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Single Parameter Fault Identification Technique for DC Motor through Wavelet Analysis and Fuzzy Logic

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Abstract – DC motors are widely used in industries like cement, paper manufacturing, etc., even today. Early fault identification in dc motors significantly improves its life time and reduces power consumption. Many conventional and soft computing techniques for fault identification in DC motors including a recent work using model based analysis with the help of fuzzy logic are available in literature. In this paper fuzzy logic and norm based wavelet analysis of startup transient current are proposed to identify and quantify the armature winding fault and bearing fault in DC motors, respectively. Results obtained by simulation using Matlab and Simulink are presented in this paper to validate the proposed work.

Keywords: Discrete wavelet transform, Fuzzy logic, Fault identification, DC motor, Norm analysis

1. Introduction

DC motors are majorly used for constant speed operation in industries. Fault identification in these motors leads to cost saving because of its increased life time and decreased power consumption. Recently DC motor faults can be found out by model based analysis with the help of fuzzy logic [1&2]. Before that various methods such as observer based fault identification by current monitoring [3], fault identification by analyzing various parameters of DC motor with the help of fuzzy logic and neural network [4] and fault identification by thermal monitoring [5] are reported in the literature. Soft computing techniques for classification of faults are reported in [6]. Review of different fault classification techniques are discussed in [7]. Discrete wavelet analysis and its application in identification of fault is discussed in [8]. Neural network based wavelet analysis for fault classification is discussed in [9]. Single parameter fault identification through entropy based wavelet analysis of startup transient currents of induction motor 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 [10]. Discrete wavelet transform is very useful to decompose a signal in to various frequency bands [9].

In this paper, norm based wavelet analysis of startup transient current is used to identify the faults in DC 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 [9]. The fuzzy logic approach may help to diagnose DC 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 [4]. 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 armature winding fault and bearing fault in DC motor.

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2. Frequency Effects on Fault Signal

In DC motor during the startup period the energy content of different frequency regions in current waveform varies according to the fault [10]. 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.

3.1 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:

$$\varnothing_{j,n}[\mathbf{t}] = 2^{\mathbf{j}/2} \sum_n c_{j.n} \varnothing\left[2^j t - n\right] \quad (1)$$

$$\varphi_{j,n}[\mathbf{t}] = 2^{\mathbf{j}/2} \sum_n d_{j,n} \varphi\left[2^j t - n\right] \quad (2)$$

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:

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

Assuming the original signal $x_j(t)$ at scale j is sampled at constant time intervals, thus $x_j(t) = (v_0, v_1 \ldots v_{n-1})$ 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:

$$\begin{aligned} \text{DWT } x_j(t) &= \sum_K x_j(t) \varnothing_{j,k}[\mathbf{t}] \\ &= 2^{\frac{\mathbf{j}+1}{2}} \sum_n u_{j+1,n\varnothing}\left[2^{j+1} t - n\right] \\ &\quad + \sum_n w_{j+1,n\varphi}\left[2^{j+1} t - n\right] \\ &\quad 0 \le n \le \frac{N}{2^j} - 1 \end{aligned} \quad (4)$$

Where

$$u_{j+1,n} = \sum_k c_{j,k} v_{j,k} + 2n, 0 \le k \le \frac{N}{2^j} - 1 \quad (5)$$

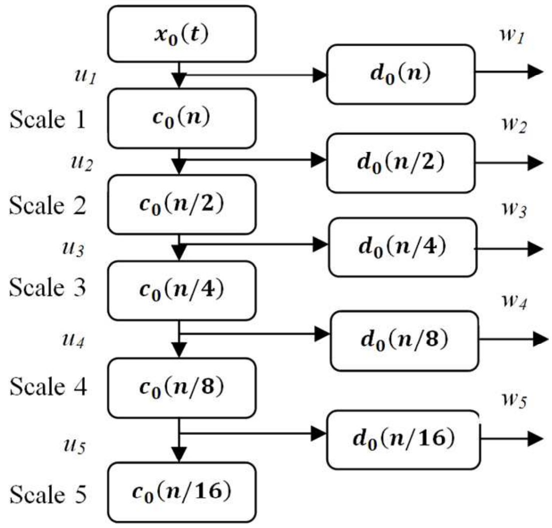

Fig.1. Five level decomposition of DWT

$$w_{j+1,n} = \sum_k d_{j,k} v_{j,k} + 2n, 0 \le k \le \frac{N}{2^j} - 1 \quad (6)$$

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

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. Fig. 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.

3.2 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..... x_n, and every x_i with a probability p(x_i); then, the information entropy of a random event x is given by Eq. (8) [3].

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

3.3 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 Eq. (9). In Eq. (9) x_1, x_2....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).

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

4. Proposed Method

The objective of the proposed work is to identify and quantify the bearing fault and the armature winding fault in DC 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 [9]. Simulations are performed on 5 Hp and 240V DC motor in Matlab. The parameters such as friction coefficient and armature resistance are used to create the bearing fault and armature winding fault respectively. The increase in bearing fault is simulated by increase in the friction coefficient and the increase in armature winding fault is simulated by decrease in armature resistance. The startup transient current signal of DC motor up to 0.5 second is used to identify and quantify the fault [9]. Nearly 200 samples of startup transient current signal are collected within this 0.5 second for healthy condition, armature winding 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 4 and 5 [9]. Norm value for the wavelet coefficients corresponding to different condition is found using Eq. (9).

Startup current during healthy condition is shown in Fig. 2. DWT wavelet coefficients for healthy condition are shown in Fig. 3. Norm of wavelet coefficients during healthy condition is shown in Fig. 4 and their values are shown as H in Table 1. Startup current during bearing fault condition is shown in Fig. 5. DWT wavelet coefficients for bearing fault condition are shown in Fig. 6.

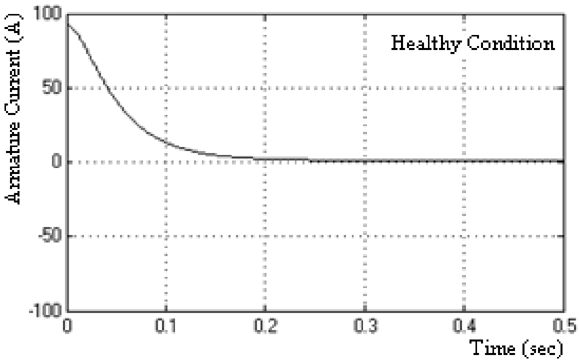

Fig. 2. Startup current during healthy condition

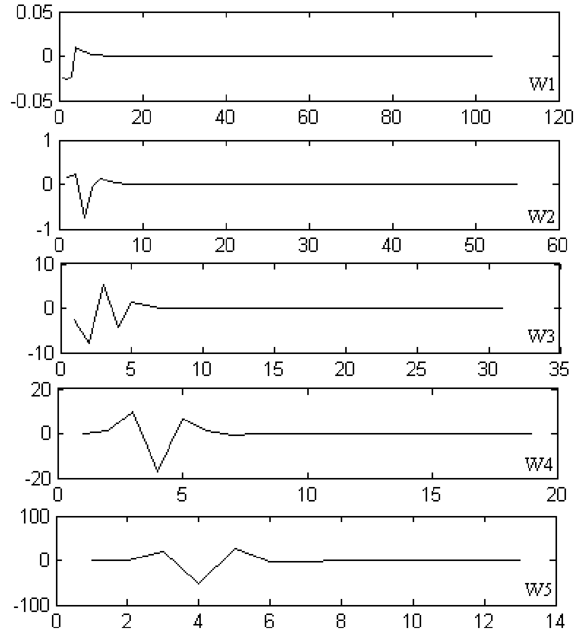

Fig. 3. DWT wavelet coefficients for healthy condition

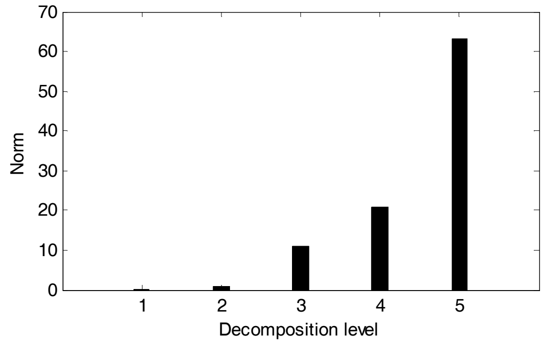

Fig. 4. Norm of wavelet coefficients during healthy condition

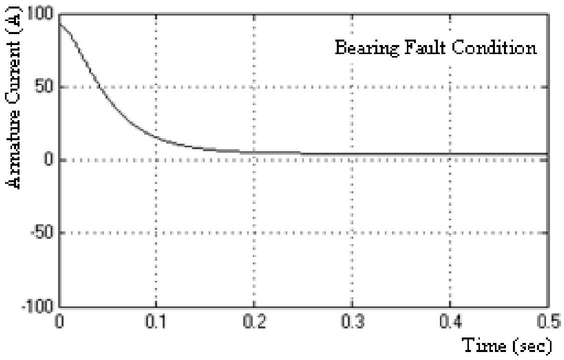

Fig. 5. Startup current during Bearing fault condition

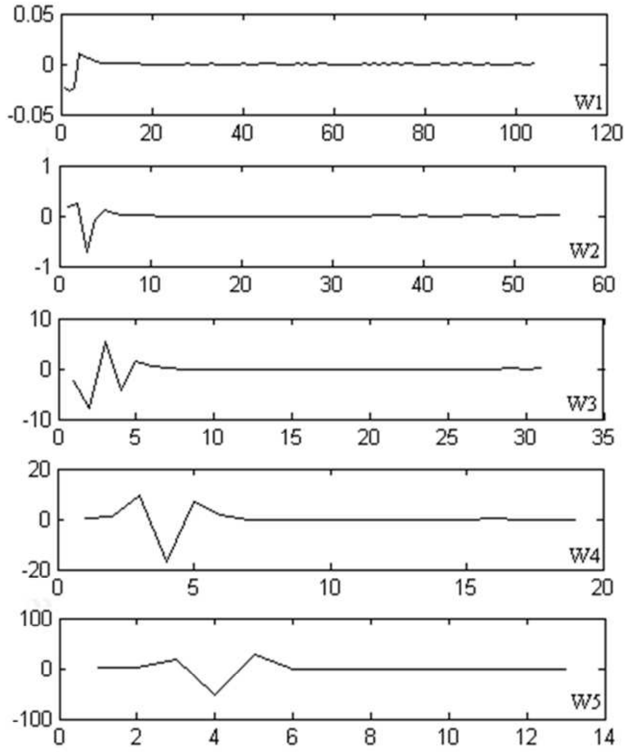

Fig. 6. DWT wavelet coefficients for Bearing fault condition

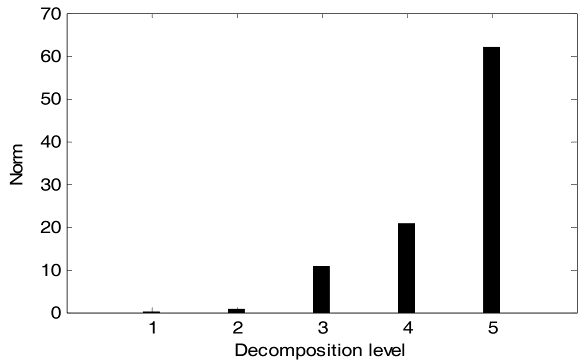

Fig. 7. Norm of wavelet coefficients during Bearing fault condition

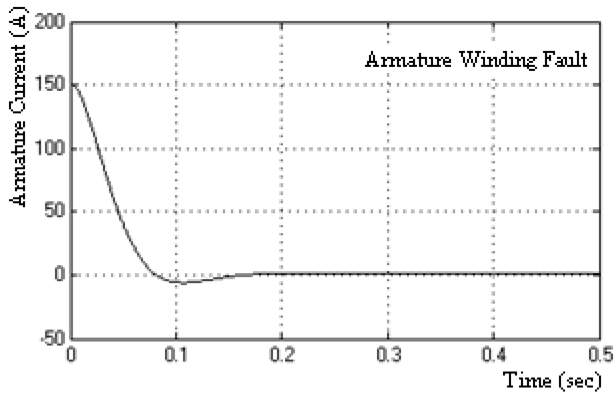

Fig. 8. Startup current during armature winding fault

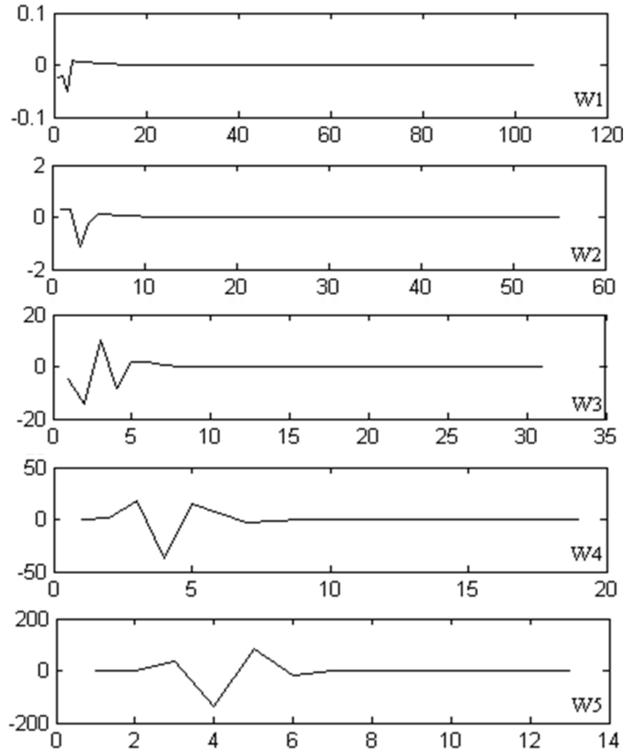

Fig. 9. DWT wavelet coefficients for armature winding fault condition

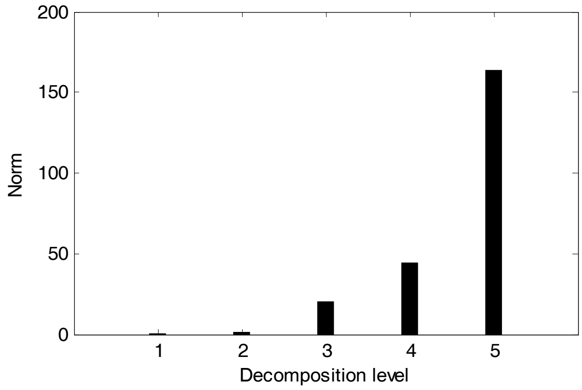

Fig. 10. Norm of wavelet coefficients during armature winding fault condition

Norm of wavelet coefficients during bearing fault condition is shown in Fig. 7 and their values are shown as MBF in Table 1. Startup current during armature winding fault condition is shown in Fig. 8. DWT wavelet coefficients for armature winding fault condition are shown in Fig. 9. Norm of wavelet coefficients during armature winding fault is shown in Fig. 10 and their values are shown as DAF in Table 1. The norm of wavelet coefficients for maximum armature winding fault condition is shown as Max DAF in Table 1 and wavelet coefficients for maximum bearing fault condition is shown as Max DBF in Table 1.

From the Table 1, it is analyzed that the norm of wavelet coefficients w_4 and w_5 varies with respect to type and level of the fault. In this paper wavelet coefficients w_4 and w_5 corresponding to healthy condition is taken as reference (base). Compared to the norm of w_4 and w_5 under healthy condition, the norm of w_4 and w_5 increases corresponding to the level of bearing fault and during the armature winding fault, the norm of w_4 and w_5 decreases. Thus fault can be easily identified by comparing the norm of w_4 and w_5 with the norm of w_4 and w_5 under healthy condition. Schematic diagram for fuzzy logic implementation of the proposed work is shown in Fig. 11. Here fuzzy logic is used to quantify the fault by analyzing the norm of wavelet coefficient w_4 and w_5 [9].

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

Table 1. Norm of wavelet coefficients' during the faults and healthy conditions

Norm	H	DAF	MBF	Max DAF	Max DBF
$\lvert w_1 \rvert$	0.045	0.062	0.045	0.186	0.059
$\lvert w_2 \rvert$	0.081	1.234	0.081	3.025	0.882
$\lvert w_3 \rvert$	10.88	20.21	10.75	62.79	8.956
$\lvert w_4 \rvert$	20.90	44.13	20.66	169.8	15.62
$\lvert w_5 \rvert$	63.14	163.62	62.17	1014	29.96

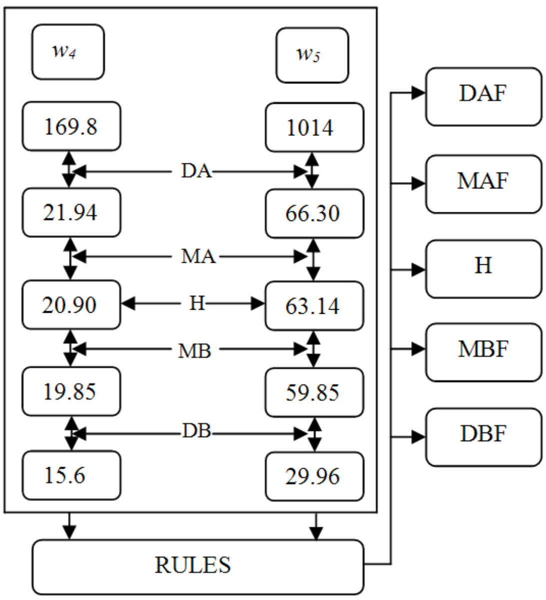

Fig. 11. Schematic diagram for Fuzzy logic implementation of the proposed work

experience. From the point of view that sees DC motor condition as a fuzzy concept, there has been some fuzzy logic approaches for diagnosis. In the proposed work, wavelet coefficient w_4 and w_5 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. Fig. 11 clearly illustrate the values of the wavelet coefficient w_4 and w_5 for various levels of faults. In this 'DB' represents dangerous bearing fault values, 'MB' represents minor bearing fault values, 'H' represents healthy condition values, 'MA' represents minor armature winding fault values and 'DA' represents dangerous armature winding fault values. The fuzzy rules are

- If (w4 is DA) and (w5 is DA) then (output1 is DAF)
- If (w4 is MA) and (w5 is MA) then(output1 is MAF)
- If (w4 is DB) and (w5 is DB) then(output1 is DBF)
- If (w4 is MB) and (w5 is MB) then(output1 is MBF)
- If (w4 is H) and (w5 is H) then (output1 is H)
- If (w4 is DA) and (w5 is MA) then (output1 is DAF)
- If (w4 is MA) and (w5 is DA) then (output1 is DAF)
- If (w4 is MB) and (w5 is DB) then (output1 is DBF)
- If (w4 is DB) and (w5 is MB) then (output1 is DBF)
- If (w4 is H) and (w5 is MA) then (output1 is MAF)
- If (w4 is MA) and (w5 is H) then (output1 is MAF)
- If (w4 is H) and (w5 is MB) then (output1 is MBF)
- If (w4 is MB) and (w5 is H) then (output1 is MBF)
- If (w4 is MB) and (w4 is H) then (output1 is MBF)

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

Minor Armature Winding Fault (MAF) - Norm of wavelet coefficients (w_4 and w_5) is higher, but within 5%

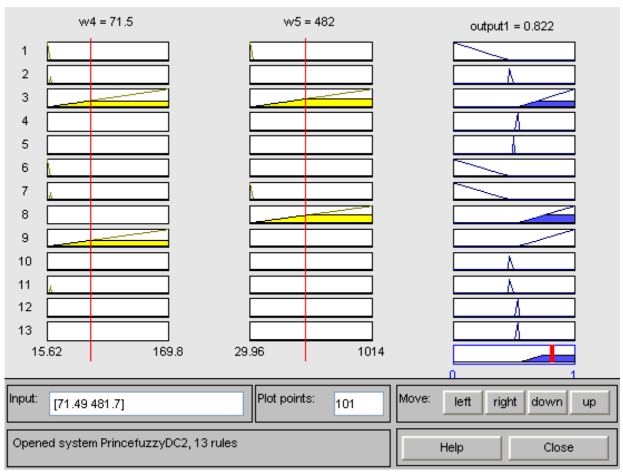

Fig. 12. Fuzzy rule view for the proposed work

deviation from the base value. The fuzzy output value is between (0.5 MBF 0.55).

Dangerous Armature Winding Fault (DAF) - Norm of wavelet coefficients (w_4 and w_5) is higher, but more than 5% deviation from the base value. The fuzzy output value is between (0.55 DBF).

Healthy condition (H) - Norm of wavelet coefficients (w_4 and w_5) must be equal to the base value. The fuzzy output value is (H 0.5).

Minor Bearing Fault (MBF) - Norm of wavelet coefficients (w_4 and w_5) is lower, but within 5% deviation from the base value. The fuzzy output value is between (0.5 MRF 0.45).

Dangerous Bearing Fault (DBF) - Norm of wavelet coefficients (w_4 and w_5) is lower, but more than 5% deviation from the base value. The fuzzy output value is between (0.45 DRF 0).

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 Fig. 12. The fuzzy surface view for the proposed work is shown in Fig. 13. Fuzzy output for the various wavelet coefficients is shown in Table 2 and the output value shows the level of fault. The increase of fuzzy output from 0 to 0.45 represents the decrease of dangerous bearing fault (DBF) from its maximum value to minimum value and the increase of fuzzy output from 0.451 to 0.499 represents the decrease of minor bearing fault (MBF) 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 armature winding fault (MAF) from its minimum value to maximum value and the increase of fuzzy output from 0.556 to 1.0 represents the increase of dangerous armature winding fault (DAF) from its minimum value to maximum value.

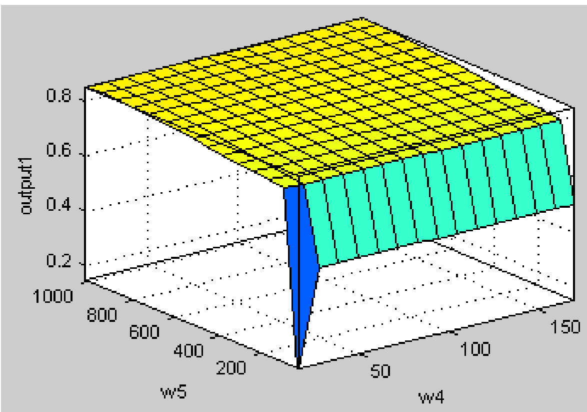

Fig. 13. Fuzzy surface view for the proposed work

Table 2. Fuzzy output and wavelet coefficients' values for different fault conditions

$\lvert w_4\rvert$	$\lvert w_5\rvert$	Type of Fault	Fuzzy Output
20.9	63.1	H	0.5
71.5	482.0	DAF	0.822
20.0	61.0	MBF	0.471
21.5	66.0	MAF	0.533
16.0	32.0	DBF	0.148

5. Conclusion

This paper presents a wavelet analysis and fuzzy logic based technique for identification and quantification of the bearing and armature winding faults in DC motor. The proposed methodology is able to quantify the level of faults in addition to identifying the fault by analyzing startup-transient current from DC 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 (DWT) 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 5H.P and 240V DC motor to verify the results.

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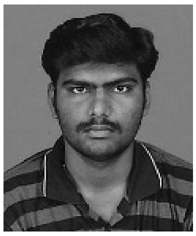

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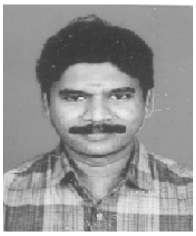

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