Journal of Theoretical and Applied Information Technology
20th May 2014. Vol. 63 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

PROGNOSTIC OF ELECTRICAL MOTOR VIBRATION SIGNALS: A HYBRID TECHNIQUE

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ABSTRACT

In this paper, a hybrid technique is proposed for detecting the vibration signal of electric motor. The proposed hybrid technique is the combination of S-transformation algorithm and radial basis function neural network (RBFNN) technique. Initially, the pre-processing is applied in the electric motor signal such as normal and vibration. Then, the features of the signal are extracted by using S-transformation algorithm. With the help of the extracted features, the network is trained by back propagation training algorithm and the respective classes. The proposed hybrid technique is implemented in MATLAB working platform. The performance of the proposed hybrid technique is evaluated with three types of vibration signals. Performance of proposed method is analyzed by statistically measured and compared with S-transform-FFBNN and DWT-RBFNN techniques. From the comparative analysis, it has been shown that the proposed method has better accuracy, sensitivity and specificity.

Keywords: *Fault detection, pre processing, fault classification, S-transformation, FFBNN and RBFNN*

1. INTRODUCTION

Induction motors are generally applied in the industry because of its robustness, effortlessness of its construction and need minimum maintenance [1]. We can never keep away from the possibility of failure even though induction motors are dependable [2]. The induction motor errors can be categorized into bearing failures, stator faults, rotor faults, air gap eccentricity, mechanical vibrations, etc [3]. The bearing error happens in motor is owing to the unnecessary load, rise of temperature within the bearing, apply of bad lubricant and so on [4]. As soon as any mechanical part of the motor wears or breaks up, it effects in change in oscillations and thus the vibration spectrum will vary. Besides any defect in air gap flux distribution alters the torque and thus effects in change in vibration pattern [5]. These letdowns may be extremely dangerous to the motor and therefore early detection of failure is required before they affect the entire operational performance [6]. To identify the trends of improving errors and find out the sources of problems, measurements and watching of parameters such as vibration, temperature, noise level and power consumption can be assisted [7]. Hence, the suitable condition monitoring method of motor is required.

In industries, Condition monitoring of induction motor have an exigent task for engineers. There are lots of conditions monitoring techniques together with vibration monitoring, thermal monitoring, and chemical monitoring all these monitoring techniques necessary high-priced sensors or specialized devices [8]. For watching the sensors, there are many devices are accessible and which employed for measuring the speed, output torque, vibrations, temperature, flux densities etc [9]. In several circumstances, vibration monitoring techniques are applied to identify the existence of an incipient bearing failure [10]. For bearing failures, vibration monitoring is a dependable device. The vibration data classically have fault signatures and salient fault features since of the direct measurement of the crucial signal and post of the vibration sensor. Vibration-based monitoring methods, both in the time and frequency domains, have been broadly employed for detection and diagnosis of bearing defects [11]. In several applications, placing a sensing tool on the motor might not be feasible or practical on the other hand [12].

As not all errors can be identified with a single measurement method, several errors have related symptoms, and the error may not be evident while

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the motor is operating under a light load. Besides, there is a lack of detailed understanding of the effect of the errors on the outputs of dissimilar sensor types [13]. With algorithms and architectures, these sensors are collectively coupled which permits for competent monitoring of the machines condition. The most famous methods of induction motor condition watching employ the steady state spectral components [14]. The steady state methods are motor current signature analysis (MCSA), extended park's vector approach (EPVA) and discrete wavelet transform (DWT) to identify the fault in the motor [15]. Famous signal processing devices of Fourier, Wavelet, and Hilbert–Huang transformations are used to attain motor current data to remove necessary characteristics for motor fault detection [16]. The conventional technique systems contain number of restrictions such as inflexible, high cost, hardware limitations which are greatly reliant upon specialized tools. The error detection of electrical machines shifted from traditional methods to AI technique in latest years [17]. The induction motors are subject to the occurrence of incipient errors [18]. In diagnosing Induction motor bearing, there are several kinds of ANNs that are appropriate. These are such as, FFNN, EN, RBFN and ANFIS networks. For example RBFN can coach quicker than FFNN and its concealed layer is easier to understand than that of FFNN [19] [20]. For categorizing the errors of the electric motor, the S-transformation and RBFNN is proposed in the text. The proposed control strategies are made cleared in section 3. The most recent research works are disputed in section 2. The results and discussion of the proposed strategy is described in section 4. The section 5 finishes the document.

2. RECENT RESEARCH WORK: A BRIEF REVIEW

Numbers of research work are previously existed in literature which based on errors watching of electrical motor. A few of them reassessed here.

In electrical machines, a reassess of existing methods accessible for online stator inter turn fault detection and diagnosis (FDD) has been offered by Gandhi, A. et al. [21]. Unique consideration was specified to short-circuit-fault diagnosis in permanent-magnet machines, which were rapid substituting traditional machines in an extensive range of applications. Modern methods that employ signals analysis, models, or knowledge-based systems for FDD were reassessed. For error analysis, Motor current was the most generally analyzed indicator. Therefore, motor current signature study was a subject of detailed conversation.

An uncomplicated technique for additional on-line detection of broken rotor bars in a squirrel cage induction motor controlled in rotor field co-ordinates by existing hardware has been suggested by Klemen Drobnic et al. [22]. Based on a formerly existing strategy, an algorithm for on-line calculation of the variance of stator voltage reference, which depends on the number of broken bars, has been improved. Owing to its effortlessness, it could run in equivalent with a standard control algorithm in field reference frame by means of modern fixed- and floating-point processors, hence needed minimum processing time. The algorithm was employed internal reference values of the stator voltage; as a result no extra devoted measurements are required.

A wavelet based neuro detector strategy has been offered by Duygu Bayram et al. [23] used to identify the aging indications of an electric motor. Study of the aging indications, which could be noticed in the low frequency region, was executed by vibration signals. Further particularly, two vibration signals were watched for healthy and faulty cases which were measured from the similar electric motor. In order to attain low and high frequency bands of the vibration signals, Multi Resolution Wavelet Analysis (MRWA) was employed. Therefore for identifying the aging properties in the spectra, the Power Spectral Density (PSD) of the sub band for the healthy case was applied to coach an Auto Associative Neural Network (AANN). The PSD amplitudes, which were calculated for the faulty case, were used to input nodes of the coached network for the re-calling process of AANN.

Manjeevan Seera et al. [24] have suggested a hybrid soft computing replica containing the Fuzzy Min-Max (FMM) neural network and the Classification and Regression Tree (CART) for motor fault recognition and analysis. Chiefly, the hybrid model, identified as FMM-CART, was employed to distinguish and categorize error conditions of induction motors in both offline and online surroundings. A chain of tests was carried out, whereby the Motor Current Signature Analysis (MCSA) technique was employed to form a database enclosing stator current signatures under dissimilar motor conditions. The signal harmonics from the PSD were removed, and employed as the discriminative input characteristics for fault classification with FMM-CART. Three major

Journal of Theoretical and Applied Information Technology
20th May 2014. Vol. 63 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

induction motor conditions, viz. broken rotor bars, stator winding faults, and unbalanced supply, were employed to assess the efficiency of FMM-CART.

Using magnetic flux and vibration analysis methods, the finding and analysis of electrical errors in the stator winding of three phase induction motors has been offered by P.C.M. Lamim Filho et al. [25]. A correlation was launched between the main electrical errors and the signals of magnetic flux and vibration, so as to recognize the feature frequencies of those errors. The experimental effects illustrated the competence of the conjugation of these methods for detection, diagnosis and monitoring tasks. In industries, the effects were certainly notable and could be adapted and employed in actual predictive maintenance programs.

Omid Geramifard et al. [26] have introduced semi-nonparametric approach based on hidden Markov model for fault detection and diagnosis in synchronous motors. In their proposed approach, after training the hidden Markov model classifiers (parametric stage), two matrices named probabilistic transition frequency profile and average probabilistic emission were computed based on the hidden Markov models for each signature (nonparametric stage) using probabilistic inference. Moreover, a pre-processing method, named squeezing and stretching was proposed which rectified the difficulty of dealing with various operating speeds in the classification process. Finally, the experimental results were provided and compared. Further investigations were carried out, providing sensitivity analysis on the length of signatures, the number of hidden state values, as well as statistical performance evaluation and comparison with conventional hidden Markov model-based fault diagnosis approach.

Xiaohang Jin et al. [27] have proposed a health index, Mahalanobis distance (MD) to indicate the health condition of cooling fan and induction motor based on vibration signal. Anomaly detection and fault classification were accomplished by comparing MDs, which were calculated based on the feature data set extracted from the vibration signals under normal and abnormal conditions. Since MD was a non-negative and non-Gaussian distributed variable, Box–Cox transformation was used to convert the MDs into normal distributed variables, such that the properties of normal distribution could be employed to determine the ranges of MDs corresponding to different health conditions. Experimental data of cooling fan and induction motor were used to validate the proposed approach. Their results show that the early stage failure of cooling fan caused by bearing generalized-roughness faults could be detected successfully, and the different unbalanced electrical faults of induction motor could be classified with a higher accuracy by Mahalanobis–Taguchi system.

Liqun Hou et al. [28] have proposed industrial wireless sensor network (IWSN) for industrial machine condition monitoring and fault diagnosis. In their proposed work, the induction motor was taken as an example of monitored industrial equipment due to its wide use in industrial processes. Motor stator current and vibration signals were measured for further processing and analysis. On-sensor node feature extraction and on-sensor fault diagnosis using neural networks are then investigated to address the tension between the higher system requirements of IWSNs and the resource-constrained characteristics of sensor nodes. A two-step classifier fusion approach using Dempster–Shafer theory was also explored to increase diagnosis result quality. Four motor operating conditions normal without load, normal with load, loose feet, and mass imbalance were monitored to evaluate their proposed system. Here, the suggested hybrid method is employed for identifying the vibration signal of electric motor. The suggested hybrid technique is the combination of S-Transformation algorithm and RBFNN. At this point, the vibration signals are pre-processed at first. After that S-Transform is employed to examine the vibration signals attained from ball bearing in four conditions that is- Normal, IR, BB and OR. By relevance of S-transform, the rare vibration signals of the bearing are decayed into numerous frequency levels. Characteristics have been removed from S-transform and are employed as inputs to the RBFNN classifier to assess the presentation of the classifier.

3. VIBRATION SIGNALS OF THE ELECTRIC MOTOR (EM)

The vibration signals are examined in the normal and the faulty conditions in the electric motor. The electric motor errors are due to mechanical and electrical stresses. Mechanical stresses are caused by burdens and sudden load changes, which can generate bearing errors and rotor bar breakage. When an error happens in a bearing, the impulse vibrations are generated at a particular frequency. It can be generated the different types of errors namely, Outer race (OR) fault, Inner race (IR) fault and ball bearing (BB) fault correspondingly. In defective conditions, these vibration signals

Journal of Theoretical and Applied Information Technology
20th May 2014. Vol. 63 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

produce difficult time series waveforms. After that the different feature frequencies for different types of errors are assessed by the some equations.

Inner race (IR) fault

The IR error can be described in reference with the frequency level. The rate, at which the bearing balls go by all through the point of error on the inner race, is the rate that depends by the IR error frequency. And moreover, the rate for which, the variation of inner race and angular speed of cage is proportional, each ball is moved across the flaw point. The error frequency of the inner race defect is furthermore proportional to the number of balls in the bearing.

Outer race (OR) fault

The OR error frequency depends on the rate at which bearing balls cross the point of fault on the OR. The OR fault rate is directly proportional to the deviation of angular speed. The OR error frequency is furthermore proportional to the number of balls in the bearing.

Ball bearing (BB) fault

The BB sustains the balls at every time balanced positions and helps the rolling of balls along the raceways. The bearing cage spins at a stable angular velocity in the rotating period of the motor shaft. The angular velocities means that the inner and outer race angular velocities. The suggested hybrid method is applied for examining the vibration signals of the electric motor. The detailed description of the suggested method is section 3.1.

3.1. Proposed hybrid technique for analyzing the vibration signals of EM

The vibration signals of electric motor are analyzed by using the proposed hybrid method. Here, the vibration signals are considered in two cases such as normal and faulty conditions. Initially, the pre processing operations are done in the vibration signal and the noiseless signal is obtained. Then features of the vibrating signal and thenormal signal is extracted by the S-transformation. After that, the extracted signal is given to the input of RBFNN. These signals are trained to get the output of the network. The output specified the types of bearing faults occurred in the motor based on the certain condition. The proposed controller block diagram is illustrated in figure 1. The detailed description of the proposed technique is explained in below section.

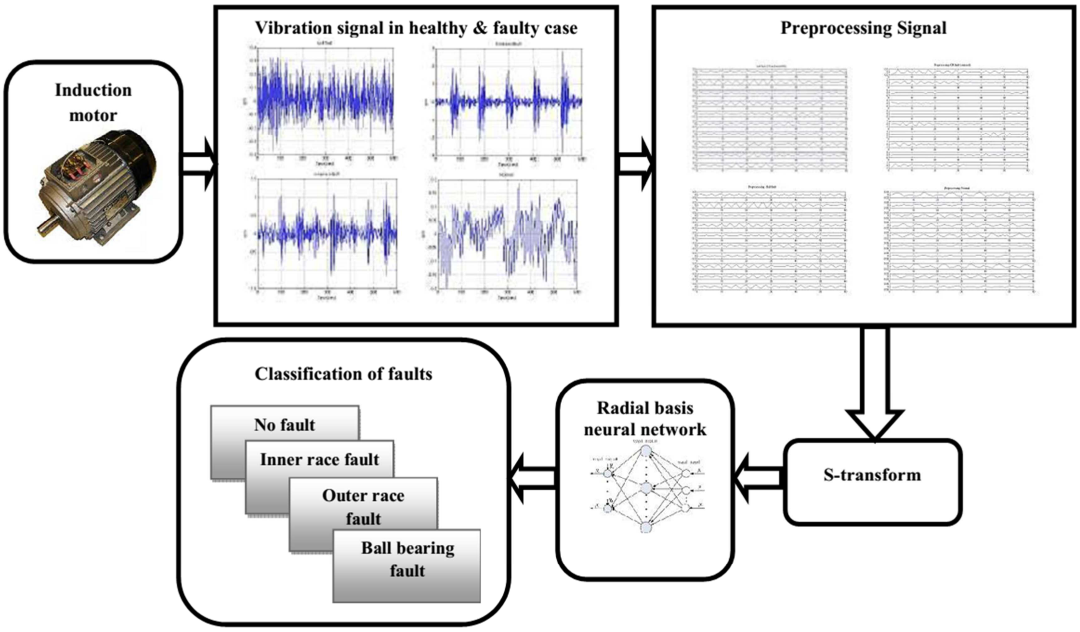

Fig 1: Block Diagram Of Proposed Hybrid Control Model

In the electric motor, the vibration signals are analyzed in the normal, IR, OR and BB fault conditions. The OR, IR and BB fault frequencies are calculated by using the following equations,

$$f_{or} = \frac{N}{2}\left[F_r * (1 - \psi \cos\beta)\right] \qquad (1)$$

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$$f_{ir} = \frac{N}{2}\left[F_r * (1+\psi \cos\beta)\right] \quad (2)$$

$$f_{br} = \frac{1}{2\psi}\left[F_r * \left(1-(\psi)^2 \cos^2\beta\right)\right] \quad (3)$$

Where, ψ is the denoted as the $\left(\frac{d}{D}\right)$. Then d, D are the inner and outer raceway diameters and f_r is the rotational frequency, β is the slip angle. These various frequencies are calculated depending on their faults. The rotational frequency is denoted as F_r . Then these vibration signals are pre-processed. The pre-processing technique is described in the following,

3.1.1. Pre-processing and Feature extraction on the vibration signals

3.1.1.1. Pre-processing Stage

The pre processing is used to the vibration signals of the electric motor for attaining the real vibration signals of the electric motor in this part. At this point, the input of the vibration signals is précised as the $X_N(t)$. The input sampling signal frequently comprises noise, so the noise moreover encloses random disturb signal. The sampling signal curve is unsmooth, and there are also some spurs because of the extensive frequency band of the random disturb signal, and majority of high frequency. The sampling signal should be pre-processed in order to obtain a smooth curve. The signal processing method applied to remove the repetitive signals from the additive noise. The raw information is partitioned into sections of equal length associated to the synchronous signal and after that standard together. In this way the adequate averages the arbitrary noise is terminated and the desired signal is left.

$$X_N(t) = (x_1(t), x_2(t), x_3(t), x_4(t) \ldots\ldots x_i(t) \ldots\ldots x_n(t)) \quad (4)$$

Where, $N = 1,2,3 \ldots. n$. The signals can function the five points smooth to smooth the curve. The subsequent equations are applied to dealing out the data.

$$x_1(t) = \left\{x_1^{\,1}(t), \left(x_1^{\,2}(t), x_1^{\,3}(t)\right), x_1^{\,4}(t), x_1^{\,5}(t)\right\} \quad (5)$$

$$x_2(t) = \left\{\left(x_2^{\,1}(t), x_2^{\,2}(t)\right), x_2^{\,3}(t), x_2^{\,4}(t), x_2^{\,5}(t)\right\} \quad (6)$$

$$x_i(t) = \left\{x_{i-2}^{\,1}(t), x_{i+2}^{\,2}(t), x_{i-1}^{\,3}(t), x_{i+1}^{\,4}(t), x_i^{\,5}(t)\right\} \quad (7)$$

$$x_i(t) = \left\{x_{n4}^{\,1}(t), x_n^{\,2}(t), x_{n-3}^{\,3}(t), x_{n-2}^{\,4}(t), x_{n-1}^{\,5}(t)\right\} \quad (8)$$

$$x_i(t) = \left\{x_{n-4}^{\,1}(t), x_{n-3}^{\,2}(t), x_{n-1}^{\,3}(t), x_{n-2}^{\,4}(t), x_n^{\,5}(t)\right\} \quad (9)$$

After that, the pre processing is carried out the original signals can be obtained.

3.1.1.2. Using S-Transformation for feature extraction

In this section, the S-transformation [30] is used for extracting the features of the vibration signals of the electric motor. Here, the vibration signals are given as the input signals of the S-transform. The input signals are described as the following equation,

$$S_{T_d,f} = \int_{-\infty}^{\infty} x_N(t) w_d(T_d - t, f) e^{-i\omega t} dt \quad (10)$$

Where, $x_N(t)$ and w_d is denoted as the vibration signal and the Gaussian windowing function respectively. The Gaussian windowing function (w_d) selected as a positive value which is denoted as the following,

$$w(T_d - t, f) = \frac{|f|}{k\sqrt{2\pi}} e^{\frac{-f^2}{2P^2}\left((\Gamma - t)^2\right)} \quad (11)$$

From the above equation, f , t , T_d and P is denoted as the frequency of the signal, the time, time delay and scaling factor respectively. The scaling features of the signals can be supervising the time-frequency resolution. After that by applying the invertible S-transform, the windowing function of the signal should be regularized. The windowing function of the signal is described as,

$$\int_{-\infty}^{\infty} w_d(t, f) dt = 1 \quad (12)$$

From the fourier transform of the signal $x_N(t)$ and $\hat{x}_N(f)$ signals, the S-transform can furthermore be computed directly. As a result, the convolution of the signal is assessed by applying equ. (13) and the convolution property is employed to the fourier transform. Next, acquired signal is named as follows,

$$S_{T_d,f} = x_N(t) w_d(t, f) e^{-i\omega t} dt \quad (13)$$

$$S_{T_d,f} = F^{-1}\left(\hat{x}_N(\alpha + f)\hat{w}_d(\alpha, f)\right) \quad (14)$$

In equation (5), F^{-1} is the inverse Fourier transform and α is the Fourier transform pair of t. Then the Gaussian window function is determined by using equ.(15) and the S-transform is described

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

that that summing $S_{T_d,f}$ over T_d yields the spectrum of x, which is denoted as the following,

$$S_{T_d,f} = \int_{-\infty}^{\infty} (\hat{x}_N(\alpha + f)) e^{-2\left(\frac{k\alpha\pi}{f}\right)^2} e^{i2\pi\alpha T} d\alpha \qquad (15)$$

$$\hat{x}_N(f) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_N(t) w_d(T_d - t, f) e^{-i\omega t} dt \; dT_d \qquad (16)$$

The above equation can be simplified to a simple Fourier transform. Then the $\hat{x}_N(f)$ is determined from the following equations

$$\hat{x}_N(f) = \int_{-\infty}^{\infty} S_{T,f} \quad dt \qquad (17)$$

This property defines the inverse S-transform through the inverse Fourier transform of the spectrum of $x_N(t)$. The given vibration signals of the electric motor can be extracted based on the selection of windowing function, after that the vibration signals of the electric motors are extracted properly.

3.2. Using RBFNN for classifying the faulty signals of electric motor

NN is the non-natural intelligence method for estimating the output based on its teaching and doesn't require any mathematical replica for its structure. The RBFNN is the kind of NN, which has three layers, such as input layer, hidden layer and output layer. The concealed nodes execute a set of radial basis function and the output nodes execute linear summation functions as in MLP [29]. The RBFNN is employed to categorize the kind of error of the electric motor at this point. The extracted vibration signals of the motor are used to the input of the RBFNN, which is indicated as X_i. After that the neurons are coached with the different operating conditions drive at the particular target. At this point, the back propagation training algorithm is employed for training the neural network. The trained network is applied to remove the fault frequencies by the assist of the motor vibration signals in defective case. The inputs are categorized into no fault, IR fault, OR fault and BB fault correspondingly. After that the output of the network is indicated as Y1, Y2, Y3 and Y4 correspondingly. In Figure 2, the structure of the network is shown. The detail description of RBFNN is explained in the subsequent section.

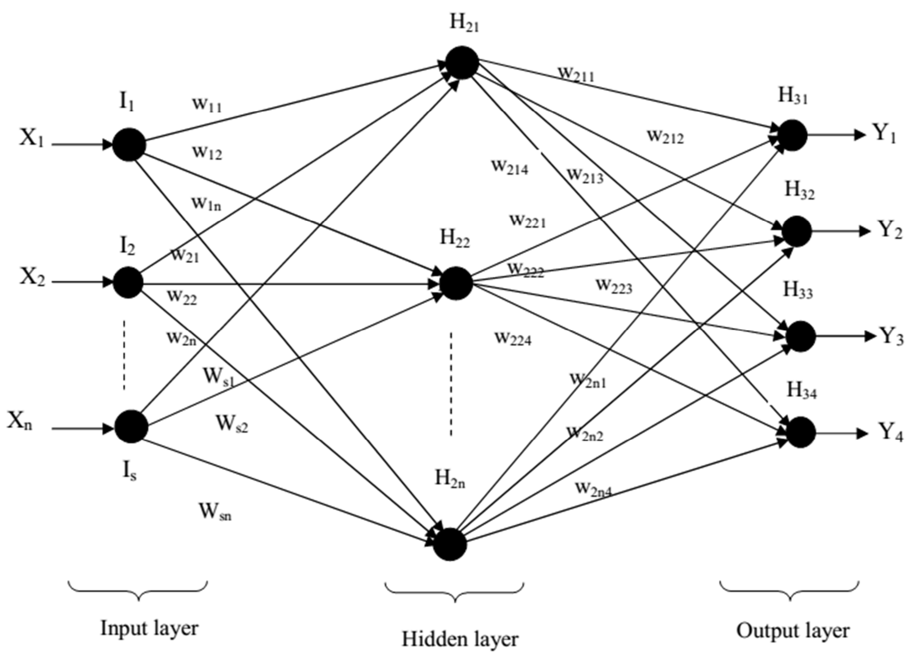

Fig 2: Structure Of Proposed RBFNN Technique

Journal of Theoretical and Applied Information Technology
20th May 2014. Vol. 63 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Steps for back propagation training algorithm

Step 1: Initialize the input layer, hidden and output layer weights of the neural network randomly. Here the input is denoted as $X_i = (x_1, x_2, ...x_n)$, which contains the low frequency extracted signals of the induction motor. The neuron weights of the hidden layer & output layer are initiated in the particular interval $[w_{\min}, w_{\max}]$. The input layer to the hidden layer weights are specified as $(w_{111}, w_{112}, ...w_{11n})$. Also, the hidden layer to the output layer weight are described as the $(w_{211}, w_{212}, ...w_{2nk})$.

Step 2: Learning the network according to the input and the corresponding target.

Step 3: Evaluate the back propagation error of the target (output) $Y_m = Y_1, Y_2, Y_3, Y_4$ are determined by following them,

$$BP_{Error}^{m} = (Y_m^{NN})_T - (Y_m^{NN})_{out} \tag{18}$$

Where, $(Y_m^{NN})_T$ is the network target of the mth node and $(Y_m^{NN})_{out}$ is the current output of the mth node network. The error variation of the network is shown by the dominant frequency components which are interpreted as the fault indications. By comparing the input frequencies with desired output, the faults are identified. If the network output value is ±10% of the desired output value then it is correctly classified. The actual outputs are analyzed and based on them, the faults are classified.

Step 4: The current output of the network is determined by following them,

$$(Y_m^{NN})_{out} = f(Y_m) + \sum_{n=1}^{N} W_{mp} Y_m^{NN}(n) \tag{19}$$

Where, $m = 1,2,3,4$ and the bias function is $f(Y_1), f(Y_2), f(Y_3)$ and $f(Y_4)$ in the m^{th} node respectively.

$$Y_m^{NN}(n) = \frac{1}{1 + \exp(-w_{11n} Y_m - w_{111} Y_m)} \tag{20}$$

The above equation is the activation function of output and hidden layer. The bias function of radial bias function is expressed as follow,

$$f(Y_m) = \sum_{k=1}^{N} w_{mk} H_i(Y_m) \tag{21}$$

Where, N is the number of neuron, w_{mi} is the weight of the i^{th} neuron, $H_k(Y_m)$ are the response of the i^{th} neuron of the hidden layer.

Step 5: The function of hidden layer is determined by the following equation,

$$H_i(Y_m) = \exp\left(\frac{-\left\|Y_m - C_p\right\|^2}{R_p}\right) \tag{22}$$

In the above equations, C_p is the centre value of the p^{th} neuron and R_p is the scalar factor.

Step 6: Then, the new weights of the each neurons of the network are updated by the following equation.

$$w_{new} = w_{previous} + \Delta w \tag{23}$$

Where, $\Delta w = \delta . Y_m . BP_{Error}^{m}$ is the change in weight, with δ is the learning rate (0.2 to 0.5).

Step 6: Repeat the above steps till the BP_{Error}^{m} gets minimized.

Once the training process is completed, the network is trained well to provide the target output. The output for all the faulty signals has different frequencies and sizes. It is seen that, for that specific faulty signal, only respective output node gives a maximum output. This neural network can classify the faults as IR, OR, BB and no fault.

4. RESULTS AND DISCUSSION

The proposed hybrid technique was implemented in MATLAB/simulink working platform. In this section, the vibration signals are analyzed in the healthy and faulty case motors. By using S-transform, the feature extraction signals can be obtained from the normal and faulty case motors. Before that, the pre-processing operation is done in the input signal for removing the noises. After that, the extracted faulty & healthy signals are applied to the input of the RBFNN. Then the neural network is trained and tested. Here, the back propagation training algorithm is used for training the network. Then the back propagation error is calculated, which is defined as their difference between the present state error and the previous error. After that, the input signals are classified into the types of signals. The classified outputs are No fault, IR fault, OR fault and BB fault. The performances of

Journal of Theoretical and Applied Information Technology
20th May 2014. Vol. 63 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the proposed hybrid technique are evaluated and their performances are illustrated.

4.1. Performance analysis

In this section, the performances of the proposed hybrid method are analyzed. The disturbance signal is measured with the different amplitude at the different time instant. The performance of the different faults of the induction motor signals is determined. Then, these vibration signals are pre-processed and their performances are evaluated in normal and faulty conditions of the motor. Similarly, the amplitude of the disturbance signal in IR fault, OR fault and BB faulty condition is measured and these are pre-processed. Then applying S-Transformation for obtaining the extracted feature signal and their performances are illustrated. After that, the signals can be classified correctly by using RBFNN. The proposed method's performances are compared with the S-transformation-FFBNN and DWT-RBFNN. By using S-transformation with FFBNN, the classified signals are correctly identified and their performances are illustrated in figure 6. In the DWT-RBFNN method, DWT is used for obtaining the decomposed signals and their performances are illustrated in the figure 5. After that, the signals can be detected by using RBFNN. The normal and IR, OR & BB fault signals are illustrated in the figure 3 (a, b, c and d).

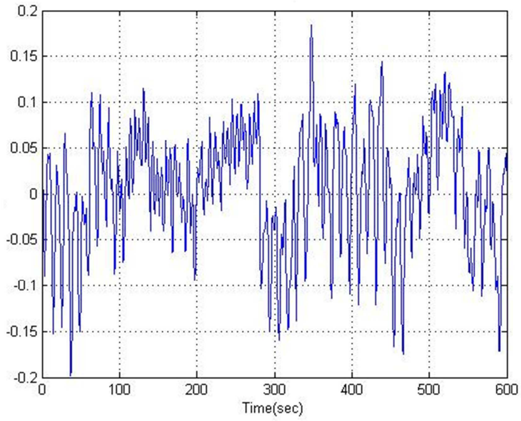

Fig 3(A): Normal Signal

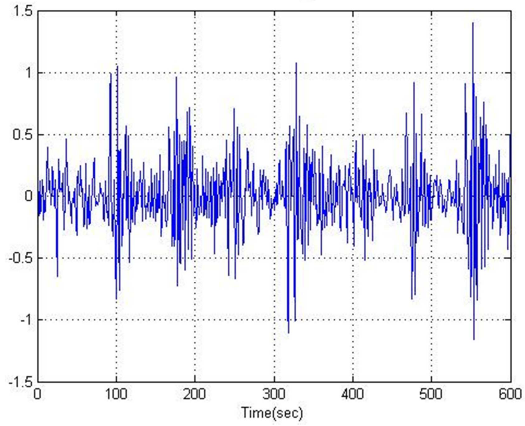

Fig 3(B): IR Faulty Signal

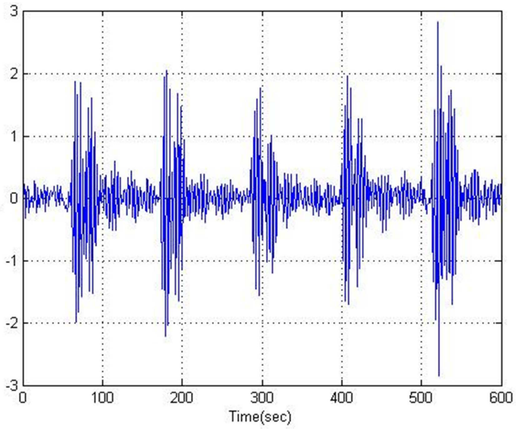

Fig 3(C): OR Faulty Signal

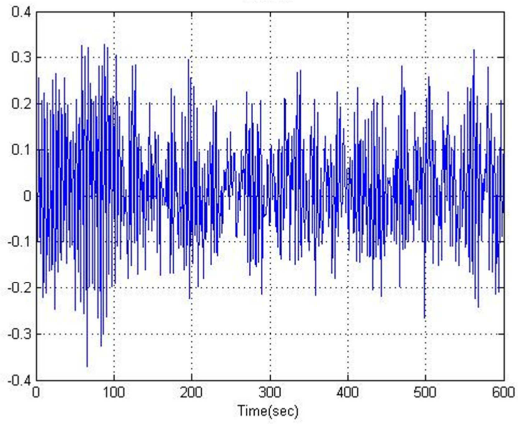

Fig 3(D): BB Faulty Signal

The four types of vibration signals are divided into small segments if equal length related to the synchronous signal and then averaged together. This process is called as pre-processing.

Here, the given signal ($X_N(t)$) is measured with the various time instants such as 100, 200, 300, 400, 500 and 600 (seconds). These signals are

Journal of Theoretical and Applied Information Technology
20th May 2014. Vol. 63 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

processed into small segments $X_N(t) = (x_1(t), x_2(t), x_3(t), x_4(t)......x_i(t)......x_n(t))$ (i.e., 10, 20, 30, 40, 50 and 60). It is used to remove part of the noise present in the signal or to remove some sources of variation. Therefore, the faulty signals can be easily detected. The type of pre-processing depends on the nature of the signal. In this process, the figure 3(a) signals are divided into 0-10, 10-20, 20-30, 30-40, 40-50 and 50-60 (seconds) time instants. In this way the random noise is cancelled and the desired signal is obtained. After that, the faulty signals are easily identified. Similarly, IR, OR and BB faulty signals are divided into these periods and these are pre-processed. The preprocessing normal signal is illustrated in figure 4 and determines the pre-processing IR, OR and BB signals.

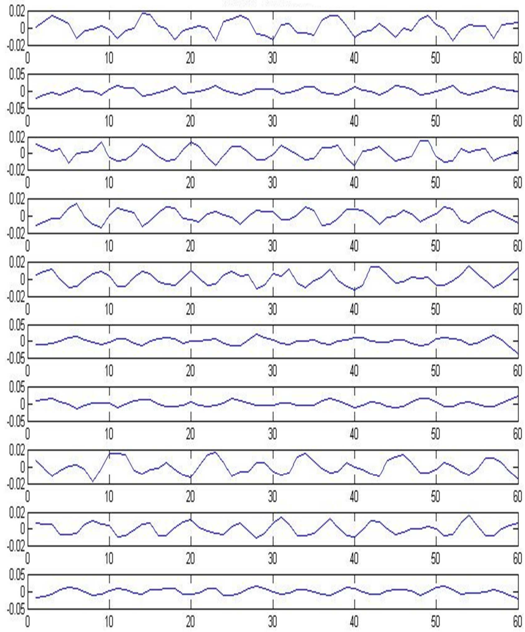

Fig 4:Pre-Processed Normal Signal

In the existing method, DWT is used for extracting the feature of the decomposed signal. The above pre-processed normal, IR, OR and BB fault signals are applied to the input of the DWT. These signals are decomposed into low and high frequency components. The decomposed low and high frequency components of normal signals, IR, OR and BB faults are illustrated in figure 5 (a, b, c and d). In the proposed hybrid technique, the pre-processed signals are normalized by using S-transformation and their performances are illustrated in the figure 6(a, b, c and d).The decomposed signals are applied to the neural network. The NN is used to classify the signal whether it is faulty or not.

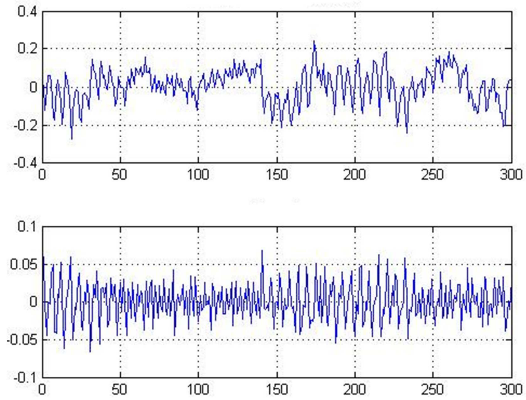

Fig 5(A): Feature Extraction Of Normal Signal Using DWT

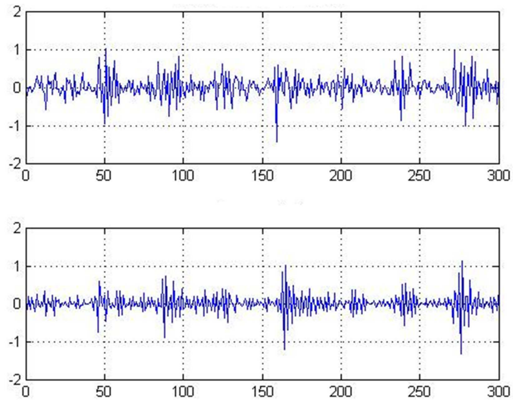

Fig 5(B): Feature Extraction Of IR Fault Using DWT

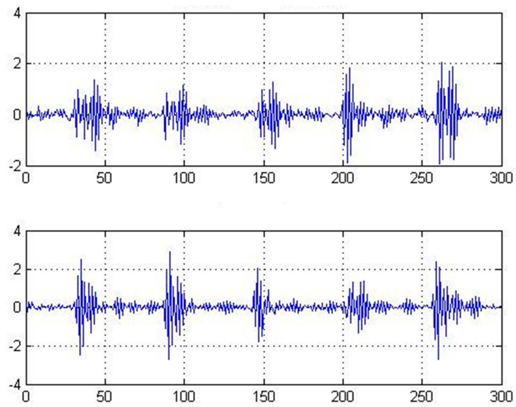

Fig 5(C): Feature Extraction Of OR Fault Using DWT

Journal of Theoretical and Applied Information Technology
20th May 2014. Vol. 63 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

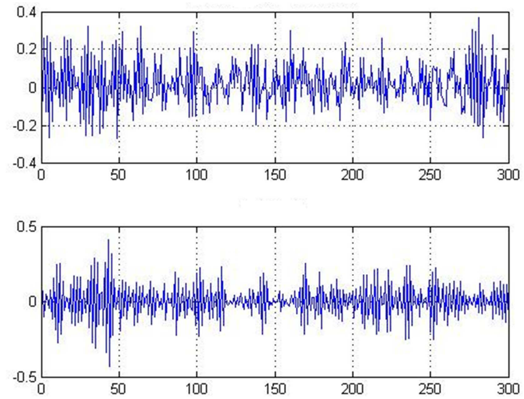

Fig 5(D): Feature Extraction Of BB Fault Using DWT

By using DWT, the signals can be decomposed into low level and high level frequency components. The low level and high level frequency components are specified as the approximation and detailed signal coeffeicents. Here, the low level frequency components are decomposed. Here, the normal and IR, OR and BB faulty signals of low frequency components are decomposed and their features are extracted.

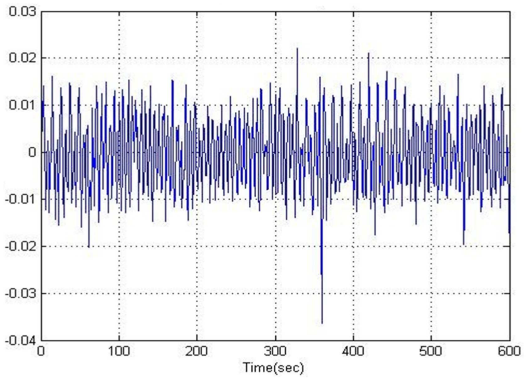

Fig 6(A): Feature Extraction Of No Fault Using S-Transform

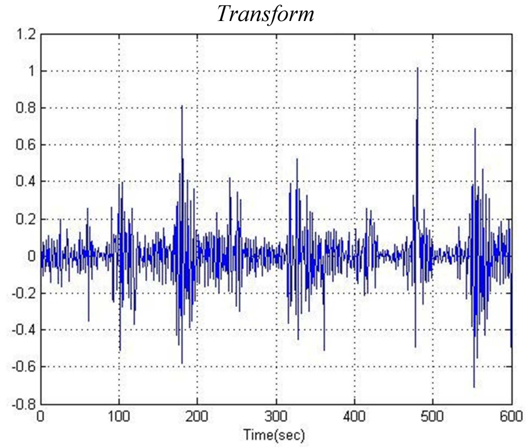

Fig 6(B): Feature Extraction Of IR Fault Using S-Transform

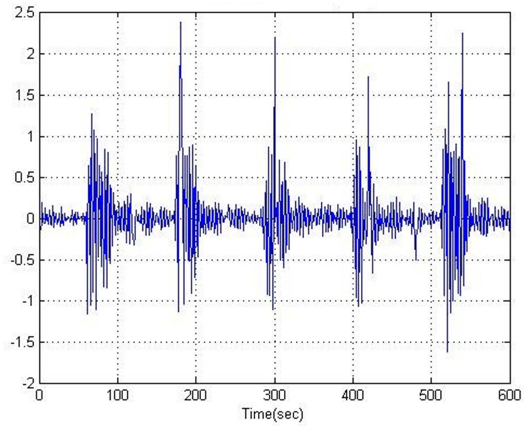

Fig 6(C): Feature Extraction Signal Of OR Fault Using S-Transform

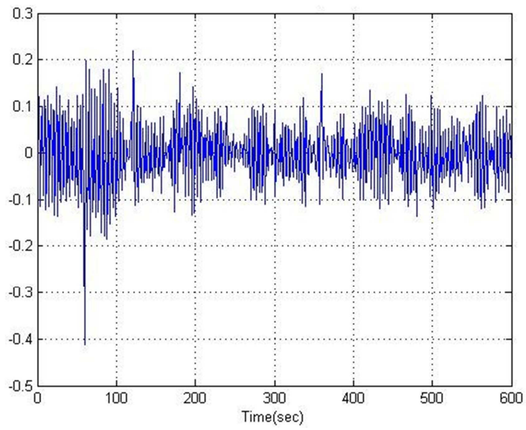

Fig 6(D): Feature Extraction Of BB Fault Using S-Transformation

Then the extracted signals of normal, IR, OR and BB faulty signals are applied to the input of the RBFNN and performance of the proposed hybrid technique was analyzed. Here, the faulty (IR fault, OR fault & BB fault) and healthy induction motor vibration signals are analyzed. The performance of the proposed hybrid method is compared with the wavelet transform-RBFNN and S-transform-FFBNN techniques. The proposed hybrid method, S-transform- FFBNN and DWT-RBFNN methods are analyzed with the accuracy, sensitivity and specificity. These terms are calculated in the four conditions, such as, IR faulty signal, OR faulty signal, BB faulty signal and No fault condition. Also, these terms are calculated from the TP, FP, TN and FN values. These values specified in the signal can be described as,

True positive (TP): IR signal is correctly identified as faulty signal.

Journal of Theoretical and Applied Information Technology
20th May 2014. Vol. 63 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

False negative (FN): IR signal is incorrectly identified as faulty signal.

False positive (FP): Normal signal is incorrectly identified as faulty signal.

True negative (TN): Normal signal is correctly identified as normal.

4.1.1 Performance Evaluation Metrics

Accuracy: The accuracy value is calculated in the four types of fault signal condition of induction motor. Accuracy is defined as ratio of the number of correctly classified patterns to the total number of patterns.

Sensitivity: In the fault condition of the induction motor, the sensitivity values are calculated. Ratio of the number of correctly detected positive patterns to the total number of actual positive patterns is called as sensitivity.

Specificity: The specificity value is calculated in the fault condition of induction motor. Specificity is defined as ratio of the number of correctly detected negative patterns to the total number of actual negative patterns. These values are calculated by using the formulae, which are presented in [31]. Then the TP, TN, FP and FN values are tabulated in table 1(a), 2(a), 3(a) and 4(a) for various methods. Based on these values, the Accuracy, Sensitivity and Specificity values are calculated and tabulated in table 1(b), 2(b), 3(b) and 4(b).

Table 1(A): TP, TN, FP And FN Values For IR Fault Condition

S.No	IR Fault											
	Proposed method (S-transform-RBFNN)				S-transform-FFBNN				DWT-RBFNN			
	TP	FP	FN	TN	TP	FP	FN	TN	TP	FP	FN	TN
1	10	1	0	9	10	2	0	8	8	1	2	9
2	10	1	0	9	9	1	1	9	7	1	3	9
3	10	1	0	9	9	1	1	9	8	1	2	9
4	10	2	0	8	8	2	2	8	9	2	1	8
5	10	2	0	8	8	0	2	10	10	3	0	7
6	10	1	0	9	9	2	1	8	7	0	3	10
7	10	1	0	9	10	3	0	7	8	2	2	8
8	10	1	0	9	9	1	1	9	8	2	2	8
9	9	0	1	10	8	0	2	10	7	0	3	10
10	9	0	1	10	10	2	0	8	8	2	2	8

Table 1(B): Accuracy, Sensitivity And Specificity Values Of IR Fault Condition In Various Methods

S.No	IR fault								
	Proposed Method (s-transform-RBFNN)			S-transform-FFBNN			DWT-RBFNN		
	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
1	95	100	90	90	100	80	85	80	90
2	95	100	90	90	90	90	80	70	90
3	95	100	90	90	90	90	85	80	90
4	90	100	80	80	80	80	85	90	80
5	90	100	80	90	80	100	85	100	70
6	95	100	90	85	90	80	85	70	100
7	95	100	90	85	100	70	80	80	80
8	95	100	90	90	90	90	80	80	80
9	95	90	100	90	80	100	85	70	100
10	95	90	100	90	100	80	80	80	80

Table 2(A): TP, TN, FP And FN Values For OR Fault Condition

S.No	OR Fault											
	Proposed method (S-transform-RBFNN)				S-transform-FFBNN				DWT-RBFNN			
	TP	FP	FN	TN	TP	FP	FN	TN	TP	FP	FN	TN
1	10	1	0	9	10	2	0	8	9	3	1	7
2	9	1	1	9	10	2	0	8	9	2	1	8
3	10	1	0	9	8	0	2	10	7	0	3	10

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

4	10	1	0	9	9	2	1	8	7	0	3	10
5	10	1	0	9	8	1	2	9	9	2	1	8
6	10	1	0	9	10	2	0	8	7	0	3	10
7	10	2	0	8	9	2	1	8	8	2	2	8
8	10	1	0	9	8	0	2	10	8	2	2	8
9	10	2	0	8	8	0	2	10	10	2	0	8
10	9	0	1	10	9	2	1	8	8	2	2	8

Table 2(B): Accuracy, Sensitivity And Specificity Values Of OR Fault Condition In Various Methods

S.No	OR fault								
	Proposed Method (s-transform-RBFNN)			S-transform-FFBNN			DWT-RBFNN		
	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
1	95	100	90	90	100	80	80	90	70
2	90	90	90	90	100	80	85	90	80
3	95	100	90	90	80	100	85	70	100
4	95	100	90	85	90	80	85	70	100
5	95	100	90	85	80	90	85	90	80
6	95	100	90	90	100	80	85	70	100
7	90	100	80	85	90	80	80	80	80
8	95	100	90	90	80	100	80	80	80
9	90	100	80	90	80	100	90	100	80
10	95	90	100	85	90	80	80	80	80

Table 3(A): TP, TN, FP And FN Values For BB Fault Condition

S.No	BB Fault											
	Proposed method (S-transform-RBFNN)				S-transform-FFBNN				DWT-RBFNN			
	TP	FP	FN	TN	TP	FP	FN	TN	TP	FP	FN	TN
1	10	1	0	9	9	1	1	9	10	3	0	7
2	9	1	1	9	10	2	0	8	8	2	2	8
3	10	1	0	9	7	0	3	10	7	0	3	10
4	10	2	0	8	9	2	1	8	7	1	3	9
5	10	1	0	9	8	1	2	9	9	2	1	8
6	10	1	0	9	7	1	3	9	10	3	0	7
7	9	1	1	9	9	2	1	8	8	2	2	8
8	10	1	0	9	8	1	2	9	7	1	3	9
9	10	1	0	9	8	1	2	9	8	0	2	10
10	10	1	0	9	10	2	0	8	7	1	3	9

Table 3(B): Accuracy, Sensitivity And Specificity Values Of BB Fault Condition In Various Methods

S.No	BB fault								
	Proposed Method (s-transform-RBFNN)			S-transform-FFBNN			DWT-RBFNN		
	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
1	95	100	90	90	90	90	85	100	70
2	90	90	90	90	100	80	80	80	80
3	95	100	90	85	70	100	85	70	100
4	90	100	80	85	90	80	80	70	90
5	95	100	90	85	80	90	85	90	80
6	95	100	90	80	70	90	85	100	70
7	90	90	90	85	90	80	80	80	80
8	95	100	90	85	80	90	80	70	90
9	95	100	90	85	80	90	90	80	100
10	95	100	90	90	100	80	80	70	90

Journal of Theoretical and Applied Information Technology
20th May 2014. Vol. 63 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 4(A): TP, TN, FP And FN Values For No Fault Condition

S.No	No Fault											
	Proposed method (S-transform-RBFNN)				S-transform-FFBNN				DWT-RBFNN			
	TP	FP	FN	TN	TP	FP	FN	TN	TP	FP	FN	TN
1	10	1	0	9	7	1	3	9	8	0	2	10
2	10	1	0	9	10	2	0	8	7	1	3	9
3	10	1	0	9	7	0	3	10	10	3	0	7
4	10	2	0	8	8	1	2	9	8	2	2	8
5	10	1	0	9	8	1	2	9	9	2	1	8
6	9	1	1	9	10	2	0	8	7	0	3	10
7	9	1	1	9	9	2	1	8	7	1	3	9
8	10	1	0	9	8	1	2	9	7	1	3	9
9	10	1	0	9	8	1	2	9	8	2	2	8
10	10	1	0	9	9	1	1	9	10	3	0	7

Table 4(B): Accuracy, Sensitivity And Specificity Values Of No Fault Condition In Various Methods

S.No	No fault								
	Proposed Method (s-transform-RBFNN)			S-transform-FFBNN			DWT-RBFNN		
	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
1	95	100	90	80	70	90	90	80	100
2	95	100	90	90	100	80	80	70	90
3	95	100	90	85	70	100	85	100	70
4	90	100	80	85	80	90	80	80	80
5	95	100	90	85	80	90	85	90	80
6	90	90	90	90	100	80	85	70	100
7	90	90	90	85	90	80	80	70	90
8	95	100	90	85	80	90	80	70	90
9	95	100	90	85	80	90	80	80	80
10	95	100	90	90	90	90	85	100	70

In the proposed hybrid technique (S-transform - RBFNN), the feature of faulty signals is used as the input of the neural network. The no fault, IR, OR and BB fault of the induction motor is detected from this neural network, also, the performance are estimated. The TP, FP, TN, and FN values are calculated from the neural network output. These values are used to evaluate the accuracy, sensitivity and specificity of the normal, IR, OR and BB faults of an induction motor. The proposed hybrid technique output is computed and tabulated. Also, the existing techniques accuracy, sensitivity and specificity vales are calculated from the normal, IR, OR and BB faults of an induction motor, which is calculated and illustrated in figure 7, 8, 9 and 10.

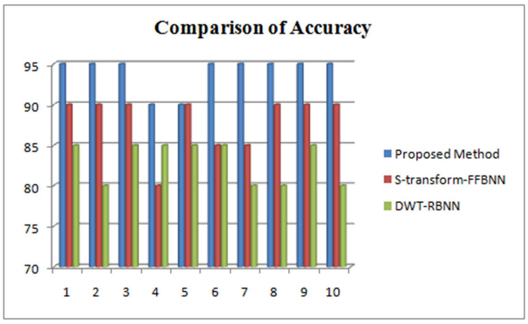

Fig 7(A): Comparison Of Accuracy In IR Fault

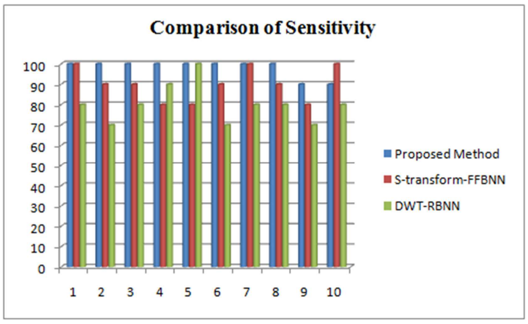

Fig 7(B): Comparison Of Sensitivity In IR Fault

Journal of Theoretical and Applied Information Technology
20th May 2014. Vol. 63 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

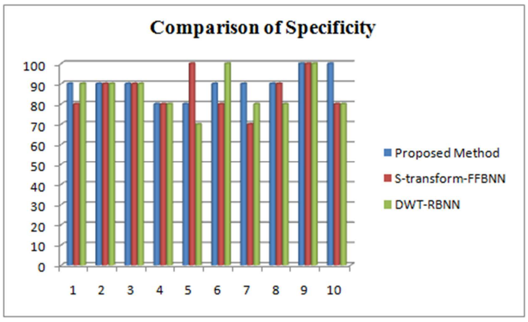

Fig 7(C): Comparison Of Specificity In IR Fault

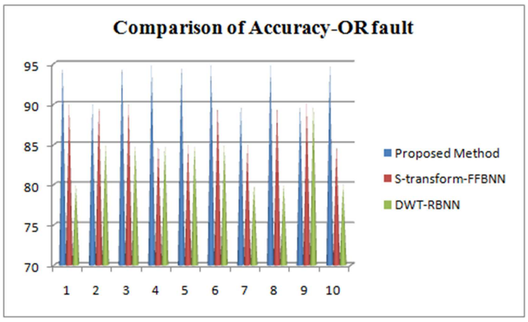

Fig 8(A): Comparison Of Accuracy In OR Fault

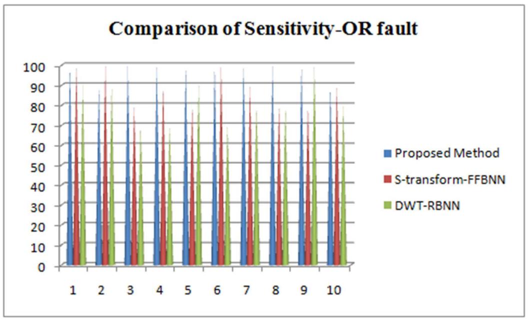

Fig 8(B): Comparison Of Sensitivity In OR Fault

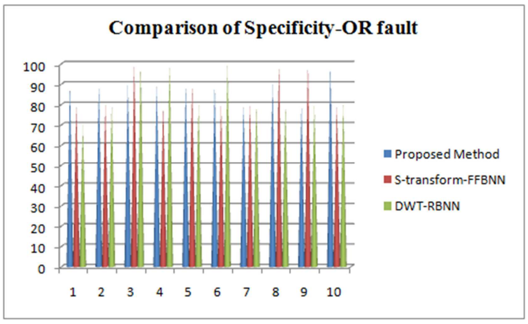

Fig 8(C): Comparison Of Sensitivity In OR Fault

From the above performance, the accuracy, sensitivity and specificity of the proposed method are calculated and compared with the existing techniques. In the IR fault condition, the overall accuracy, sensitivity and specificity of the proposed integrated techniques are 94%, 98% and 90%. But, the accuracy, sensitivity and specificity of S-transform-FFBNN are 88%, 90% and 86%. Also, the accuracy, sensitivity and specificity of DWT-RBFNN are 83%, 80% and 86%. In OR fault condition, the accuracy, sensitivity and specificity of the proposed integrated techniques are 93.5%, 98% and 89%. But, the accuracy, sensitivity and specificity of S-transform-FFBNN are 88%, 89% and 87%. Also, the accuracy, sensitivity and specificity of DWT-RBFNN are 83.5%, 82% and 85%. From the above considerations, the proposed hybrid technique is effective for detecting the faulty condition of induction motor. Similarly, the BB faulty and No fault conditions accuracy, sensitivity and specificity values are evaluated. And their comparison performances are illustrated in the following figure.

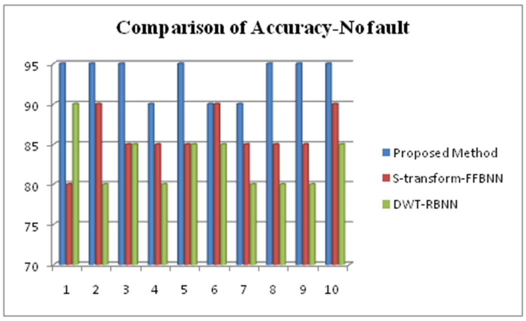

Fig 9(A): Comparison Of Accuracy In No Fault

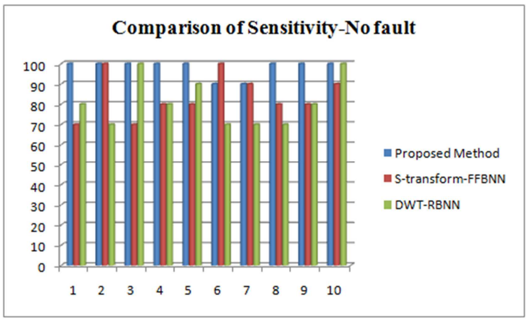

Fig 9(B): Comparison Of Sensitivity In No Fault

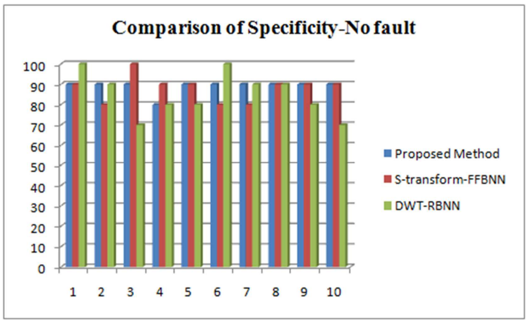

Fig 9(C): Comparison Of Specificity In No Fault

Journal of Theoretical and Applied Information Technology
20th May 2014. Vol. 63 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

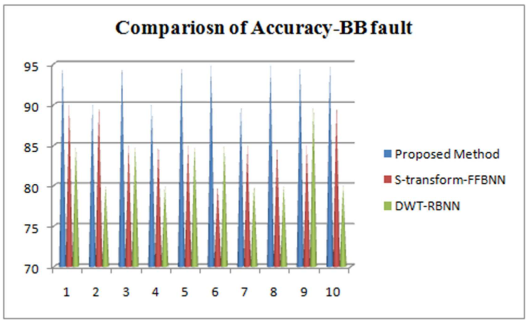

Fig 10(A): Comparison Of Accuracy In BB Fault

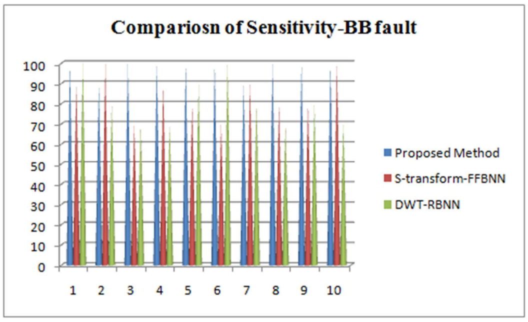

Fig 10(B): Comparison Of Sensitivity In BB Fault

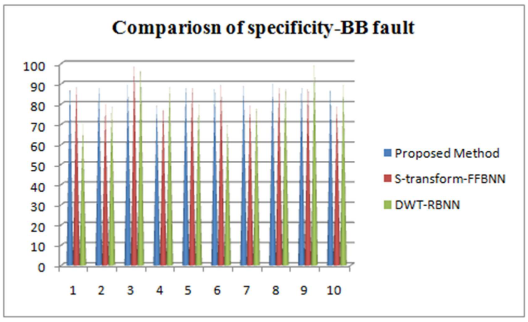

Fig 10(C): Comparison Of Specificity In No Fault

In the no fault condition, the overall accuracy, sensitivity and specificity of the proposed integrated techniques are 93.5%, 98% and 89%. But, the accuracy, sensitivity and specificity of S-transform-FFBNN are 86%, 84% and 88%. Also, the accuracy, sensitivity and specificity of DWT-RBFNN are 83%, 81% and 85%. In BB fault condition, the accuracy, sensitivity and specificity of the proposed integrated techniques are 85.2%, 98% and 89%. But, the accuracy, sensitivity and specificity of S-transform-FFBNN are 78.7%, 85% and 87%. Also, the accuracy, sensitivity and specificity of DWT-RBFNN are76.2%, 81% and 85%. From the above considerations, the proposed hybrid technique is effective for detecting the faulty condition of induction motor.

5. CONCLUSION

The proposed hybrid technique was made to detect the faults of the electric motor. The motor vibration signal was applied to the input of pre-processing stage. The pre-processed signals are applied to the S-transform. The extracted features are obtained from the output of S-transform. The extracted features were in the form of vector and that was applied to the RBFNN. The output of the neural network identified the condition of the induction motor whether faulty or normal and also classified the type of faults. Here, the performances of the proposed hybrid technique are evaluated and the output of the proposed hybrid technique was compared with S-transform-FFBNN and DWT-RBFNN. Hence, the accuracy, sensitivity and specificity values of the proposed and existing methods are determined and compared. Thus the comparative results have proven that the proposed controller was much better than the S-transform-FFBNN and DWT-RBFNN techniques.

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