t)\varnothing_{j,k}[\mathbf{t}] \tag{4}$$

$$= 2^{\frac{\mathbf{j}+1}{2}}\sum_{n} u_{j+1,n\varnothing}\left[2^{j+1}t-n\right] + \sum_{n} w_{j+1,n\varphi}\left[2^{j+1}t-n\right]$$

$$0 \le n \le \frac{N}{2^{j}} - 1$$

Where

$$u_{j+1,n} = \sum_{k} c_{j,k}v_{j,k} + 2n, 0 \le k \le \frac{N}{2^{j}} - 1 \tag{5}$$

$$w_{j+1,n} = \sum_{k} d_{j,k}v_{j,k} + 2n, 0 \le k \le \frac{N}{2^{j}} - 1 \tag{6}$$

$$d_k = (-1)^k c_{2p-1-k,}\, p = \frac{N}{2^{j}} \tag{7}$$

Where $u_{j+1,n}$ the approximated version at scale j + 1 is, $w_{j+1,n}$ is the detailed version at scale $j+1$, and j is the translation coefficient. Figure 1 illustrates the five decomposed level of the DWT algorithm. At each decomposition levels, the length of the signals (e.g., u_1 and w_1) is half of that of the signal x_0.

5. ENTROPY ANALYSIS

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy in information theory describes the amount of information provided by a signal or event. It relates the amount of uncertainty about an event associated with a given probability distribution. The entropy is a measure of the average information contents associated with a random outcome [3]. Considering a random event x with possible outcomes $x_1, x_2, x_3 \ldots x_n$, and every x_i with a probability $p(x_i)$; then, the information entropy of a random event x is given by equation (8) [3].

$$H(x) = -\sum_{i=1}^{n} p(x_i)\log_2[p(x_i)] \tag{8}$$

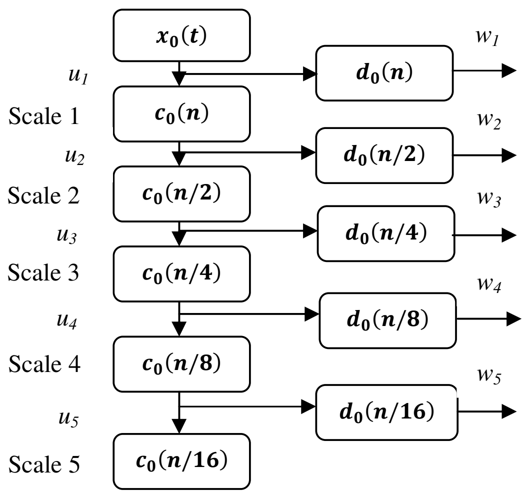

Fig.1. Five level decomposition of DWT

6. NORM ANALYSIS

The norm is used to quantify the strength of the various frequency band signals by measuring its magnitude and its mathematical expression is given in equation (9) [20]. In equation (9) $x_1, x_2 \ldots x_n$ are the values corresponding to a wavelet coefficient of particular frequency band (w_1 or w_2 or w_3 or w_4 or w_5). Since norm measures the magnitude, quantifying the level of fault using norm is better compared to entropy which measures the randomness (for a particular fault, the magnitude level of the current signal increases or decreases when the corresponding fault increase or decrease, but randomness does not vary very much).

$$|W_i| = \sqrt[2]{(x_1)^2 + (x_2)^2 \ldots .(x_n)^2} \tag{9}$$

7. PROPOSED METHOD

The objective of the proposed work is to identify and quantify the bearing fault and broken rotor bar fault in three phase induction motor with a help of startup transient current signal analysis using fuzzy logic and norm based DWT. Here norm based DWT is used to identify the faults and fuzzy logic is used to quantify the level of fault. Norm based DWT analysis is used in this work due to its good quantification compared to entropy based DWT analysis [20].

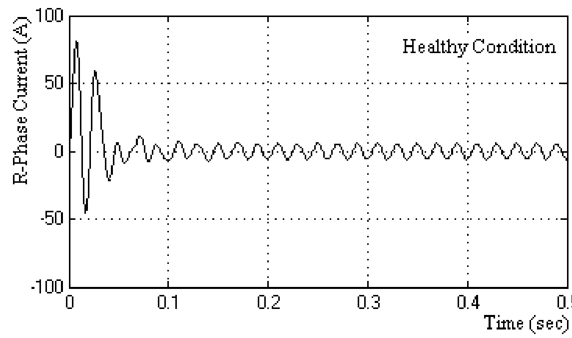

Fig.2. Startup current during healthy condition

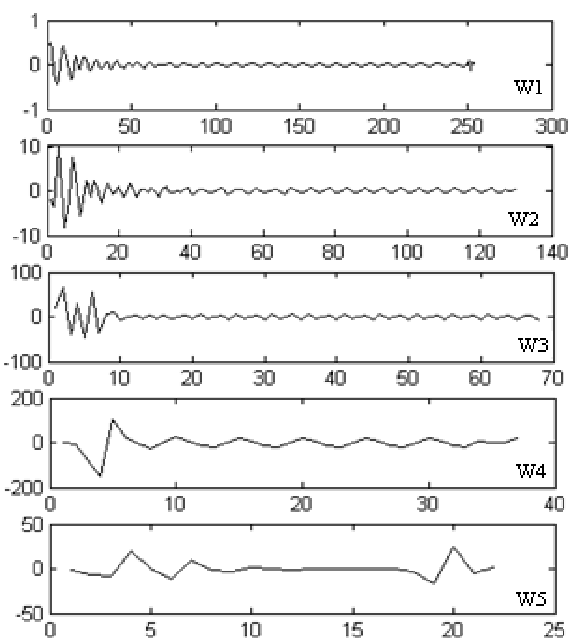

Fig.3. DWT wavelet coefficients for healthy condition

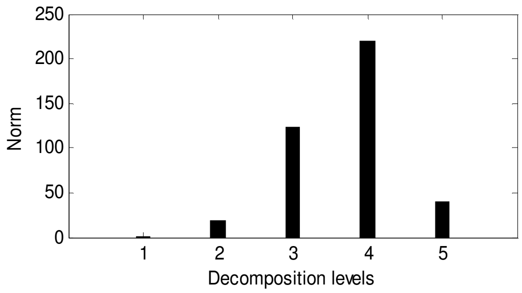

Fig.4. Norm of wavelet coefficients during healthy condition

Simulations are performed on 5.4 Hp, 400V and 50Hz three phase squirrel cage induction motor in Matlab. The parameters such as friction coefficient and rotor resistance are used to create the bearing fault and broken rotor fault respectively. The increase in bearing fault is simulated by increase in the friction coefficient and the increase in broken rotor fault is simulated by increase in rotor resistance.

The startup transient current signal of three phase induction motor up to 0.5 second is used to identify and quantify the fault [3]. Nearly 500 samples of startup transient current signal are collected within this 0.5 second for healthy condition, broken rotor bar fault condition and bearing fault condition.

Then five level DWT decomposition is performed on the collected samples. The Daubanchie "db4" wavelet function was adopted to perform the five level decomposing DWT, thus resulting in the larger energy distributions of the decomposition levels 3 and 4 [20]. Norm value for the wavelet coefficients corresponding to different conditions are found using equation (9).

Startup current during healthy condition is shown in figure 2. DWT wavelet coefficients for healthy condition are shown in figure 3. Norm of wavelet coefficients during healthy condition is shown in figure 4 and their values are shown as H in table I. Startup current during bearing fault condition is shown in figure 5. DWT wavelet coefficients for bearing fault condition are shown in figure 6.

Norm of wavelet coefficients during bearing fault condition is shown in figure 7 and their values are shown as DBF in table I. Startup current during broken rotor bar fault condition is shown in figure 8. DWT wavelet coefficients for broken rotor bar condition are shown in figure 9.

Norm of wavelet coefficients during broken rotor bar fault is shown in figure 10 and their values are shown as DRF in table I. The norm of wavelet coefficients for maximum broken rotor bar fault condition is shown as Max DRF in table I and norm for maximum bearing fault condition is shown as Max DBF in table I.

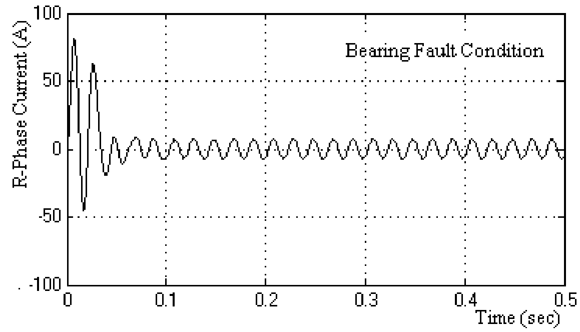

Fig.5. Startup current during Bearing fault condition

TABLE I

NORM OF WAVELET COEFFICIENTS DURING THE FAULTS AND HEALTHY CONDITIONS

Norm	H	DRF	DBF	Max DRF	Max DBF
$\lvert w_1 \rvert$	1.4	1.1	1.5	0.497	4.39
$\lvert w_2 \rvert$	18.2	13.4	18.1	6.15	29.13
$\lvert w_3 \rvert$	123.0	76.5	131.0	46.09	231.2
$\lvert w_4 \rvert$	220.0	140.4	229.0	92.16	448.8
$\lvert w_5 \rvert$	40.5	32.0	38.8	30.28	82.84

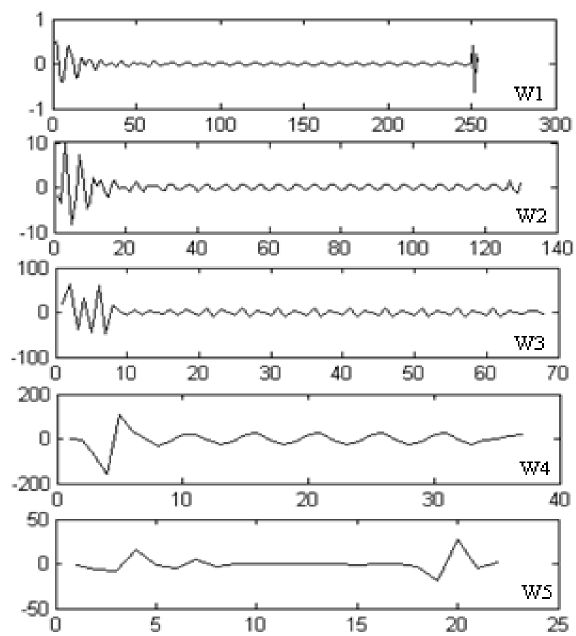

Fig.6. DWT wavelet coefficients for Bearing fault condition

From the table I, it is analyzed that the norm of wavelet coefficients w_3 and w_4 varies with respect to type and level of the fault. In this paper wavelet

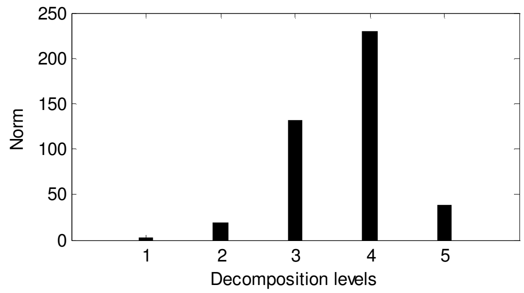

Fig.7. Norm of wavelet coefficients during Bearing fault condition

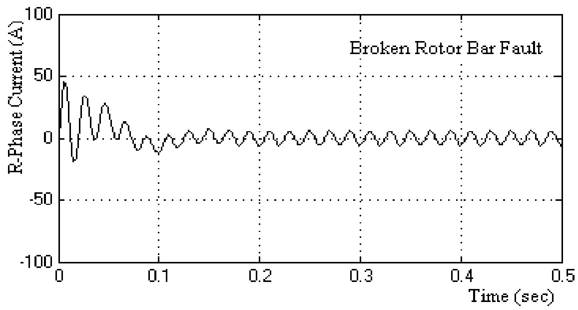

Fig.8. Startup current during broken rotor bar fault condition

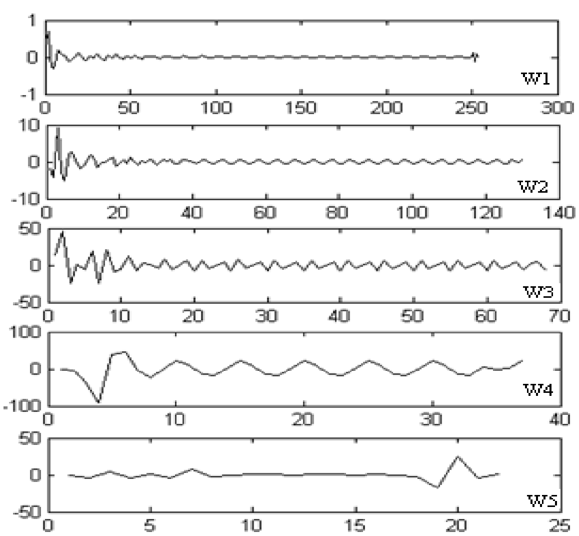

Fig.9. DWT wavelet coefficients for broken rotor bar fault condition

coefficients w_3 and w_4 corresponding to healthy condition is taken as reference (base). Compared to the norm of w_3 and w_4 under healthy condition, the norm of w_3 and w_4 increases corresponding to the level of bearing fault and during the broken rotor bar fault, the norm of w_3 and w_4 decreases. Thus fault can be easily identified by comparing the norm of w_3 and w_4 with the norm of w_3 and w_4 under healthy condition. Schematic diagram for fuzzy logic implementation of the proposed work is shown in figure 11. Here fuzzy logic is used to quantify the fault by analyzing the norm of wavelet coefficient w_3 and w_4 [20].

Primarily, the motor condition constitutes a fuzzy set. In practice, the users are concerned about the condition of the motor in terms of a linguistic variable that can be expressed as ‘‘Healthy’’, ‘‘Minor Fault’’ or ‘‘Dangerous Fault’’. Further, a fuzzy system can store certain knowledge, which allows it to make decisions with a high percent of accuracy. This knowledge expressed in rules and membership functions is obtained from the analytical study of the motor startup transient current and power engineer experience. From the point of view that sees induction motor condition as a fuzzy concept, there has been some fuzzy logic approaches for diagnosis.

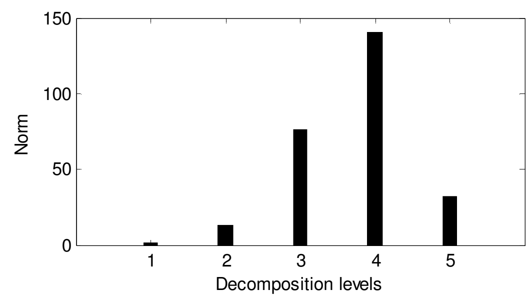

Fig.10. Norm of wavelet coefficients during broken rotor bar fault condition

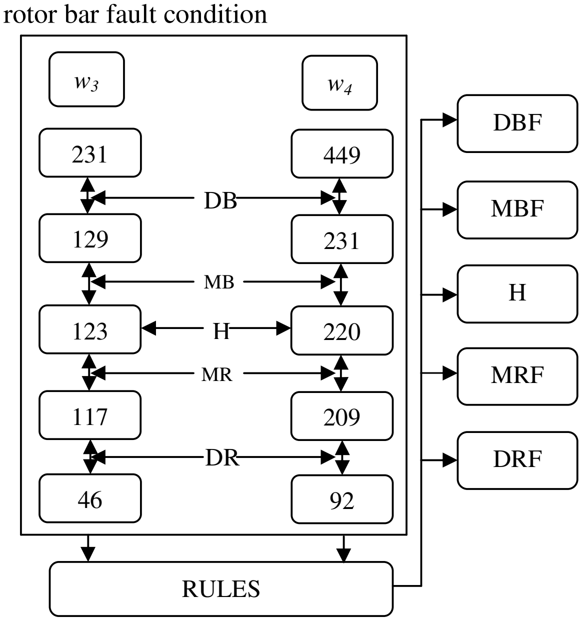

Fig.11. Schematic diagram for Fuzzy logic implementation of the proposed work

In the proposed work, wavelet coefficient w_3 and w_4 for healthy condition is taken as base. Each fault is separated into two categories one is minor fault (5% deviation from the healthy condition values) and the dangerous fault (above 5% deviation from the healthy condition values). In electrical system, 5% is the global tolerance limit. So, less than 5% deviations are considered as minor fault and deviations above 5% are considered as dangerous faults. Figure 11 clearly illustrate the values of the wavelet coefficient w_3 and w_4 for various levels of faults. In this 'DB' represents dangerous bearing fault values, 'MB' represents minor bearing fault values, 'H' represents healthy condition values, 'MR' represents minor broken rotor bar fault values and 'DR' represents dangerous broken rotor bar fault values. The fuzzy rules are

- If (w3 is DR) and (w4 is DR) then (output1 is DRF)
- If (w3 is MR) and(w4 is MR) then (output1 is MRF)
- If (w3 is DB) and (w4 is DB) then (output1 is DBF)
- If (w3 is MB) and (w4 is MB) then(output1 is MBF)
- If (w3 is H) and (w4 is H) then (output1 is H)
- If (w3 is DR) and (w4 is MR) then (output1 is DRF)
- If (w3 is MR) and (w4 is DR) then (output1 is DRF)
- If (w3 is MB) and (w4 is DB) then (output1 is DBF)
- If (w3 is DB) and (w4 is MB) then (output1 is DBF)
- If (w3 is H) and (w4 is MR) then (output1 is MRF)
- If (w3 is MR) and (w4 is H) then (output1 is MRF)
- If (w3 is H) and (w4 is MB) then (output1 is MBF)
- If (w3 is MB) and (w4 is H) then (output1 is MBF)

The membership functions for inputs and output are framed such that:

Minor Bearing Fault (MBF) - Norm of wavelet coefficients (w_3 and w_4) is higher, but within 5% deviation from the base value. The fuzzy output value is between ($0.5<MBF\leq 0.55$).

Dangerous Bearing Fault (DBF) - Norm of wavelet coefficients (w_3 and w_4) is higher, but more than 5% deviation from the base value. The fuzzy output value is between ($0.55<DBF\leq 1$).

Healthy condition (H) - Norm of wavelet coefficients (w_3 and w_4) must be equal to the base value. The fuzzy output value is ($H\approx 0.5$).

Minor broken Rotor bar Fault (MRF) - Norm of wavelet coefficients (w_3 and w_4) is lower, but within 5% deviation from the base value. The fuzzy output value is between ($0.5>MRF\geq 0.45$).

Dangerous broken Rotor bar Fault (DRF) - Norm of wavelet coefficients (w_3 and w_4) is lower, but more than 5% deviation from the base value. The fuzzy output value is between ($0.45>DRF\geq 0$).

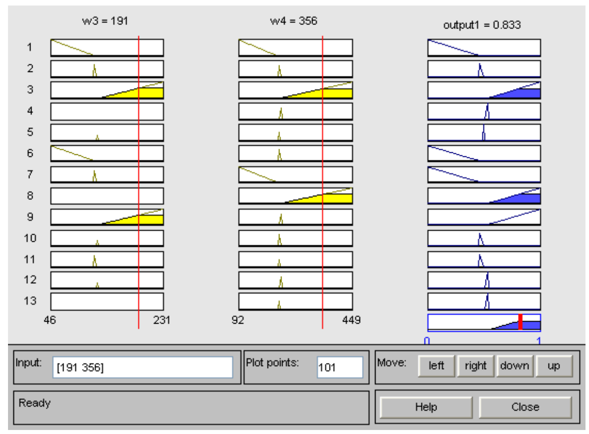

Fig.12. Fuzzy rule view for the proposed work

Thus fault level is quantified between the values 0 to 1 in addition to identification of the fault with the help of fuzzy logic. The fuzzy rule view for the proposed work is shown in figure 12. The fuzzy surface view for the proposed work is shown in figure 13. Fuzzy output for the various wavelet coefficients is shown in table II and the output value shows the level of fault. The increase of fuzzy output from 0 to 0.45 represents the decrease of dangerous broken rotor bar fault (DRF) from its maximum value to minimum value and the increase of fuzzy output from 0.451 to 0.499 represents the decrease of minor rotor fault (MRF) from its maximum value to minimum value and the fuzzy output value 0.5 represents the healthy condition (H) and the increase of fuzzy output from 0.501 to 0.550 represents the increase of minor bearing fault (MBF) from its minimum value to maximum value and the increase of fuzzy output from 0.556 to 1.0 represents the increase of dangerous bearing fault (DBF) from its minimum value to maximum value.

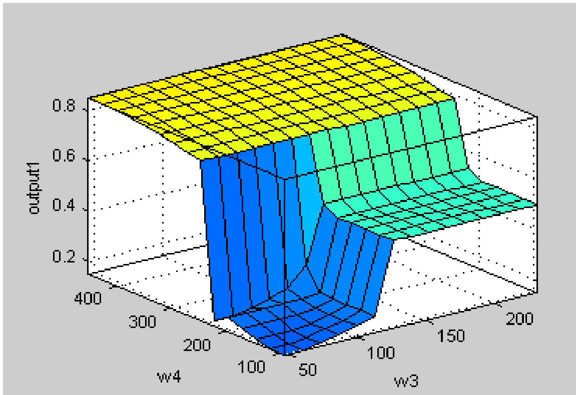

Fig.13. Fuzzy surface view for the proposed work

TABLE II

NORM VALUES AND FUZZY OUTPUT FOR DIFFERENT FAULT CONDITIONS

$\lvert w_3 \rvert$	$\lvert w_4 \rvert$	Type of Fault	Fuzzy Output
123.0	220.0	H	0.5
55.44	112.0	DRF	0.151
191.3	355.9	DBF	0.833
119.4	214.8	MRF	0.493
126.2	226.1	MBF	0.531

8. PRACTICAL VERIFICATION

The practical verification of the proposed method is done in 2Hp 3 Phase Induction Motor. The current samples are collected using ARDUINO Mega 2560 controller. Then the current samples are normalized and DWT is applied to find the wavelet coefficients. Finally fuzzy is used to classify the faults. Figure 14 shows the picture of healthy rotor, broken rotor, healthy bearing and faulty bearing.

TABLE III

PRACTICAL OUTPUT FOR DIFFERENT FAULT CONDITIONS

$\lvert w_3 \rvert$	$\lvert w_4 \rvert$	Type of Fault	Fuzzy Output
113.0	217.0	H	0.495
50.32	103.0	DRF	0.191
186.2	345.5	DBF	0.816

Table3 shows the fuzzy output for the practical readings. From the results it is clear that the proposed method classify the fault accurately. The simulation results are on par with the practical results.

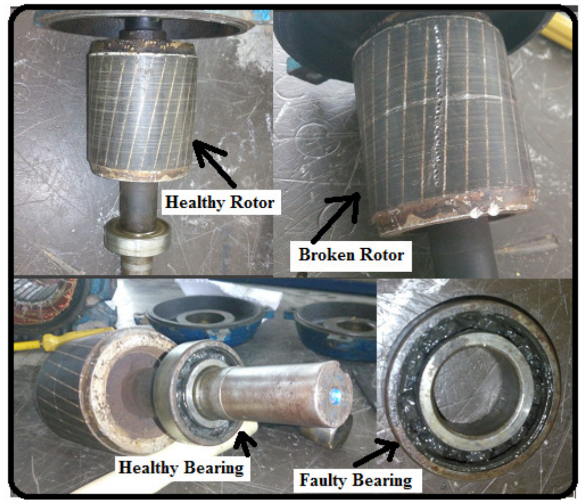

Fig.14. Rotor and Bearing for 3 Phase Induction Motor

9. CONCLUSION

This paper presents a fuzzy logic and wavelet analysis based technique for identification and quantification of the bearing and broken rotor bar faults in three phase induction motor. The proposed methodology is able to quantify the level of faults in addition to identifying the fault by analyzing startup-transient current from the three phase induction motor, which is different from previously proposed methodologies or expert systems that only identify the faults. The proposed method can reduce the complexity and computing time by utilizing single parameter startup transient current analysis in identifying and quantifying the faults. In this paper discrete wavelet transform is applied to the startup transient current signal for finding the wavelet coefficients and the norm of the wavelet coefficients are used to identify the fault. Finally fuzzy logic is used to indicate the level of fault by checking the norm of the wavelet coefficient values with the wavelet coefficient values for different faults and healthy conditions. Simulations are successfully performed in Matlab Simulink for a 400V, 50Hz and 5.4Hp three phase squirrel cage induction motor to verify the results. Practical verification is also done for 2Hp Induction Motor.

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