Fault detection in Induction motor using WPT and Multiple SVM

Aravindh Kumar.B, Saranya G, Selvakumar R, Swetha Shree R, Saranya M, Sumesh.E.P
Department of Electronics and Communication Engineering,
Amrita Vishwa Vidyapeetham,
Coimbatore, India.
ep_sumesh@cb.amrita.edu

Abstract

In this paper a novel approach to detect various faults occurring in the induction motor is presented. Both vibration and motor current signature analysis are performed to detect the mechanical and electrical faults. Multi-scale decomposition process using wavelet packet transform is performed on the obtained signal to extract the features. The extracted features are given to a classifier to identify whether a fault has occurred. If a fault exists, it identifies the fault location and isolates it. The various faults discussed in this paper are: mechanical faults— such as bearing faults and electrical faults occurring in the rotor and stator parts of an induction motor. Multiple Support Vector Machine using the one-against-others approach is used to obtain multi-class classification of fault.

Keywords: *Wavelet packet transform; Accelerometer; Hall Effect sensor; Neural network..*

1. Introduction

Condition monitoring and fault diagnosis of induction motors are of great importance in production lines. It can significantly reduce the cost of maintenance and the risk of unexpected failures by allowing the early detection of potentially catastrophic faults. In condition based maintenance, one does not schedule maintenance or machine replacement based on previous records or statistical estimates of machine failure. Rather, one relies on the information provided by condition monitoring systems assessing the machine's condition. Thus the key for the success of condition based maintenance is having an accurate means of condition assessment and fault diagnosis. On-line condition monitoring uses measurements taken while a machine is in operating condition.

There are around 1.2 billion of electric motors used in the United States, which consume about 57% of the generated electric power. Over 70% of the electrical energy used by manufacturing and 90% in process industries are consumed by motor driven systems [1]. Among these motor systems, squirrel-cage induction motors (SCIM) have a dominant percentage because they are robust, easily installed, controlled, and adaptable for many industrial applications. SCIM find applications in pumps, fans, air compressors, machine tools, mixers, and conveyor belts, as well as many other industrial applications. Moreover, induction motors may be supplied directly from a constant frequency sinusoidal power supply or by an a.c. variable frequency drive. Thus condition based maintenance is essential for an induction motor.

It is estimated that about 38% of the induction motor failures are caused by stator winding faults, 40% by bearing failures, 10% by rotor faults, and 12% by miscellaneous faults[1]. Bearing faults and stator winding faults contribute a major portion to the induction motor failures. Though rotor faults appear less significant than bearing faults, most of the bearing failures are caused by shaft misalignment, rotor eccentricity, and other rotor related faults. Besides, rotor faults can also result in excess heat, decreased efficiency, reduced insulation life, and iron core damage. So detection of mechanical and electrical faults are equally important in any electrical motor.

In the proposed method, vibration signals are obtained using piezo-electric sensor and motor current signature analysis is performed using Hall Effect sensor. The features of the signal are analyzed using wavelet packet transform. Besides other signal processing techniques, wavelet packet transform is preferred because it has certain advantages [2]. Traditional signal processing techniques like Fourier transform can perform only on stationary signals. Since it is not well suited for non-stationary signals short time Fourier transform (STFT) is used. STFT uses a constant window function as a base to obtain the frequency spectrum coefficients. The size of the window function cannot be changed which led to the need for wavelet transform [3]. Wavelet transform uses a varying size window function as its base. In wavelet transform low frequency signals are decomposed repeatedly to obtain low frequency information. In wavelet transform the information about high frequency signals are limited. In the proposed method, wavelet packet transform decomposes both low frequency and high frequency information. It can analyze both stationary and non-stationary signals.

There are many classifier models to effectively classify the faulty data from the healthy one. They are: Analytical model-based methods, Artificial Intelligence-based methods. Analytical model based methods are efficient monitoring systems for providing warning and predicting certain faults in their early stages [4]. Artificial Intelligence based methods are of two categories: Knowledge based models and Data based models. When considering fault diagnostics of induction motor it is difficult to develop an analytical model that describes the performance of a motor under all its operation points. It is difficult for a human expert to distinguish faults from the healthy operation [5]. Though analytical based methods and knowledge based methods are effective classification methods, their performance in induction motors is not good [6]. Moreover conventional methods cannot be applied effectively for vibration signal diagnosis due to their lack of adaptability and the random nature of vibration signal [6]. In such a situation, data based models are used to classify faults in induction motors.

Data based models are applied when:

- the process model is not known in the analytical form
- expert knowledge of the process performance under faults is not available

Some of the popular data based models are neural networks, fuzzy systems and Support vector machine. Neural networks and fuzzy logic are widely used in the field of fault diagnostics. Fuzzy logic provides a systematic framework to process vague and qualitative knowledge. Using fuzzy logic it is possible to classify a fault in terms of its degree of severity [6].Artificial neural network are modeled with artificial neurons. Each artificial neuron accepts several inputs, applies preset weights to each input and generates a non-linear output based on the result. The neurons are connected in layers between the inputs and outputs.

Support Vector Machine, a novel machine learning technique is used in this paper. It is based on statistical learning theory, and is introduced during the early 90's. SVM is opted in this paper since it is shown to have better generalization properties than traditional classifiers. Efficiency of SVM does not depend on the number of features of classified entities. This property is very useful in fault diagnostics, because the number of features to be chosen to be the base of fault classification is thus not limited.

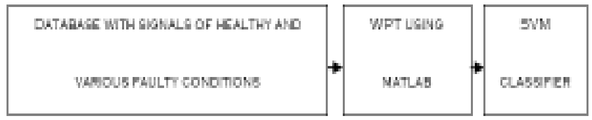

Figure 1.Schematic representation of training a classifier.

Fig.1 represents the training phase of the classifier with database signals. The database consists of signals of known condition like healthy, inner race bearing fault, outer race bearing fault, rotor fault and stator fault. So the known signals are analysed to extract the features for training the classifier to classify whether fault has occurred and if so then the location of fault occurrence is too stated.

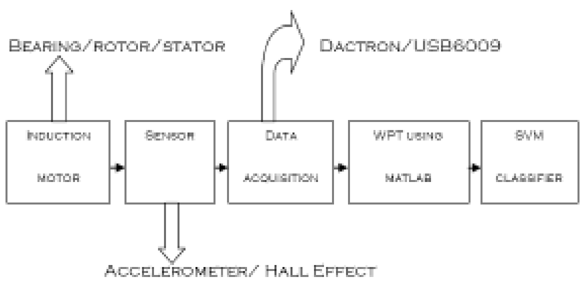

Figure 2. Schematic representation of the proposed method.

Fig.2 represents the flow of the signals from motor to classify the fault and proceed with the condition monitoring. The signals acquired from the motor parts with the help of sensors are analysed with WPT to extract the features. These features are given to the trained classifier to state the fault location if fault exists.
This paper is organized as follows. A brief review of Sensors and motor current features, Wavelet Packet Transform and Support vector machine are discussed in section 2, 3 and 4. The predicted experimental results of the proposed techniques are described in section 5. And then the conclusion is given in section 6.

2. Sensor

The sensor used for vibration analysis is the accelerometer and for MCSA is the Hall Effect sensor.

2.1. Acceleromter

Commonly used accelerometers are strain gauge type, capacitive type, and piezoelectric type. Here we use piezoelectric type since it has high natural frequency. For frequency ratios, the ratio between the vibrating member and the natural frequency of the accelerometer greater than 0.4, the response was found to be non-linear for other type of accelerometers; thus piezoelectric type is preferred.

Advantages of piezoelectric accelerometer.

- Instrument is quite small and weightless
- Natural frequency of the instrument is very high so they can be used for vibration and shock applications which produce sudden change in the frequency spectrum
- Good linearity throughout the range.

Piezoelectric accelerometer used is BRUEL & KJAER type because of the following advantages:

- Temperature ranges cover – 74° to + 250°C
- Low sensitivity to extraneous environmental influences including temperature fluctuations
- Acceleration ranges cover 20 ms–2 to 1000 kms–2 Frequency ranges cover from a fraction of a Hz to 60 kHz
- Frequency ranges cover from a fraction of a Hz to 60 kHz

Figure 3.BRUEL &KJAER piezoelectric

The hall transducer that we used for MCSA is HX03.This works based on Hall Effect measuring principle and requires a single supply ranging from +12 V to +15 V. It has low power consumption and isolation voltage as high as 3000 V. Further it provides galvanic isolation between primary and secondary circuit and has an extended measuring range of 3x $I_{PN.}$

It is preferred due to following advantages.

- Easy to mount with automatic handling system.
- Small size and space saving.
- Only one design for wide current ratings range.
- High immunity to external interference.

Figure 4.HX-03 Hall effect sensor

2.2. MCSA

When induction machine runs at fault conditions, some special components occur at the stator current. For example,

- When the rotor bar breaks, the feature components in the motor stator line current are

$$f = (1 \pm 2ks) f_1 \quad (k=1, 2, 3\ldots) \tag{2}$$

Where f_1, supplied frequency and s is the slip.

- When rotor eccentricities occurs, the feature frequencies in the motor stator line current are

$$f_{ecc} = f_1 [(R \pm n_d)(1-s)/p \pm n_w] \tag{3}$$

where R, the number of rotor bars,
p , the pole pairs,
$n_d=0$, in static eccentricity,
$n_d=1$, in dynamic eccentricity.
$n_w = 1, 3, 5, ..$

From eqn(3) it is evident that the fault conditions in induction machines can be easily detected by monitoring the stator currents.

3. Wavelet Packet Transform

Wavelet transform is known as multi scale decomposition process [2]. Decomposition of the signal provides frequency information about the discrete time signal. This is done by convolution of signal with high pass and low pass filters. The convolution of signal with high pass and low pass filter provides two vectors such as the detail coefficient and approximation coefficient. The detail coefficient provides high frequency information whereas approximation provides low frequency information. In WT, multi scale decomposition is basically done only on approximation coefficient. So time-frequency localization of any fault is not more accurate [3]. Hence Wavelet packet transform is proposed to obtain more flexible and wider base result of the fault location.

Wavelet packet transform performs multi scale decomposition on both approximation and detail coefficient. Thereby good localization is obtained [3].

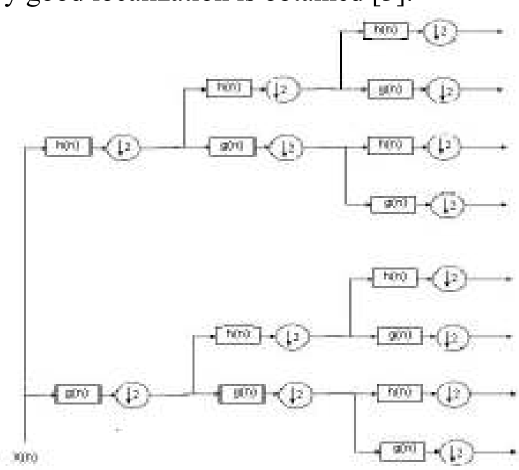

Figure 5.Three level wavelet packet decomposition tree.

Each node of the WPT decomposition tree is assigned with a variable and indexed with a pair of integers {i,j} (where 'i' representing the level of decomposition and 'j' representing the order of node position at that level of decomposition). This wavelet packet node energy is assigned and indexed basically to provide a robust signal feature. These features can be used for classification of fault rather than direct usage of the wavelet coefficients in classification. The main motto behind this usage of node energy is because the direct usage of coefficients in classification provides inaccurate results in fault detection.

Each node in the WPT has coefficient vector C(i, j) and those coefficient vector is used to measure a specific sub-band frequency content [7]. In wavelet packet transform, node energy is given by

$$E_{i,j} = \sum_j |c_{i,j}|^2 \qquad (1)$$

Equation (1) represents the signal energy in a particular level of specific node. The node energy calculation gives us with a more robust signal classification feature than using the wavelet packet coefficients. In this paper the energy of the wavelet packet decomposition coefficient C is used as a quantitative feature for fault classification and detection [7]. The following steps are followed for analysis of a particular signal in classification:

— The obtained signal from sensor is first decomposed at level I and 2^i $C_{i,j}$ are the wavelet packet transform coefficients produced. This is proceeded by using specific wavelet family.
— Decomposition is done till it reaches the final level 'K'. The specific value of 'K' is practically determined in the literature [8]. For rotating machinery fault detection, K is normally 3 or 4, as this much decomposition is well enough to extract the features of the obtained signal.
— Then energy of each node at all decomposition levels are calculated using the eqn (1). This would result in a vector containing 2^k energy values and its mean is computed.
— Then above steps are repeated for all wavelet family used.
— The resulting mean-energy vector is then plotted against the wavelet families used. This plot is finally used to identify the fault type.

The wavelet families used in this paper are Daubechies (db7), Symlet (sym3), Coiflet (coif4), Biorthogonal6.8 (bior6.8), Reverse Biorthogonal6.8 (rbio6.8).

4. Support Vector Machine

This section presents and introduction to SVM applicability classification of data. The SVM is basically a binary classifier. It is used to map the data at input side to a feature by using a nonlinear map. Linear decision function is designed in the feature space basically to classify the input data. Support vector machine maps the inner product of feature space using the kernel function nonlinearly.

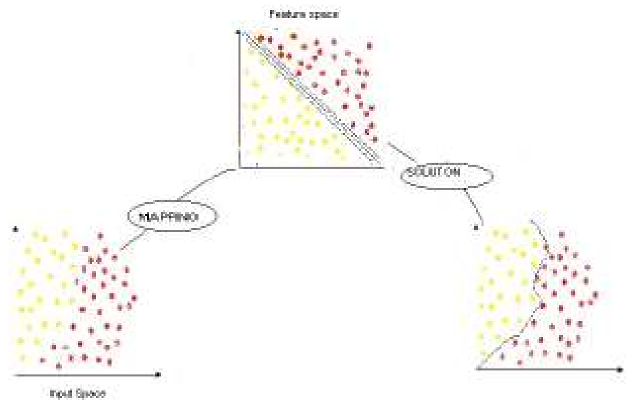

Figure 6.Schematic diagram of SVM in Classification

Support vector machine constructs a hyper plane or a set of hyper planes in an infinite dimensional space for performing classification or regression tasks in an application. There are many possible choices of hyper plane for classification of data. But the best among those planes is determined by examining the margin levels, which exist between the two classes. The margin level should be chosen such that the there exists a trade-off between margin level and error in generalization. The hyper plane with maximum separation distance is chosen as it has low generalization error. Such a distance between two class hyper planes is given by the maximum separating margin level. Such a classifier with maximum margin levels is known as maximum margin linear classifier.

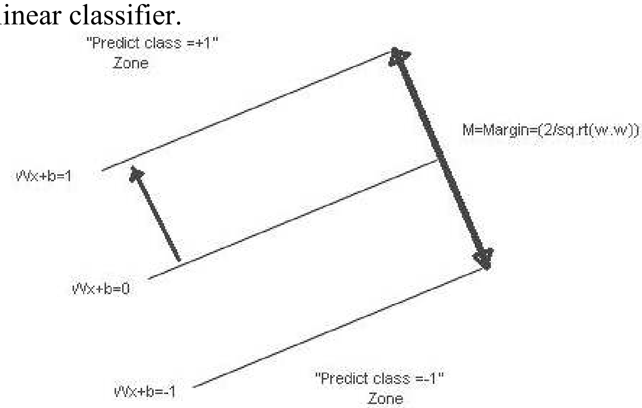

Figure 7.Maximum margin linear SVM.

4.1. Multi-class classification

SVMs are binary classifiers [9], which are designed to separate only two classes from each other. But for the fault detection in induction motor we are in need of multi-class SVM. Such multi-class SVM is obtained by decomposing the multi-class problem into several number of binary class problems. Then classifiers are trained to solve the problems assigned to each binary SVM. Finally the classifiers are coupled to reconstruct the solution of the multi-class problem from the outputs of the individual classifiers.

The multi-class classification structure is basically given by two methods:

- One-against-others approach.
- Pair-wise coupling approach.

4.2. One-against-others approach

This approach can also be defined as one-versus-all. In this method, one class is compared with all other classes in multi- class structure. Classification of new instances using one-versus-all method is done, in which the classifier with the highest output function assigns the class [9].

4.3. Pair-wise coupling approach

This approach is defined as one-versus-one. In this, the classification is obtained by a max-wins strategy in which every classifier assigns the instance to one of the two classes. Then the vote for the assigned class is increased by one vote; finally the class with most votes determines the instance classification [9].

4.4. Comparison between two structures

In one-against-others method, **M** classifiers are defined for each classifier to facilitate the separation of one class from all the others. But in most of the applications, this method has found to be inferior when compared with next method, a pair wise coupling method. In pair-wise coupling method, 0.5*M*(M-1) classifiers are constructed, for each separating one class from another (ignoring all the other classes). Outputs of the one-versus-one classifiers are then coupled to find the final solution to the M-class problem [9]. In this approach, more binary classifiers are used than in former method, but by using more classifier too, the total classification performance can be improved efficiently high.

4.5. Synthesizing scheme

The result from each binary classifier used in multi-class is coupled together by synthesizing scheme. Such scheme can be any one of the following methods.

- Majority voting method
- Binary tree decision method
- Neural network method
- Hybrid matrix method.

5. Results and Discussions

5.1. SETUP used in the experiment.

Induction motor used for this analysis is three phase, 1.5KW, 50Hz, 430V. Five different conditions are tested at different speed: Bearing inner race, Outer race, ball fault, Rotor winding and Stator crack. The sampling frequency is 8192Hz; the MCSA samples are acquired to computer with the help of National Instruments DAQ (USB6009) card. DACTRON accelerometer is used for obtaining vibration signals from the motor. The tests are repeated for 250 times and the analysis is performed in Matlab^{R} with wavelet (db4) function. Wavelet packet transform tree is shown below for 4 levels (K=4). Fig.8 shows WPT for outer race fault condition monitored for 800RPM.

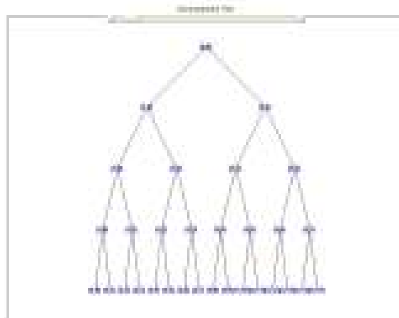

Figure 8.Wavelet packet decomposition tree.

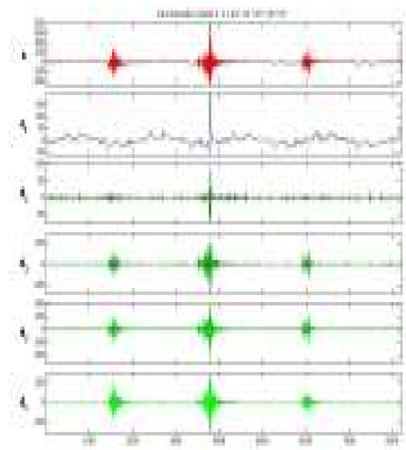

Figure 9.Vibration signal of outer race fault decomposed with DB4 wavelet for 4 levels.

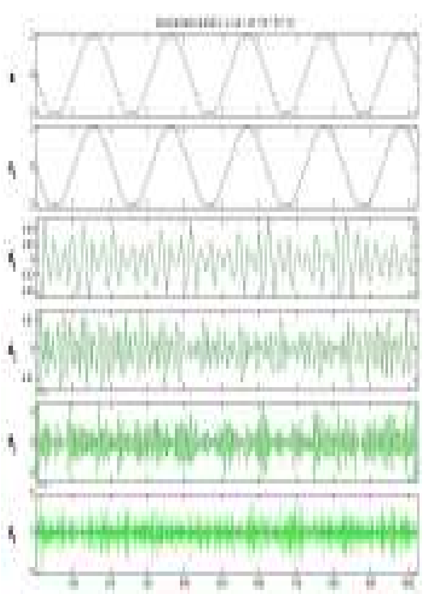

Figure 10. Analysis of current signal in good condition.

Fig.9 shows decomposition of signal. This gives the clear view of variation in amplitude and frequency from ideal case. Features are extracted from appropriate level approximation and detail coefficients which is more correlated to the fault.

SVM is trained with random set of data with RBF as kernel function. 50% of data set is used for training and remaining is used for testing purpose. RBF kernel is taken for multi class classification [9]. Best classification parameter values are found from literature review. Value taken for our analysis are C=0.5, σ=2.5. Multi class SVM gives the result up to 97% with very less time consumption. This uses one-against –other approach which is still under development, aims up to 99% accuracy for almost all common faults in induction motor [9]. The multi class structure is obtained by using one-against others approach. This method is chosen because of easy understanding in design than the other.

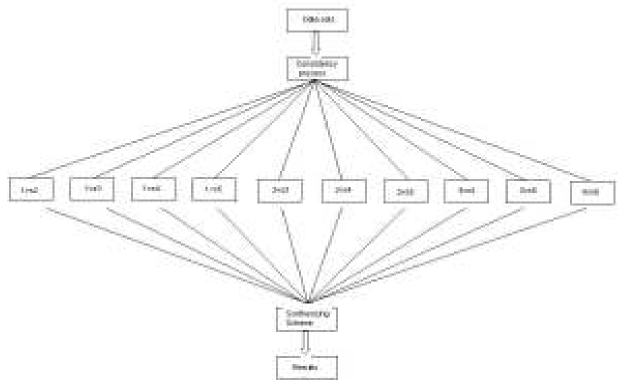

Figure 11. One-against-other approach for rotor fault diagnosis (five classes)

Synthesizing scheme is necessary for coupling the results from each binary classifier to decide the final result [9]. Such synthesizing scheme can be of either hybrid matrix method or neural network method for ensuring best classification.

Table 1.Synthesizing scheme comparison in case of rotor fault diagnosis

Correct classification (%)	Majority voting	Binary tree	Neural network	Hybrid matrix
Healthy	97.2	98.4	100	100
Broken bar	98.4	96.8	100	100
Broken end-ring	93.2	95.4	98.2	97.8
Static eccentricity	79.6	88.5	94.8	94.1
Dynamic eccentricity	72.8	86.7	93.9	94.7
Average value	88.2	93.16	97.38	97.32

The table 1 shows comparison between the synthesizing schemes. Among the hybrid matrix method and neural network, neural network method produces the best result with good classification accuracy than the other. But since identification of arbitrary values for the hidden neuron to classify into various classes is not much easier and time consuming one. So hybrid matrix method is chosen for coupling [9].

6. Conclusion

The proposed method can provide a methodology to detect various kinds of fault that can occur in induction motor. Both electrical and mechanical fault can be identified by using sensors. After that signal obtained from sensor, is used for extracting feature (energy content) by wavelet packet decomposition. These extracted features are given to multi-class SVM for identification and classification the fault if it has occurred. Thus by combining WPT and SVM, the best classification of fault is achieved. A quantitative comparison for improvement needed.

7. References

[1] M.L.Sin, W.L.Swong, N.Eartugrul, University of Adelaide, "Induction Machine Online Condition Monitoring and Fault Diagnosis-Survey in 2003."
[2] Basel Isayed, Lahouari Cheded, Fadi Al-Badour, "Vibration monitoring and fault detection using wavelet analysis" IEEE transaction on 1-4244-0779-6/07 .
[3] K.P. Soman, K.I.Ramachandran , "Insight into Wavelets From Theory To Practice," Second edition, 2008.
[4] Sanna Pöyhönen, "Support Vector Machine Based Classification in Condition Monitoring of Induction Motors," Helsinki University of Technology Control Engineering Laboratory, June 6, 2004, Report 141.
[5] M Deriche, King Fahd University of Petroleum & Minerals Dhahran, "Bearing fault diagnosis using wavelet analysis," IEEE transaction 1-4244-0011-2-2005.
[6] Neelam Mehla, Ratna Dahiya, "An Approach of Condition Monitoring of Induction Motor Using MCSA," International Journal of Systems Applications, Engineering & Development, vol.1, Issue 1, 2007
[7] G.Yen, K.C. Lin "Wavelet Packet Feature Extraction for Vibration Monitoring," IEEE Transactions on industrial electronics, vol. 47, no. 3, June 2000.
[8] N.G Nikolaou, I.A. Antoniadis "Rolling element bearing fault diagnosis using wavelet packets," NDT&E International vol.3, pp. 197-205, 2002.
[9] Ruiming Fang, Hongzhong Ma, "Application of MCSA and SVM to Induction Machine Rotor Fault Diagnosis," Proceedings of the 6th World Congress on Intelligent Control and Automation, June 21 - 23, 2006, Dalian, China, IEEE transaction 1-4244-0332-4-2006.
[10] MATLAB^R software, MATLAB help, version 7.0
[11] Sanna Poyhonen, Pedro Jover, Heikki Hyotyniemi, "Signal Processing of Vibrations for Condition Monitoring of an Induction motor," IEEE Transactions on 0-7803-8379-6/04.
[12] K.Abbaszadeh, J.Milimonfared, M.Haji, H.A.Toliyat, "Broken Bar Detection in Induction Motor via Wavelet Transformation," IECON'01(the 27th Annual Conference of the IEEE Industrial Electronics Society), IEEE Transaction on 0-7803-7108-9/01.

Authors

Aravindh kumar . B

He has completed his B.Tech in Electronics and Instrumentation Engineering from Amrita Vishwa Vidyapeetham, Coimbatore in May 2010. His areas of interest includes Industrial automation and Analytical Instrumentation.

Saranya . G

She has completed her B.Tech in Electronics and Instrumentation Engineering from Amrita Vishwa Vidyapeetham, Coimbatore in May 2010. Her areas of interest includes Microcontrollers (PIC 16F877) and wavelets.

Selva Kumar . R

He has completed his B.Tech in Electronics and Instrumentation Engineering from Amrita Vishwa Vidyapeetham, Coimbatore in May 2010. His areas of interest includes Embedded systems and wavelet signal processing.

Swetha Shree . R

She has completed her B.Tech in Electronics and Instrumentation Engineering from Amrita Vishwa Vidyapeetham, Coimbatore in May 2010. Her areas of interest includes Industrial automation and Microcontrollers (PIC16f877).

Saranya . M

She has completed her B.Tech in Electronics and Instrumentation Engineering from Amrita Vishwa Vidyapeetham, Coimbatore in May 2010. Her areas of interest includes Process Control Instrumentation, Signal processing and wavelets.

Sumesh ep

He completed his BTech in Electronics and Communication Engineering from NSS college of Engineering, Palakkad in the year 1995 and MTech in Optoelectronics and Laser electronics in 1999 from Cochin University of Science & Technology with first rank. He completed his Phd form NIT Calicut in the year 2009.He is having several publications in National/International Journals and conferences to his credit. His research area includes wavelets, multiwavelet, Signal processing and communications.