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Fault Detection of Induction Motors Using Continuous Curvelet Wavelet and Support Vector Machines

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Abstract : One of the fast emerging applications in the electrical field is monitoring and detecting the conditions of induction motors to avoid criticality, un-expected failure and other faults of the electrical system. It also helps to main any electrical system integrated with induction motors. This idea can be applied in the bearing fault detection in a three phase induction motor. In order to analyse vibration a signal processing method is used while beginning of the system. Here Continuous Curvelet Wavelet Theory (CCWT) is used for frame vibration and classified using Support Vector Machine (SVM). From the analysis result the condition of the induction motor is monitored and the entire system is saved. The experiment is carried out and the obtained results are compared with the existing approach to prove that the proposed approach is better.

Keywords : Induction Motors, Bearing, Fault Detection, Fault Prevention Discrete Wavelet Theory, Support Vector Machine.

1. INTRODUCTION

Most of the industrial processes use AC induction motors as actuators [1]. Even though induction motors are reliable, due to various kinds of unexpected stresses faults occurs in induction motors. Faults in induction motors make an electrical system as a failure. There are various methods and techniques are used for detecting and preventing faults in induction motors. In most of the industry and daily life induction motor is used as a key element for the energy consuming device in the system. Research works presented in [2, 3] were focused on fault detection in induction motors. Using faulty induction motors in the industry leads low production. Earlier research works focus on detecting single-isolated fault detection and identification. There are various kinds of faults affects the machines such as: (*i*) bearing related faults, (*ii*). Rotor faults, (*iii*). Faults inside machine. But at the same time two or more faults can be present in the machine. Because this, one fault reason may interfere other fault and decision making on detecting faults individually and this provides a wrong decision making on detecting the condition faults according to the condition of the motor. The more number of faults are bearing faults only [4-7] and various techniques were developed and proposed for bearing faults in the last decades. All those techniques focused on vibration analysis for detecting damages on the surface, inner and outer damages and faults in rolling elements. Vibration analysis perceives improper lubricants and lubricant starved bearings.

From light to heavy industrial electrical system merely depends on the induction motors where if the motor fails, then the entire electrical system fails and it is very expensive. So industries need a reliable, fault diagnosis method for detecting and identifying faults in an electrical system accurately and timely. Also, it is felt that induction motor is a critical component in various industrial processes. It is difficult to predict

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the time of its failure will lead lot of problems and it is very costly. Hence monitoring the conditions of electrical system becomes very essential in recent years. Many people used many methodologies directly or indirectly to find out the electrical or mechanical problems due to induction motors. Finding and identifying the problems can be analysed by various parameters like vibration, noise, stator phase current, air gap and flux density. Some of the earlier research works used Neural Networks (NNs) for monitoring the motor condition of the electrical system. For fault diagnosing on rotating machines, vibration analysis is suggested as better method in electrical systems [2-4]. Author in [4] said that the vibration analysis is the most reliable method for diagnosing the entire electrical system. Faults in the electrical system makes vibration with various characteristics which can be calculated with reference one to do perfect diagnosis and detecting the faults. Conventional techniques like Fast Fourier Transformation (FFT) methods are not appropriate one for analysing the signals which have transitory characteristics. From the above discussion, it is clear that detecting and identifying multiple faults occur in the electrical system is a challenging task and still it needs a better solution. Identifying the fault condition for more than one fault is too difficult [8].

Existing System

Vibration analysis can be obtained using Wavelet Theory [9-11]. Due to the monitoring of induction motor is applied in a stipulated interval of time, a time based signal analysis be an efficient approach for vibration analysis. There are various methods developed directly from wavelet systems nowadays with the same aim. All the wavelet based approaches used for representing the directional features from the signal generated in higher dimensions. But no approaches got familiarity like curvelet wavelet transform method. Hence, in this paper, it is motivated to utilize curvelet wavelet transform method for extracting signal local information. Some of the famous wavelet transform methods are Steerable wavelets [12-13], Gabor wavelets [14], wedgelets [15], beamlets [16], bandlets [17, 18], contourlets [19], shearlets [20, 21], wave atoms [22], platelets [23], surface lets [24] have been proposed to analyze the signal features.

Hargis et al. used vibration analysis to find out the variations of the stator motor which indicates the mechanical defects [1-6]. Steele et al. said that per-phase current monitoring is utilized to obtain mechanical defects by monitoring the current. Benefit of current monitoring through per-phase based is, it is easy to measure and recognizing the fault pattern is same and estimating the number of variations in the signal can be obtained easily [7-12]. Stephan et al. [13] used air-gap searching methods to detect and calculate both the peripheral and radial component of the leakage flux. Another method used to detect rotor short circuits and other malfunction is through an axial flux sensing method. [14].

Various numbers of applications used DWT for detecting faults in power systems, power electronics, electrical systems and mechanical systems. Some of the applications used DWT for detecting fault in induction motors [12, 14-20]. DWT decompose the wave signal into decomposed coefficients. But the number of coefficients is lesser than CWT, since CWT can provide more redundant coefficients to do a lot of signal processing activities like compression, decompression and other reconstruction [11] methods. Comparing with DWT, CWT can provide more efficient in the granularity manner for extracting detailed information about a signal. CWT is used for motor fault detection in terms of multi-class faults [10, 13].

Hence this paper motivated utilizes DWT for vibration analysis. Continuous wavelet transforms used for getting local information of the data. But DWT [25-26] uses orthogonal wavelet information and it is used mainly used for image compression. Than CWT and DWT, Continuous Curvelet Wavelet Transform obtains curvature based local information of the signal data. Also, it provides more redundant data where it gives more information for detecting and identifying different types of faults. CCWT is easier to interpret and implement to extract the signal information. There are some advantages using CCWT analysis like readability, lossless information extraction and distinct feature extraction.

The more redundant dictionaryy can be provided in CCWT where it helps to obtain the sparse representation of the signals having edges along the regular curve. From the beginning stages CCWT the curvelet construction is redesigned and re-introduced as FDCT (Fast Digital Curvelet Transform). After some time the curvelet transform is less redundant comparing with first generation, then it is defined as the continuous and digital domain for higher dimension signals. Due to this reason, in this paper the signal analysis is obtained by Continuous Curvelet Wavelet Transform (CCWT) method. The types of faults can be obtained using vibration monitoring is shown in Figure-1.

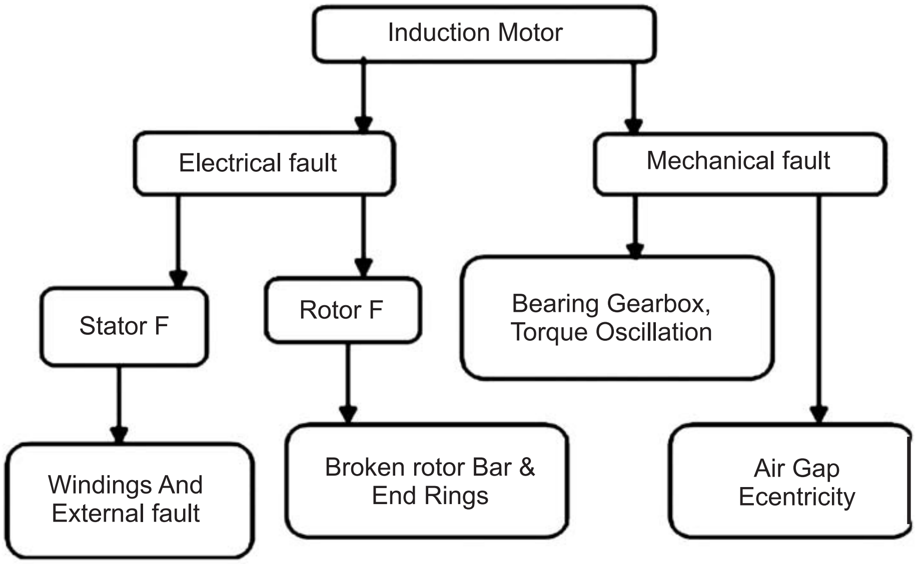

Figure 1: Various Types of Faults

Vibration Monitoring

Noise and vibration are generated from all kinds of electrical motors. The information about the Motor condition can be fetched by analysing the produced noise and vibration. The level of noise is increased proportionally due to the increased vibration of the machine. The forces applied to the electrical system such as mechanical, magnetic and aerodynamic cause's noise and vibration. Motor Current Signature Analysis (MCSA) is used as a best approach for analysing stationary signals not for non-stationary signals. Amplitude, Frequency, Phase and modulation are the four properties of vibration to be understood in a better manner for resolving the problems occur in the electrical system. The severity level of the motor condition can be gotten by amplitude, the repeated rate of source contributions is measured by frequency, time interval between two signals can be measured by phase and the process helps to response amplitude at a frequency is measured by modulation. From this information it is able to get the asymmetric information of a motor [4]. MCSA and vibration analysis are easier methods for finding the fault in an electrical system. Hence, in this paper vibration analysis is used to detect the motor fault, whereas vibration information is obtained from the signal using CCWT.

Vibration Analysis Approach for bearing fault

In this paper CCWT based vibration analysis is applied to detect faults in terms of frequencies. The analyzation on the signal is carried out by obtaining some parameters such as kurtosis, root square mean and crest factor with some more statistical parameters. The vibration is affected by the motor faulty whereas the vibration is affected by motor current signature pattern. Initially the motor is experimented and run it in normal condition and attain the vibration signal. Similarly attain the vibration signal in faulty condition. Now extract the features using CCWT from the signal and compare it with the normal and fault condition for classification using multi class SVM.

Fault Classification of Induction Motor Using Wavelet Transform

In order to simulate the proposed approach in an effective manner, 1-HP induction motor with 16 channel DAT recorder and a piezoelectric accelerometer is used in the MATLAB environment. The data files used in the simulation are stored in the form of *.mat format. The type of the induction motor is a single row, deep groove ball bearing type 6203-Z whereas each bearing consists of eight balls. Only four bearings are used in the experiment. Two bearings are taken as damaged and two is taken as un-damaged. By remembering air gap eccentricity will produce anomalies and it can be obtained by bearing vibration in the stator current. The healthy and faulty conditions of the motors are identified from the vertical frame of the vibration at 5120 Hz sampling frequency rate and the supply frequency is assigned as 50 Hz. Here there are six types of faults are considered with single motor such as fault occur in bearing, fault occur in the stator, fault in terms of voltage unbalanced and fault in terms of current unbalanced.

Continuous Curvelet Wavelet Transform

One of most important and effective mathematical signal processing tool is a wavelet transform because it can analyse the signals especially in transient ones. The wavelet is divided using widowing functions and translate into mother wavelets. The wavelet can provide multi-scale based analysis on a signal, using this it can extract the time dependent frequency features from an input signal effectively. It can be done by FFT also, but it lost the transient data. Localizing a waveform in the format of wavelets is called as wavelet transformations where it has different tasks such as translation and dilation in terms of time and scale. The continuous wavelet transform of a signal data $x(t)$ is represented in the form of mother wavelet is:

$$\mathrm{W}_{(a,\,b)} = \int_{-\infty}^{\infty} x(t)\,\frac{1}{\sqrt{|a|}}\,\varphi^*\left[\frac{t-b}{a}\right]dt$$

From the above equation, it is known that there are two variable a and b, the scale and location parameters are available, and they are the components. From the following equations such as fault frequency and current spectrum,

The vibration frequency f_{bng} is considered as fault frequencies are written as:

$$f_{bng} = \mathrm{N}_b \times \omega_{inner}\left[\frac{d - \frac{d}{\mathrm{D}}\cos\propto}{2}\right]$$

And the current spectrum is represented as:

$$f_{orf} = |f_s \pm m \times f_{bng}|$$

Where

N_b is the number of balls, ω_{inner} is shaft speed and running speed, d is the ball diameter and D is the pitch diameter and $\propto$ angel of bearing (it is a constant) and m is an integer, $m = 1, 2, 3, \ldots.$ the wavelet is represented as:

$$\mathrm{W}_{(a,\,b)} = \int_{-\infty}^{\infty} x(t)\varphi^*(t)dt$$

Continuous wavelet transforms used for getting local information of the data. But DWT [28, 29] uses orthogonal wavelet information and it is used mainly used for image compression. Than CWT and DWT, Continuous Curvelet Wavelet Transform obtains curvature based local information of the signal data. Also, it provides more redundant data where it gives more information for detecting and identifying different types of faults. CWT is one of the most important methodologies which can interpret easily. The interpreted data from CWT is readable because of its easy interpretation without loss signal information. CCWT is developed in [11, 12] as a second generation curvelet system. The very important steps of CCWT used to obtain the complete curvelet data $\mathbb{R}^2$. It is represented as $x = (x_1, x_2)^{\mathrm{T}}$ is the spatial variable, with $\xi = (\xi_1, \xi_2)^{\mathrm{T}}$ is the frequency domain. Also $r = \sqrt{\xi_1^2 + \xi_2^2}, \omega = arctan\,\frac{\xi_1}{\xi_2}$ are the polar coordinates in the frequency domain. In this paper CCWT is taken from [11, 12], which uses the second generation of curvelet system. In this paper CCWT is used to obtain the features within a continuous signal data.

Initially, window function is used to construct the curvelet functions to learn the conditions of the data. To do curvelet construction a Mayer window function [21] is used, that is

$$\mathrm{V}(t) = \begin{cases} 1 & |t| \le \frac{1}{3} \\ \cos\left[\frac{\pi}{2} v(3|t|-1)\right] & 1/3 \le |t| \le 2/3 \\ 0 & \text{else} \end{cases}$$

$$\mathrm{W}(r) = \begin{cases} \cos\left[\frac{\pi}{2} v(5-6r) \quad \begin{matrix} 2/3 \le r \le 5/6 \\ 5/6 \le r \le 4/3 \end{matrix}\right] \\ \cos\left[\frac{\pi}{2} v(3r-4\right] & 4/3 \le r \le 5/3 \\ 0 & \text{else} \end{cases}$$

Where v is the smooth function and it should satisfy the following constraint as:

$$v(x) = \begin{cases} 0 & x \le 0 \\ 1 & x \ge 1 \end{cases} v(x) + v(1-x) = 1, x \in \mathbb{R}$$

In simple case x should be 0 or 1.

Using, v, W and V are converted into smoother functions. To do these two polynomial equations may be used as

$$v(x) = 3x^2 - 2x^3 \text{ in } [0,1], \ni v \text{ is in } \mathrm{C}^1(R) \text{ or in } \mathrm{C}^2\ (\mathbb{R}).$$

Because of curvelet elements are taken as inverse Fourier transform of a suitable product of W and V. To fetch the smoothness of V and W the curvelet elements is taken from the time domain. If the window functions V(t) and W(R) should satisfy the following conditions then it will take as system curvelet functions.

$$\sum_{l=-\infty}^{\infty} \mathrm{V}^2(t-1) = 1, t \in \mathbb{R}$$

$$\sum_{j=-\infty}^{\infty} \mathrm{W}^2(2^j r) = 1, r > 0.$$

$$\int_0^{\infty} \mathrm{W}^2(r)\frac{dr}{r} = ln2$$

$$\int_{-1}^{1} \mathrm{V}^2(t)dt = 1$$

For V(t), it is observed that $\mathrm{V} \subset [-1,1]$ and the time $t \in$ R for the above conditions and $t \in [1/3, 2/3]$ for find with the substitution values. Then the continuous complex valued waveform is constructed with the help of the above described windows V(t) and W(r) with three different parameters are the scaling value $a \in (0,1]$, the location value $b \in \mathbb{R}^2$, and the orientation value $\theta \in [0, 2\pi)$. The fault is monitored by the vibration, to detect the fault frequency. The Entire functionality of the proposed approach is shown in Figure-2.

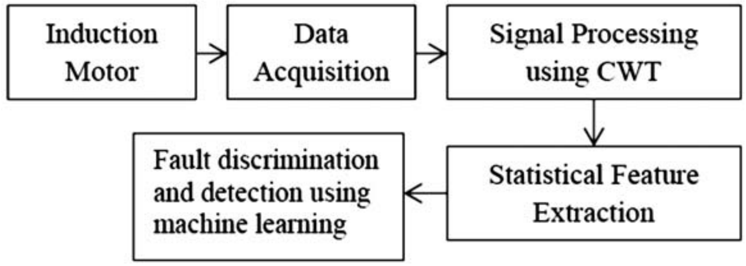

Figure 2: The Semantic Representation of the Proposed Approach

Initially various levels of noises are applied to the waveform to verify the influence of noise while feature extraction in CWT. Here various loading capacities are applied in the experiment from no-load to full-load on the belt drive system. The investigation started from constant load applied on the belt and torque is changed from 0.56 N-m to 1.13 N-m. Load is adjusted by rotating a ring from 0th position to 5th position where 0 indicates no-load and 5 indicates the full-load. Now the recorded data is decomposed using CWT as well as DWT. In this study the recorded data is decomposed sing CWT and get four mother wavelets get from 'Daubechies' family for feature extraction.

2. EXPERIMENT AND RESULTS

The stator and rotor variation of the healthy and the faulty motors at the time starting were collected by simulation results at the input sampling frequency range 8000 HZ and supply frequency 50 HZ. The experimental results were derived out under different load variation conditions such as stator current and rotor current variation, flux variation, uneven field current. The results are analyzed from following simulation results. The estimated data were decayed using SVM based CWT system. This output is implemented in MATLAB 6.5 environment. The CWT coefficients consequently gained were estimated and evaluated by the help of SVM/ANN as fault results.

The vibration analysis needs a narrow bandwidth for obtaining good frequency resolution. All the frequencies and wavelets are associated with a bandwidth f_b and a center frequency f_c within a stipulated period. In this study 'db5' and 'db8' mother wavelets are selected from 'daubechies' wavelet family based on their high period. Table-1 shows the mother wavelet, center frequency, and period. In order to compare multiple data analysis db3 and db6 with low period, high center-frequency values are taken. Similarly to improve the frequency resolution mother wavelets are selected.

Table 1
Properties of different mother wavelet used

Mother Wavelet	*Period*	*Center Frequency*	*Number of Varnishing moments*
db3	1.15	0.7	3
db5	1.8	0.65	4
db6	1.25	0.73	5
db8	1.10	0.67	7

In this research wavelet transform used as a continuous wavelet transform (CWT). Figure-3 shows the measured output waveform for testing input and wavelet based output. The output samples are changed from –6.5 to 8 samples per second. The CWT operations are implemented in MATLAB 2011a simulator. Coefficients of CWT derived by analyzed SVM classifier. Training and testing data signals were formed for analyzing motor faults at different loading conditions. Up to 100 data samples were taken under various motor operating conditions and various vector positions. 50 of the samples used as a training classifier from healthy and faulty motor operating condition. Remaining 50 samples used as a testing sample. Each of the testing and training samples decomposed using CWT. A wavelet scale range of (1–8.5) was also in use to study the effect of scale. There are two types of data samples used to calculating root mean square (RMS) and signal to noise ratio (SNR), which is evaluated from the wavelet coefficients under multiple loading condition.

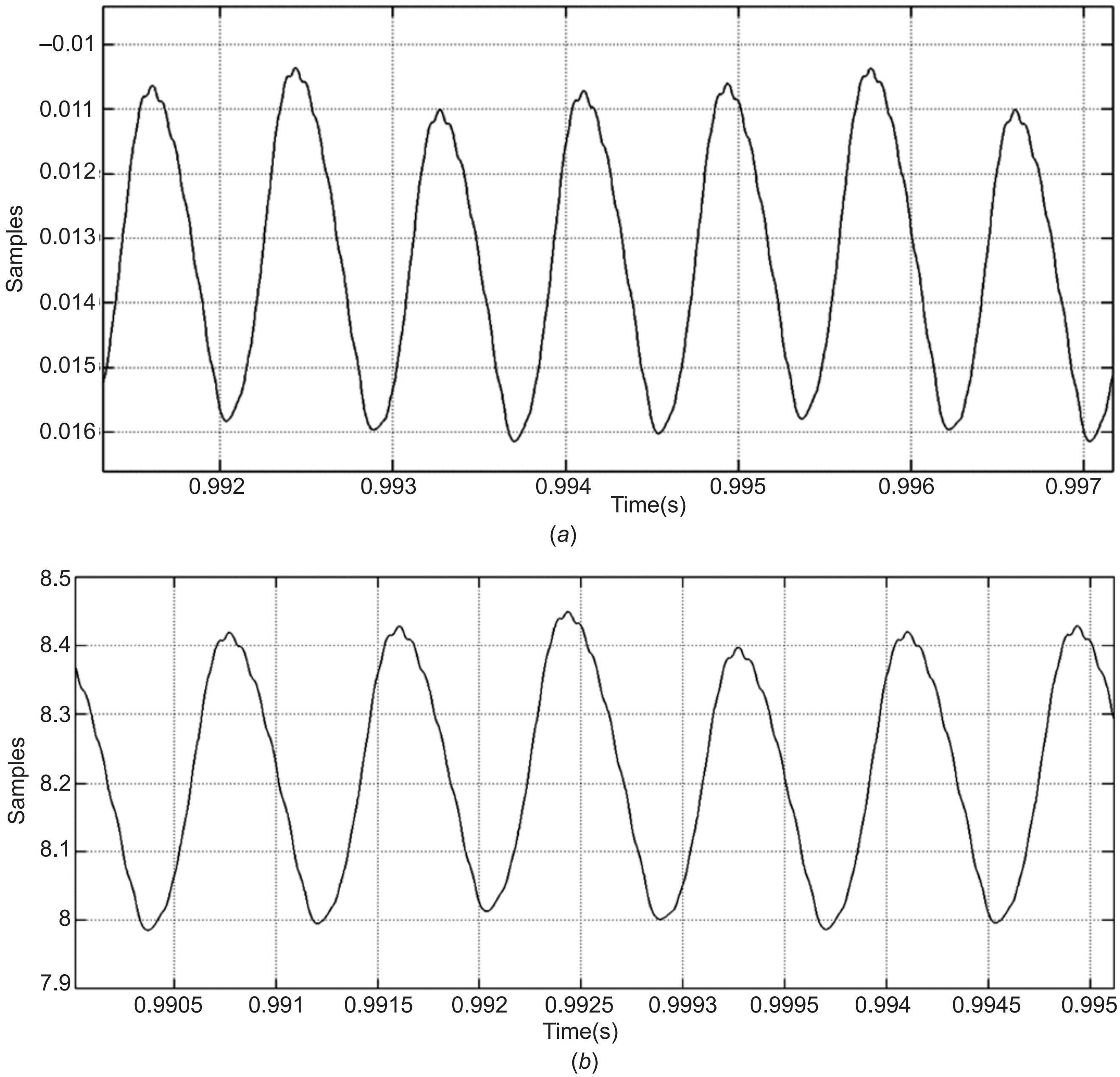

Figure 3: (*a*) Training data signal (*b*) Wavelet based output.

As shown in Figure-4, the wavelet model includes two SVM classifiers this are used to identify the three types of electrical faults: voltage variation, current variation, flux variation. Training samples of this SVM fault is trained to divide the normal state to fault state. When the input of SVM classifiers is represented as a normal state, output of SVM classifier set as 1. Otherwise input of SVM classifier are representing as a fault state, output of SVM classifier set as -1. From figure-4 the flux variation occurred from 0 to 0.5 at the time of 0.35ns to 0.6ns. Furthermore load current is also being changed from 4 amps to 10amps.

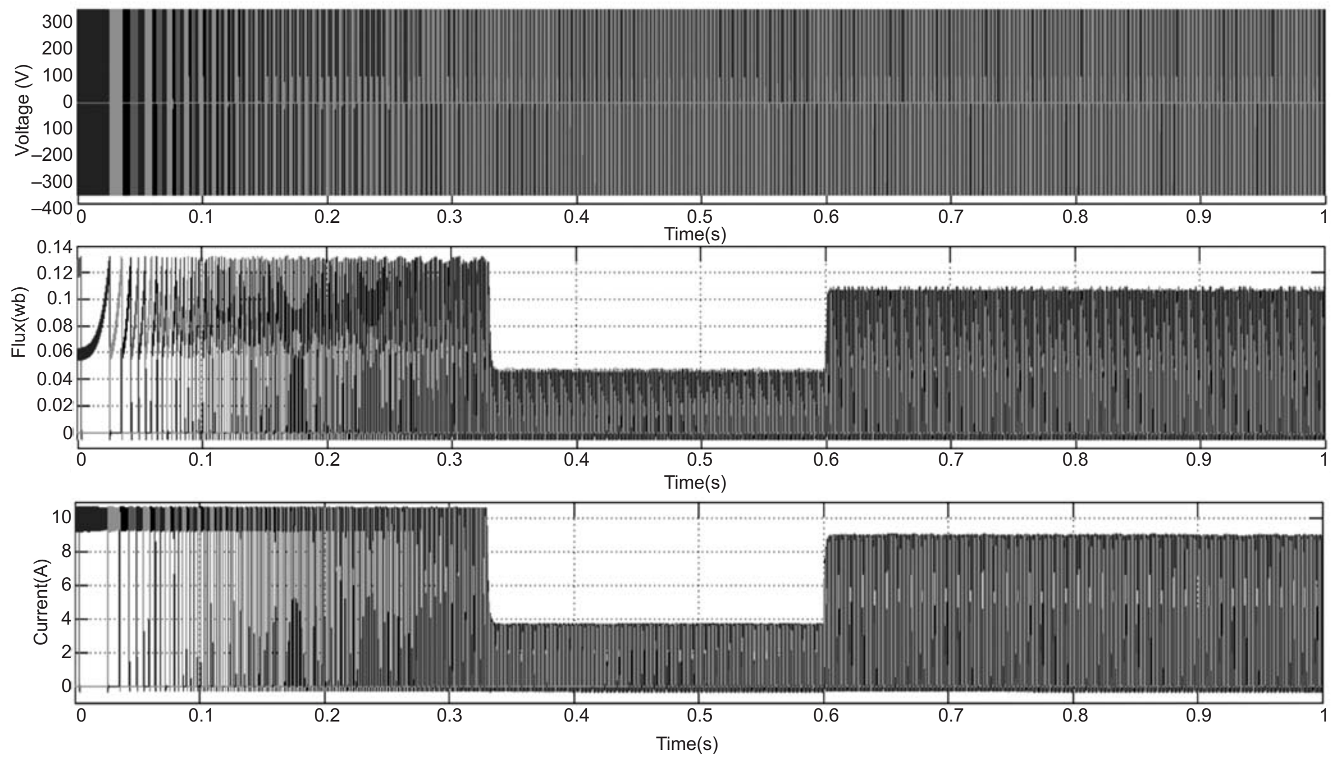

Figure 4: Illustration of fault identification and correction for stator flux, load current, load voltage

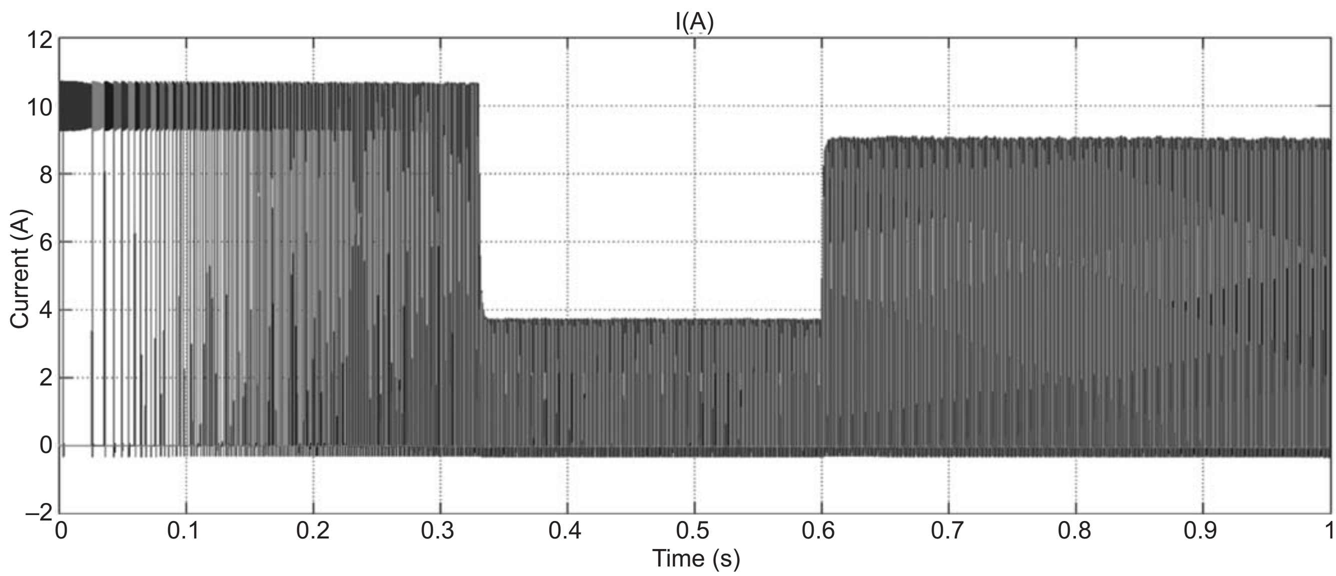

Figure 5: Illustration of constant load current after finishing wavelet function

Figure-5 shows the results of load current after finishing wavelet function and figure-6 shows the result of mechanical fault from the variation of electrical fault. The mechanical fault is divided by two: Torque is part of the basic measurement of induction motor. The output power of the motor is expressed as torque and it's multiplied by its rotational speed of the motor angle. Fault less motor produce the functional torque just over a limited range of rotational speeds. From the figure-5 Torque changes form 4 rpm to 12 rpm (usually from around 1000 to 3000rpm for three phase induction motor). The torque variation range can be calculated with a dynamometer, and shown as a torque curve. Proposed method compared with different existing methods which are shown in Table-1 under dissimilar operating conditions. The induction motor speed is calculated by analysis of rise time, speed overshoot, speed undershoot, settling time and steady state error, Flux variation, current variation, Torque variation.

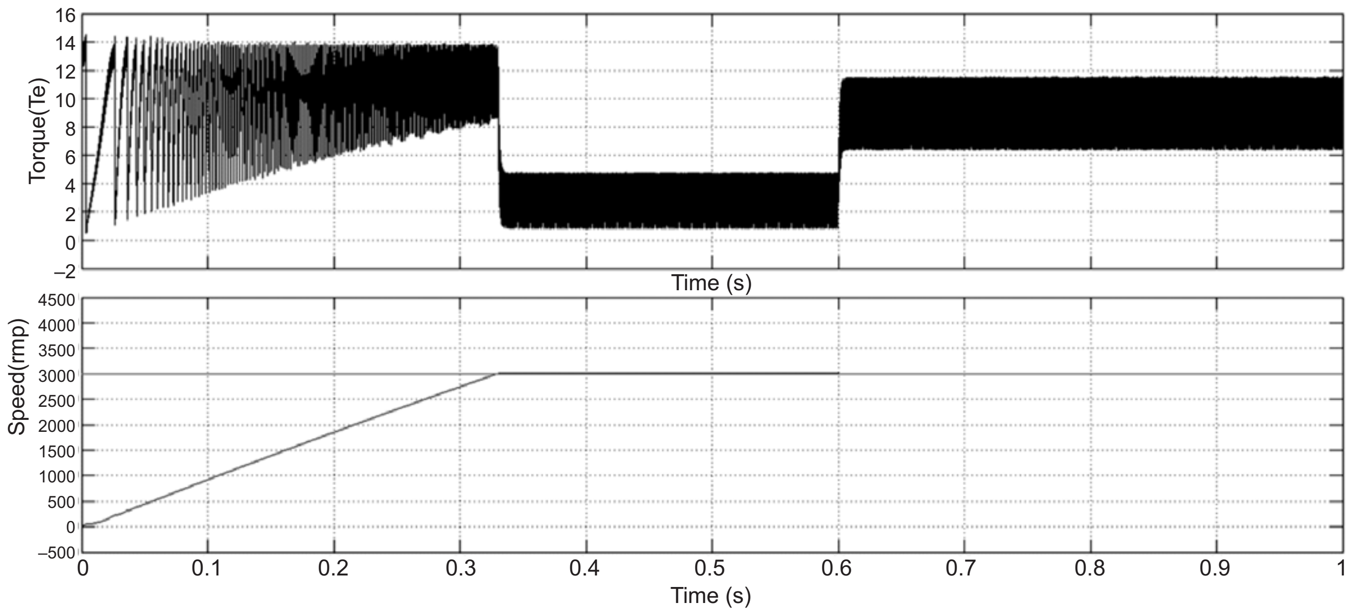

Figure 6: Illustration of motor torque and speed

Table 2
Performance Comparison

Methods to be used	*Rise Time (msec)*	*Overshoot (%)*	*Steady State Error (rad/sec)*	*Settling Time (sec)*	*Flux variation*	*current variation*	*Torque(1000 to 3000rpm)*
PI Controller	115	3.5	3.6	0.73	0.5-0.7	7-11	50-60
PID Controller	106	2.6	2.7	0.65	0.3-0.4	3-9	30-40
Fuzzy logic Controller	94	2.2	0.7	0.23	0.09-0.15	6-11	7-20
Wavelet based proposed controller	66	1.7	0.5	0.043	0.05-0.1	4-10	4- 12

There are 900 datasets are taken for experiment which has mixture of faulty and healthy motor information. 0, 1, 2, 3, and 4 are the break positions are taken to represent various loading conditions. In this paper the entire extracted feature is classified using SVM method, where SVM classifies the entire data into two different categories such as healthy or faulty.

Table 3
SVM Based Attribute Selection

Mother wavelet Type	*Scale Range*	*Frequency Range*	*Number of Attributes*	*Testing Time*	*Noise dB%*	*Training Time*	*Motor Condition Existing*	*SVM Result*
db3	8-13	35-105	18	0.50	97	0.10	Normal	Normal
db5	8-11	25-90	20	0.60	9	0.10	Fault	Fault
db6	8-13	28-100	15	0.80	97	0.10	Fault	Fault
db8	8-11	27-90	15	0.90	97	0.10	Normal	Normal

The classification of fault is obtained using CCWT with SVM are shown in Table-2. The accuracy of classification obtained from SVM is already compared with MLP and RBF and proved it is better approach for fault classification. From the table it is known that the performance of db8 is good due to is improved frequency resolution. For 8 attributes the SVM classified the dataset even though it has more noise in the data accurately than the existing approaches and obtained the accuracy of 98%. Hence this paper provides better solution for detecting and identifying the induction motor fault in an electrical system.

3. CONCLUSION

In this proposed technology SVM classifier based wavelet controller is proposed to control the induction motor fault. The proposed method compared with the existing methods; MLP, RBF, PI, PID controller and fuzzy logic controller under various operating condition and load variation. The suitable data was collected in this operating conditions including, constant operating condition, stator and rotor speed variation, magnetic torque, field current. It is exposed that using time domain features not only leads to lower computational load however also results in more accurate fault analysis. Furthermore compared with different existing methods, the proposed method is simple, accurate, reliable and economical. In the result, using time domain features is recommended to detect the stator and rotor winding faults.

4. REFERENCES

1. M. Peltola, ―Slip of ac induction motors and how to minimize it,‖ ABB Drives Press Releases Techical Paper, ABB, New Berlin, 2003, pp. 1–7.
2. A. Bellini, F. Filippeti, C. Tassoni, G.-A. Capolino, Advances in diagnostic techniques for induction machines, IEEE Trans. Ind. Electron. 55 (2008) 4109–4126.
3. R.M. Tallam, S.B. Lee, G.C. Stone, G.B. Kliman, J. Yoo, T.G. Habetler, R.G. Harley, A survey of methods for detection of stator-related faults in induction machines, IEEE Trans. Ind. Appl. 43 (2007) 920–933.
4. M. Reliability Working Group. Report of large motor reliability survey of industrial and commercial installations, part I. IEEE Transactions of Industry Applications 1985;IA-21:853–64.
5. M. Reliability Working Group. Report of large motor reliability survey of industrial and commercial installations, part II. IEEE Transactions of Industry Applications 1985;IA-21:865–72.
6. M. Reliability Working Group. Report of large motor reliability survey of industrial and commercial installations, part III. IEEE Transactions of Industry Applications 1985;IA-21:153–8.
7. Albrecht PF, Appiarius JC, Shrama DK. Assessment of the reliability of motors in utility applications. IEEE Transactions of Energy Conversion 1986;EC-1: 39–46.
8. J. Antonino-Daviu, P. Jover-Rodriguez, M. Riera-Guasp, M. Pineda-Sanchez, A. Arkkio, Detection of combined faults in induction machines with stator parallel branches through the DWT of the startup current, Mech. Syst. Signal Process. 23 (2009) 2336–2351.
9. S.H. Kia, H. Henao, G.-A. Capolino, Diagnosis of broken-bar fault in induction machines using discrete wavelet transform without slip estimation, IEEE Trans. Ind. Appl. 45 (2009) 1395–1404.
10. K. Teotrakool, M.J. Devaney, L. Eren, Adjustable-speed drive bearing-fault detection via wavelet packet decomposition, IEEE Trans. Instrum. Meas. 58 (2009) 2747–2754.
11. S. Wang, W. Huang, Z.K. Zhu, Transient modeling and parameter identification based on wavelet and correlation filtering for rotating machine fault diagnosis, Mech. Syst. Signal Process. 25 (2011) 1299–1320.
12. W. Freeman, E. Adelson, The design and use of steerable filters, IEEE Trans. Pattern Analysis and Machine Intelligence, 13 (9), 891-906 (1991).
13. E. Simoncelli, W. Freeman, E. Adelson, D. Heeger, Shiftable multiscale transforms, IEEE Trans. Inform. Theory, 38 (2), 587-607 (1992).
14. T. Lee, Image representation using 2D Gabor wavelets, IEEE Trans. Pattern Analysis and Machine Intelligence, 18 (10), 1-13 (2008).
15. D. Donoho, Wedgelets: nearly minimax estimation of edges, Ann. Statistics, 27 (3), 859-897 (1999).
16. D. Donoho, X. Huo, Beamlets and multiscale image analysis, in: Multiscale and Multiresolution Methods, Springer Lecture Notes in Comput. Sci. Eng., T. Barth et al. (Eds.), vol. 20, pp. 149-196, 2002.

17. S. Mallat, G. Peyr´e, A review of bandlet methods for geometrical image representation, Numer. Algorithms, 44 (3), 205-234 (2007).

18. E. Le Pennec, S. Mallat, Sparse geometrical image approximation with bandlets, IEEE Trans. Image Process., 14 (4), 423-438 (2005).

19. M. Do, M. Vetterli, The contourlet transform: an efficient directional multi-resolution image representation, IEEE Trans. Image Process., 14 (12), 2091-2106 (2005).

20. D. Labate, W-Q. Lim, G. Kutyniok, and G. Weiss. Sparse multidimensional representation using shearlets, SPIE Proc. Wavelets XI, vol. 5914, pp. 254-262, San Diego, CA, 2005.

21. K. Guo, D. Labate, Optimally sparse multidimensional representation using shearlets, SIAM J. Math. Anal., 39, 298-318 (2007).

22. L. Demanet, L. Ying, Wave Atoms and Sparsity of Oscillatory Patterns, Appl. Comput. Harmon. Anal., 23 (3), 368-387 (2007).

23. R. Willett, K. Nowak, Platelets: A multi-scale approach for recovering edges and surfaces in photon-limited medical imaging, IEEE Trans. Med. Imaging, 22 (3), 332-350 (2003).

24. Y. Lu, M. N. Do, Multidimensional directional filter banks and surfacelets, IEEE Trans. Image Process., 16 (4), 918-931 (2007).

25. Commander Sunil Tyagi, A comparative study of SVM classifiers and artificial neural networks application for rolling element bearing fault diagnosis using wavelet transform preprocessing, in: Proceedings of World Academy of Science, Engineering and Technology, vol. 33, September, 2008, pp. 319–327.

26. S. Abbasion, A. Rafsanjani, A. Farshidianfar, N. Irani, Rooling element Bearings multi-fault classification based on the wavelet denoising and support vector machine, Mechanical Systems and Signal Processing Journal 21 (2007) 2933–2945.

27. R.Polikar, The wavelet tutorial. Internet Resources: http:// engineering.rowan.edu/polikar/WAVELETS/ WTtutorial.html

28. P. Konar, P. Chattopadhyay, Bearing fault detection of induction motor using wavelet and support vector machines (SVMs). Applied Soft Computing 11, 4203–4211 (2011)

29. D. Saxena1, K.S.Verma, Wavelet transform based power quality events classification using artificial neural network and SVM, International Journal of Engineering, Science and Technology, 4(1), 87–96, 2012

30. P.K. Kankar, S.C. Sharma, S.P. Harsha, Fault diagnosis of ball bearings using continuous wavelet transform. Applied Soft Computing 11, 2300–2312 (2011)

31. Challenges and Surveys in Key Management and Authentication Scheme for Wireless Sensor Networks" in Abstract of Emerging Trends in Scientific Research 2014– 2015. https://ideas.repec.org/s/pkp/abetsr.html

32. R.Samsi, J.Mayer, A.Ray, Broken rotor bar detection using symbolic wavelet analysis, Proceedings of the Forty-five IEEE Conference on Decision and Control, 4058–4063, 2006

33. Automatic detection of lung cancer nodules by employing intelligent fuzzy cmeans and support vector machine ",Biomedical Research.

34. J. Shin, H.Lim, J.Qian, D.Kang, A Study on fault diagnosis of induction motor using neural-wavelet, The Eighth WSEAS International Conference on Multimedia Systems and Signal Processing, 210–213, 2008

35. X. Xie, X.Ding, Gene expression pattern extraction based on wavelet analysis, Proceedings of the 2009 IEEE International Conference on Information and Automation, 1274–1278, 2009

36. Challenges and Surveys in Key Management and Authentication Scheme for Wireless Sensor Networks" in Abstract of Emerging Trends in Scientific Research 2014– 2015. https://ideas.repec.org/s/pkp/abetsr.html

37. W.Zhaoxia, L.Fen, Y.Shujuan, W.Bin, Motor fault diagnosis based on the vibration signal testing and analysis, The Third International Symposium on Intelligent Information Technology Application, 433–436, 2009