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Wavelet Transform and Back Propagation Neural Network: A Tool for Induction Motor Fault Detection and Classification

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***Abstract*— The paper brings forward a step further towards the protection of a three phase induction motor using a Wavelet Transform and Neural network. The work discusses some of the commonly occurring faults in the motor, showing that Wavelet Transform provides a better treatment to the non stationary stator current than the used Fourier techniques. Followed by a brief overview of the error back propagation (EBP) algorithm statistical features like kurtosis, crest factor, root mean square (RMS) value, entropy and skewness are extracted to train and test the neural network. The predictability analysis of the level of decomposition to extract the statistical features from wavelet coefficients was based on Shannon entropy of the detailed wavelet coefficients. The MATLAB toolbox results show that training an error back propagation neural network using the features extracted from the detailed wavelet coefficients can be an effective agent in the detection of various faults in induction motor.**

Keywords—*Fault diagnosis; entropy; induction motor; Wavelet transform; bearing fault; Decomposition level; back propagation neural network*

I. INTRODUCTION

Even though Induction machines are the most spread electrical machines as they take part in a countless number of industrial applications and processes, owing to their quality of low requirements for maintenance, high reliability and high efficiency, they are prone to various faults which may even lead to catastrophic failures. The various types of faults occurring in an induction motor include both internal and external faults. These faults are classified as bearing fault, coupling and rotor bar faults, air gap eccentricities, stator faults and gearbox failures. Hence the repair and maintenance of the motor plays a vital role in the industry. There have been various traditional strategies employed earlier but the ultimate goal of this study is to propose a methodology for Even though Induction machines are the most spread electrical machines as they take part in a countless number of industrial applications and processes, owing to their quality of low requirements for maintenance, high reliability and high efficiency, they are prone to various faults which may even lead to catastrophic failures. The various types of faults occurring in an induction motor include both internal and external faults. These faults are classified as bearing fault, coupling and rotor bar faults, air gap eccentricities, stator faults and gearbox failures. Hence the repair and maintenance of the motor plays a vital role in the industry. There have been various traditional strategies employed earlier but the ultimate goal of this study is to propose a methodology for diagnosing different faults of induction motor using Wavelet Transform Technique with Neural Networks. Recent developments in the diagnosis of faults in motors have led to the consideration of a much cheaper though efficient system that is the artificial neural networks. They have proven to provide better performance when compared to the conventional time consuming methods. They can also be extended and modified easily. And most of all the designing of a neural network does not require any mathematical model of induction motor which completely removes the complexity [4].

The highly transient and dynamic nature of induction motor stator current during various faults, demands for a versatile approach to work appropriately in all conditions. In the past there were some signal processing techniques such as Fast Fourier Transform (FFT) which were used for induction motor fault detection, but it could not provide sufficient and accurate information for the recognition of fault conditions as it suffered from some serious drawbacks of not providing adequate information about a non-stationary signal i.e. stator line current in case of induction motors.

In the process of analyzing a Fourier signal some amount of data gets lost whenever the transformation of a signal from frequency domain to time domain occurs. FFT does not yield good results in the case of non-constant load torque and sometimes it becomes almost impossible to deduce that when exactly a particular event took place. Short Time Fourier Transform (STFT) was another digital signal processing technique which was earlier proposed to overcome the shortcomings of FFT but that too suffered from some serious drawbacks that it shows a fixed width window for all the frequencies therefore it lacks in providing multiple frequency resolution. So in order to overcome all the problems of the above stated techniques the most powerful mathematical tool so far i.e. Wavelet Transform (WT) has been used for the fault detection purpose at all loading conditions. Except FFT, Wavelet Transform and other techniques such as STFT are capable of revealing characteristics of data like discontinuities in derivatives of high orders, trends, breakdown points and self similarity [5]. Wavelet analysis represents a windowing technique for variable-sized regions. The main advantage of using Wavelet Transform is that even after decomposition of the original signal, the low frequency information can be extracted [2].It analyzes the signal at different frequency bands with different resolutions. The most commonly used wavelet families named after the name of their researchers include Haar wavelet, Daubechies, Symlets, Coiflets, Meyer and Morlet wavelet etc. These are often called as Mother Wavelets.

Fault detection of induction motors has been studied through a wide number of intelligent approaches. In order to constantly monitor the status of a motor various measurements are made so as to get accurate information about the respective faults. This paper proposes a method to diagnose the mechanical faults of an induction motor using wavelet transform and back-propagation neural network. The main idea is to select a mother wavelet correlating the main signal to decompose it into the faultiest part and then subtract certain signatures from the frequency spectrum so as to train the neural network to recognize the different fault patterns. Mainly two fault conditions are considered in this paper: bearing related faults and broken rotor bar faults. The work includes the pre-processing of the signal and the concept of extracting features to reflect the corresponding induction motor faults. An error back-propagation neural network with 3 layers including the hidden layer is employed and trained using these feature coefficients for both faulty and non-faulty conditions. The test results of this scheme indicate high accuracy for bearing and broken rotor bar faults taking place in an induction motor.

II. INDUCTION MOTOR FAULTS

Failures in an electric motor have been categorized as mechanical, insulation and magnetic faults. Table 1 shows a clear survey of the occurrence of bearing faults, broken rotor bar faults, eccentricity faults etc in an induction motor. The paper covers a study of the majority occurring faults.

TABLE I: FAILURE RATE OF INDUCTION MOTOR

Name of Fault	Occurrence in %
Bearing Fault	(40-50)%
Rotor Faults	(<10) %
Stator winding faults	(15-35)%
Others	(5-10)%

III. WAVELET TRANSFORM

Wavelet analysis is a mathematical procedure that distributes frequency into different components to study each component. In the world of time-frequency transformations being just a mathematical tool wavelet transform has gained popularity in its own way. For a time varying signal y (t), the wavelet transform of the signal can be represented as

$$W_y(b,a) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} y(t)\phi(\frac{t-b}{a})dt, b\in R, a \in R^+ \qquad (1)$$

where $a= 2^{-j}$ is known as binary or dyadic dilation and $b= k2^{-j}$ is the binary or dyadic position.

Whereas the discrete wavelet transform of a given signal y (n) can be defined as the inner product of the wavelet function and the signal y (n).

$$C(j.k) = \sum_{n\in Z} y(n)\, \varphi_{j,k}(n) \qquad (2)$$

where $\varphi_{j,k}(n)$ is known as the discrete wavelet function at scale j and position k [1].

A. Selection of Wavelet

Selection of the most optimum mother wavelet is one of the most challenging tasks in wavelet analysis. It acts as a backbone of the whole research in the proposed idea of fault diagnosis. As such there is no outright method of choosing a wavelet, but from the rich space of wavelet families Daubechies has been chosen for the further experimentation as it easily matches with all the vibration signals [9]. Another issue before moving forward in wavelet analysis is the choice of the order of wavelet which in literature was performed by trial and error methods but on the basis of cross-correlation coefficient with the original signal, out of the various 'N' orders (*db1, db2,...dbN*) of Daubechies wavelet *'db7'* is used to obtain the wavelet coefficients.

B. Selection of Decomposition Level

In 1988, the Mallat algorithm had produced a classical them for a signal using discrete wavelet transform where at every stage a signal could be decomposed into an approximation and a detail wavelet coefficient. According to the researchers in previous study the maximum level of decomposition can be calculated by

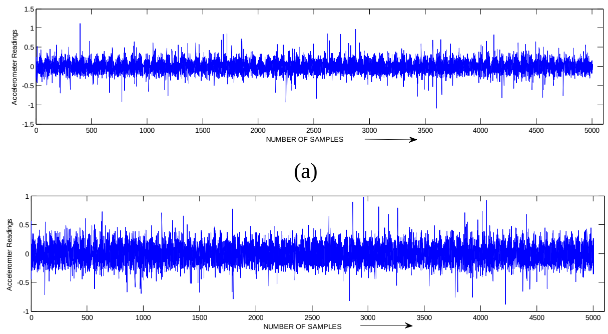
$$L_{max} = [log_2(m_{f(t)})] \qquad (3)$$

where $m_{f(t)}$ is the length *'m'* of series *f(t)* and the bracket [ ] represents that the integral part of L_{max} is considered [4].

TABLE II: SHANNON ENTROPY AT DIFFERENT LEVELS OF DECOMPOSITION

Level of Decompositi on	Shannon Entropy of Healthy signal	Shannon Entropy Faulty Bearing signal	Shannon Entropy Broken rotor-bar signal
D1	219.5725	-7.9015e+003	4.0068e+003
D2	143.7099	156.7663	3.4193e+003
D3	-2.6087e+003	-1.0361e+004	-1.2419e+005
D4	-6.9512e+004	-1.0784e+005	-2.3338e+006
D5	-165.4558	-1.0833e+004	307.1209
D6	**-5.6430**	**-255.0836**	**--105.5803**
D7	-45.8708	-286.4791	-150.2430
D8	-116.5161	-603.9058	-450.0256
D9	-203.5321	-662.7562	-1.0884e+003

For distinguishing results between the healthy and faulty signals, the level up to which the decomposition is performed was definite on the premise of Shannon entropy of the wavelet coefficients. This proposed methodology for the selection of level of decomposition is based on its definition given by Shannon, which says that entropy is the measure of the average information contents associated with the outcome of a random process [11]. So while performing the decomposition of the healthy as well as the faulty signal up to the 9th level it was found out that the maximum amount of information of the relative Shannon entropy was seen at the 6th level which can be noticed in Table 2.



(a)

(b)

Figure 1. (a) Vibration Data of Healthy motor (b) Vibration data of Defective motor

Hence the results deduced in this work are taken forward using the detailed coefficients of the 6th level of decomposed signal. Fig 1 shows the vibration data of Healthy motor and for a faulty data and Table 3 represents frequency level of the wavelet coefficients at each level [8, 10].

TABLE III: FREQUENCY LEVEL OF WAVELET COEFFICIENTS

Level of Decomposition	**Frequency Level of Wavelet Coefficients (S_f= 10KHz)**
D1	5000-10000 Hz
D2	2500-5000 Hz
D3	1250-2500 Hz
D4	625- 1250 Hz
D5	312.5-625 Hz
D6	156.2-312.5 Hz
A6	0-156.2 Hz

Fig. 1 (a) and (b) are the wavelet coefficients of the original vibration data of healthy and faulty signal at the first level of decomposition which clearly shows ripples in the coefficients of unhealthy signals. But for the sake of more accurate results use of artificial intelligence along with wavelet transform is made in this work.

IV. BACK PROPAGATION TRAINING (BPN) ALGORITHM

In the field of motor fault detection and diagnosing, artificial neural networks have made a remarkable mark. Chow proposed the use of neural networks in motor fault detection for the first time [4].

For a multi-layer feed forward neural network, back propagation algorithm follows a supervised learning procedure. Being a supervised learning algorithm both the input as well the output vectors are trained in order to train the network in this algorithm [6]. In a BPN the input layer is connected to the hidden layer and output layer by means of interconnection weights. As the name implies a BPN network algorithm steps back one layer (hidden layer) from the output layer and the error propagates backward from the output nodes to the input nodes so that the output error is minimised [7]. Using the gradient descent method to minimize the error at the output, the algorithm calculates the weights to train the BPN network. This process of error back-propagation consists of a forward pass and a backward pass through distinct layers of the network. And finally as the actual response of the system a set of outputs are assembled. The forward pass renders the fixation of all synaptic weights whereas during the backward pass the synaptic weights get accommodated following the error correction rule. As error correction learning rule is the foundation of this algorithm the actual response of the network then gets debited from the desired response to give an error signal which later propagates backward through the network. Hence the network is known as error back-propagation neural network. The flexibility in its mathematical formula used in algorithm makes it applicable to any network. Along with its simplicity in operation it also provides a way to train networks with any number of hidden units arranged in any number of layers.

In order to train a neural network successfully the input vectors must be chosen appropriately. The features that provide the most important information of the faulty conditions are taken as the input vectors. In this study the current based fault symptoms were used for the diagnosis of faults in a three phase induction motor. The indices chosen for the feature inputs of ANN training and testing are kurtosis K_f , entropy E, root mean square RMS, skewness S_f, crest factor C_f, maximum amplitude A_{max}. The stated parameters are found out to be sensitive to the changes taking place in various motor conditions [4]. The above mentioned parameters have been used to identify normal (healthy), one faulty bearing fault, and two faulty bearings and broken bar faults. Figure 2 illustrates the inputs of the neural network and Figure 3 shows the error back propagation network as a whole.

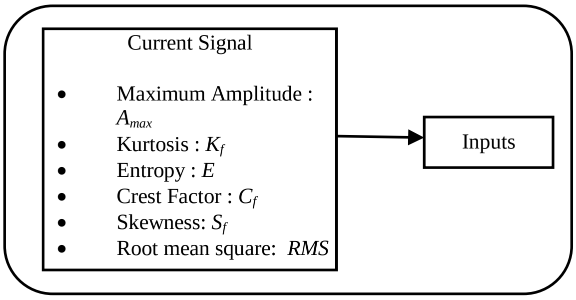


Figure 2: Proposed input vectors of neural network

The proposed strategy of training the back propagation neural network using Levenberg-Marquardt algorithm has four outputs which are given by:

- Y=0 healthy or no-fault signal
- Y=1 one faulty bearing
- Y=2 two faulty bearings
- Y=3 broken rotor bar fault

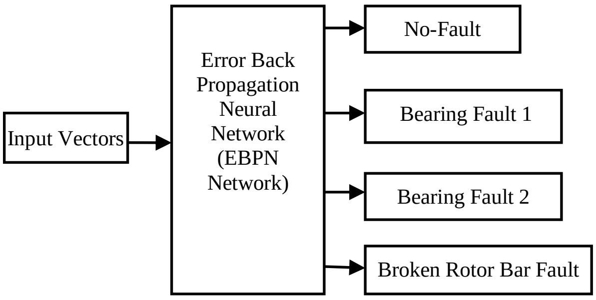


Figure 3: Back propagation neural network to identify faults

V. EXPERIMENTATION

In this diagnosis, tests and experimentation has been done in order to determine the condition of the motor either normal or defective. Using MATLAB the tests were conducted for two conditions i.e. at no-load and at full load at 10 KHz sampling frequency on a 3-phase, 1.5kW, 4P,1440 rpm squirrel cage motor to validate the proposed scheme. As discussed earlier this work is all about bringing forward a framework based on recorded statistical data extraction via Wavelet Transform to distinguish between a normally operating and defective machine using Back Propagation Neural Network.

A. Feature Extraction

Two classes of recorded vibration data i.e. normal and defective are taken into consideration as mentioned earlier. Here the stator current signals are utilized to diagnose the broken bar and bearing faults and to classify the conditions since the signals describe the dynamic characteristics of the induction motor. Wavelet transform has been illustrated as an effective tool in feature extraction and fault identification. In our experiment we have used 905 000 of vibration data in total of which 510 001 is healthy data and rest is the data with defects. Then the data are divided into 50 samples of healthy extracted features and 63 samples of faulty extracted feature by wavelet transform. As for our purpose these 113 samples consist of the six extracted parameters that are entropy, kurtosis, RMS value, crest factor, skewness and maximum amplitude. Table 4 illustrates the features extracted at 6^{th} level of decomposition using 'Daubechies-7'. These features which are very frequently used for their practical applicability and effectiveness in motor fault diagnosis are further treated as inputs to the neural network [12**].**

B. Fault Detection and Classification

Proper selection of inputs, outputs and structure of the network is very necessary for choosing an ANN for training it with appropriate data and identifying motor fault and no-faults conditions. For training the neural network three fault conditions and no-fault conditions are taken into consideration [15**]**. The work employs a three layer simple back propagation neural network (EBPN) trained to perform motor fault diagnosis. The literature has brought forward several types of training algorithms for training the neural network [13]. The back- propagation is one of the most frequently used algorithms. The performance of the network can be judged on the basis of mean squared error (MSE) of the neural network. A series of exhaustive tests have been conducted to verify and validate the effectiveness of the fault detection scheme proposed in this paper.

The framework of extraction of features and fault classification is shown in Figure 4

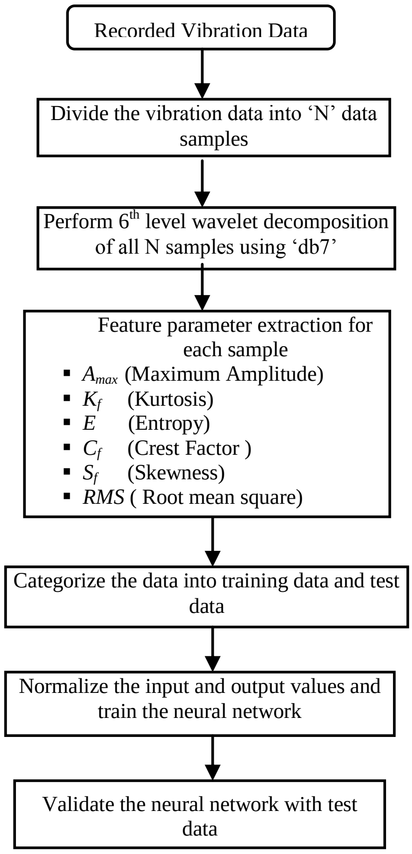


Figure 4: The framework of Fault Detection of Induction Motor

Initially the weights and biases were randomly assigned. The default values of epochs equal to 1000 and .001 learning rate are used during the training process. Once the algorithm gets trained for different faulty and normal operating conditions the testing process is initiated by repeatedly minimizing the error at the output.

TABLE IV: EXTRACTED FEATURES OF HEALTHY AND FAULTY SIGNAL

		Entropy	RMS	Kurtosis	Skewness	Maximum value	Crest factor
db7	**Healthy**	-5.6430	6.5265	26.5246	-2.2684	2.3550	0.3608
	1 Bearing Faulty	-255.0836	12.3694	33.5794	1.3855	7.4833	0.6049
	2 Faulty Bearings	-100.2836	9.1010	22.2817	1.5146	4.6116	0.5067
	Broken rotor bar	-105.5803	8.7437	22.5107	2.0368	4.4795	0.5123

VI. RESULTS AND DISCUSSION

The most appropriate network for the detection process is chosen on the basis of the fact that how efficiently the network responds to any change in the modeling process. The choice of the parameters used to train the neural network is not based on any formula, it is generally problem dependant. All the inputs and test inputs are normalized between 0 and 1 to make them compatible with the target outputs before being applied to train and test the neural network.

The performance of a neural network can be tested by the mean square error (MSE). The equation which describes the best network employing mean square error is given by

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \qquad (4)$$

where e_i represents the error, t_i and a_i the desired and actual value and N being the number of data.

TABLE V: PERFORMANCE OF EBPN FOR MOTOR FAULT DIAGNOSIS

BPN structure	MSE	Accuracy %	BPN structure	MSE	Accuracy %
6x1x4	2.63×10^{-1}	97.94	6x11x4	6.27×10^{-2}	84.70
6x2x4	2.76×10^{-2}	94.63	6x12x4	5.32×10^{-2}	92.95
6x3x4	1.29×10^{-2}	92.75	6x13x4	5.70×10^{-3}	93.97
6x4x4	1.88×10^{-2}	90.73	**6x14x4**	$\mathbf{7.948 \times 10^{-4}}$	**99.85**
6x5x4	3.27×10^{-2}	92.36	6x15x4	4.09×10^{-2}	85.91
6x6x4	1.19×10^{-2}	97.0	6x16x4	2.10×10^{-2}	86.79
6x7x4	8.40×10^{-3}	91.99	6x17x4	5.20×10^{-2}	84.43
6x8x4	5.20×10^{-3}	94.53	6x18x4	2.60×10^{-3}	95.87
6x9x4	1.54×10^{-2}	89.86	6x19x4	7.56×10^{-2}	92
6x10x4	9.27×10^{-1}	94.45	6x20x4	6.20×10^{-3}	94.64

By varying the number of neurons in the hidden layer the performance of the network is compared. As there are no ways of defining the number of neurons in a network it could only be decided using trial and error in most situations. Initiating the trial and error with initially two neurons in the hidden layer, the systems performance for the best network was determined until 20 hidden neurons. Table 1 displays the performance of each neural network varying with the number of hidden neurons. It was noticed that the performance of the network does not necessarily improve with the increase in the number of neurons. Results show the smallest mean squared error 7.948×10^{-4} was seen for 14 neurons in the hidden layer thus this network was chosen as the optimum network for detection of faults via EBPN. It is observed that the minimum validation error for the selected back propagation neural network is nearly equal to zero, hence making the system 99.85% accurate. The MATLAB Toolbox 7.8.0 was applied to all wavelet and neural network applications in the proposed work. Use of the neural network GUI has also been made in this work to cross verify the results. Randomly 90 samples were taken for training, 17 for validation and 6 for testing in using GUI of neural networks in MATLAB.

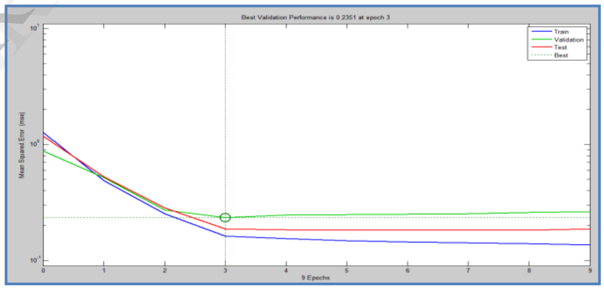


Figure 5: Training and testing performance of network for 14 hidden nodes

CONCLUSION

On the basis of vibration data, this paper brings forth a technique which puts together the attributes of Wavelet Transform and Back propagation neural network to diagnose and classify faults in an induction motor. The strategy applied in this paper was to firstly gather a data set to train the network and then use the network for testing any induction motor of unknown data set. The estimated results clearly represent the ability of the proposed system for the protection of induction motors under various hazardous conditions. This research can be taken forward by employing approaches other than BPN and also by focusing on other faults occurring in the machine.

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