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Back Propagation Algorithm for Bearing Fault Detection of Induction Motor Drive Using Wavelet Pocket Decomposition

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Abstract

A consistent monitoring of industrial drives is to avoid the performance degradation of machinery. Today's fault detection system uses wavelet transform along with neural network for proper detection of faults, however it required more attention on detecting higher fault rates with lower execution time. Existence of faults on industrial drives leads to higher current flow rate and the broken bearing detected system determined the number of unhealthy bearings but need to develop a faster system with constant frequency domain. Vibration data acquisition through digital signal processor and the featuresareextractedfrom the vibration signalsbyusingwavelet transform. This proposed work is to detect broken bearing faults in induction machine and to generate an effective fault detection of industrial drives through a Back Propagation Algorithm (BPA). This system was focused to reducing the current flow and to identify faults with lesser execution time with harmonic values obtained. Initially, the vibration signal received from the digital signal processor and features are extracted through wavelet transform. The wavelet coefficients of broken bearing signal are approximated using double scaling factor and identify the transient disturbance due to fault on induction motor.

Back Propagation Neural Network detects the final level of faults using the detailed coefficient till sixth level decomposition and the results obtained through it at a faster rate at constant frequency signal on the industrial drive. Experimental setup was carried out to detect the healthy and unhealthy motor on measuring parametric factors such as fault detection rate based on time, current flow rate and execution time.

Keywords: Back propagation algorithm, Broken bearings, Digital signal processor, Induction motor, Faults diagnosis, Wavelet decomposition.

I Introduction

Bearing fault detection is one of the most significant problems associated in the industrial drives. Early detection of fault in the bearing in induction motors helps to reduce not only the workflow in the industry and also reduction in degradation of machines to a certain extent. Many researchers have concentrated on the early fault detection in industrial drive, but certain limitations were not addressed.Induction motors are susceptible to many types of faults in industrial drives applications. The producers and the consumers of these drives were primarily relied on simple protection like earth fault, over voltage, over current and over load to facilitate for the safe and reliable function. The continuous performance of the machine develops complication which demand fault diagnosis system. If the failure is not identified at initial stage, the drive may become catastrophic and suffer severe damage. The inevitability of the sensitive drives system forces to diagnose faults at their inception and stay away from machine downtime and monetary fatalities [1].

The mechanical faults could develop a dynamic eccentricity and lead a serious damage to stator core and windings. The major faults of electrical machines can be broadly classified and the percentage of faults [2], [3] occurring in the machines is graphically represented in fig.1.

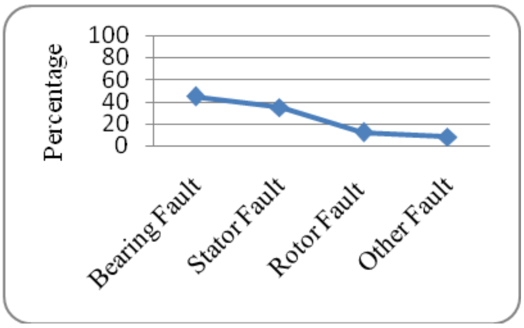


Fig. 1 Percentage of faults in induction machine

II Bearing Faults in Induction Motor

Bearings are very sensitive element in the induction motor which is frequently matured to failureand requiressuperiorcare. The major causes to bearing failures are shown in fig. 2. The faults are due to mechanical and electrical stresses. The mechanical stresses are caused by over load and abrupt load changes which leadto produce bearing fault and rotor bar breakage. The electrical stresses are caused by short circuits in stator winding and usually associated with the input power supply, since the induction motors could be energized from constant frequency sinusoidal power supplies or from variable frequency supply in case of adjustable speed ac drives. These associated stresses could be turn out and produce different type of faults and result in a complete motor failure [4].

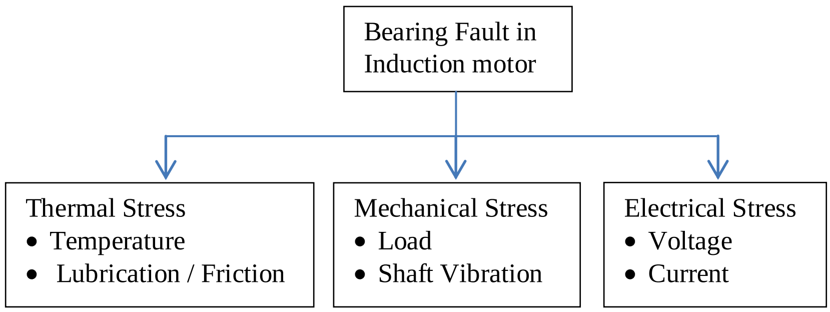


Fig. 2 Chart for bearing faults in induction motor

It is generally understood that the bearing failures progress from general roughness, which leads to single defect of the bearing components.In the past years,the condition monitoring system of bearingfailures has pinchedand brought lot of attention and many methods havebeen proposed with various types of sensors. Particularly, vibration sensors are employed to screen the vibration of thebearings to detect bearing failures and it was considered as a reliable indicatorfor bearing faultsand become popular in practice. This system requires the access to the motor and leads to cost due to thesensor and its maintenance. The fault diagnosis system of rolling ball bearingfailurescan tip in to a particularvibration frequency [4] as follows:

Outer Raceway

$$f_{out} = \frac{m}{2} N_r \left(1 - \frac{d_b}{d_p} \cos\alpha \right) \tag{1}$$

Inner Raceway

$$f_{in} = \frac{m}{2} N_r \left(1 + \frac{d_b}{d_p} \cos\alpha \right) \tag{2}$$

Ball …

$$f_{ball} = \frac{d_p}{d_b} N_r \left(1 - \frac{d_b^2}{d_p^2} \cos^2 \alpha \right) \tag{3}$$

Where
m - is the number of bearing balls,
N_r - is the rotor speed,
d_b - is the ball diameter,
d_p - is the bearing pitch diameter and
α - is the contact angle of the balls on the races.

Vibration analysis based on the condition monitoring system uses various signal processing techniques like statistical signal processingwavelet transforms, parks vector and the extended park vector. Also neuralnetworks are employed as a decision-making system. Further, it is stated that the bearing failures also lead to rotoreccentricity, hence monitoring ofgeneral irregularity of the bearings is more significant to detectbearing faults at early stage.

III Related Works

The improvement in reliability factor of mechanism by diagnosing the faults of rolling element is highly significant as breakdowns on bearing are the most frequent problems related to rotating machinery. The origin of any consistent fault diagnosis method is inclusion of the real behaviour and condition of the faulty machine. Various techniques have been introduced where their main divergences are the proposed signals used for diagnosis. The signal can be electrical, mechanical and temperature, but the criteria for the selecting the most suitable signal for fault diagnosis in the dynamic machine consists of [5]. Advantages of applying AI tools for fault diagnosis include emulating and employing human expertise, automating the diagnosis process, and gaining earlier and more precise detection. [6]. A Recent Developments on fault diagnosis of Induction Motor Drives using artificial intelligence (AI) Techniques have been established such as application of expert systems, artificial neural networks (ANNs) and fuzzy logic systems that can be integrated into each other and also with more traditional techniques [7].

A hybrid model including Empirical Model Decomposition and Hilbert Huang Transform was included to diagnose the faults in bearing by applying varied load conditionsin [8]. However, the life of the component was not considered. An intelligent method using Artificial Neural Network (ANN) was structured in [9] that efficiently removed the non bearing fault components despite the inclusion of noise. However, the irregularities in load were not considered. Motor Current Signature Analysis (MCSA) [10] detected the faults in bearings using 2D wavelet scalogram.

Condition monitoring is one of the most efficient mechanisms with which the rate of faults can be reduced to a significant rate. An integrated form of HAAR wavelet and FFT [11] was applied to measure the frequencies of faults which resulted in cost effectiveness. However, the reliability of the model remains unaddressed. Bearing fault detection was effectively evaluated in [12] using SVM and KNN that identified and classified the faults at an earlier stage. Based on the frequency of the fault being generated, a variation algorithm was designed for broken bearings in rotor bars fault detection[13].

Noise and sparseness of vibration signals are posing greater threat while detecting fault in the bearings in induction motors. Reducing noise with efficient means and early fault detection was presentedin [14] using piecewise recombination and inverse wavelet transform. With this, the detection of the system was proved to efficient and was also easy to implement. However, the energy required to eliminate the noise increased with the increase in the unhealthy bearings. To solve this issue, an integrated method combining Hilbert Huang Transform (HHT) and Singular Value Decomposition (SVD) was introduced in [15] resulting in higher precision. A new method called as the Complementary Ensemble Empirical Mode Decomposition (CEEMD) [16] was designed to accurately identify the faults in bearings in induction motors.The induction motor protection and monitoring using Wavelet Transform and Neural network and 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 the error back propagation algorithm (EBPA), a statistical features like kurtosis, crest factor, root mean square (RMS) value, entropy and skew ness are extracted to train and test the neural network. The expected analysis of the level of decomposition to extract the statistical features from the wavelet coefficients and training an error back propagation neural network using thefeatures extracted and the results shows that it could be an effective agent in the detection of various faults in inductionmotor [17].Based on the aforementioned methods and techniques discussed, in this work an efficient system to reduce the current flow and identify faults in lesser time is designed. In the forthcoming sections, detailed description about Back Propagation Wavelet Neural Network is presented in detail.

IV Back Propagation – Wavelet Neural Network (BP-WNN) System

The main objective of this work is to construct a Back propagation algorithm for the extracted detailed coefficient from wavelet transform using the vibration signal-data of the industrial drive. Normally the industrial drive is interested in constructing the induction motor without any transient disturbance while speeding up the motor, but practically it is very difficult to construct such type of induction motor. Therefore, the diagnosis system is developed to identify the right source of faults. The wavelet transform represents the vibration signal-data simultaneously at time ‘t’ with a frequency ‘f’. The wavelet decomposes the vibration signal-data into frequency and also the time factor on which the frequency gets fluctuated. The proposed BP-WNN system frequency range is maintained without any transient disturbance and also achieves higher fault detection on the induction motor with minimal execution time with detailed coefficient obtained till 6^{th} level decomposition. The Back Propagation Wavelet transform Neural Network (BP-WNN) system is illustrated in Fig. 3.

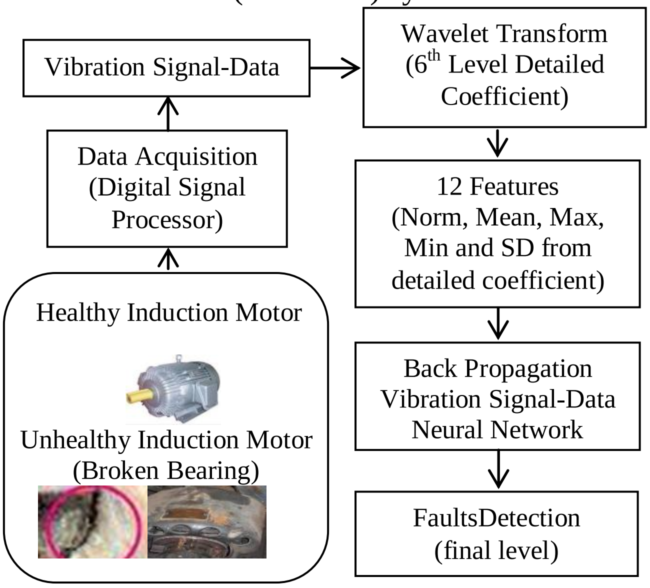


Fig. 3 Proposed BP-WNN System

The wavelet transform with vibration signal-data is used to easily localize the time and frequency domain. The time and frequency domain variation point help to easily detect the broken bearing in the induction motor. The detection of broken bearing is based on the transient disturbance on the frequency value. The FD approximate and detailed coefficients are computed using Back propagation algorithm. The detailed coefficients are grouped as two as N_1 and N_2. The twelve feature such as norm, mean, max, min, SD of N_1 and N_2, norm and SD of the energy of all the six level coefficients [17]. The overall diagrammatic functional hierarchy of proposed BP-WNN system is shown in Fig. 3. The vibration signal-data of induction motor is taken as the input parameter and using the MATLAB code, the vibration data are analyzed and carries out the double scaling factor which localized the time and frequency domain. The non-transient disturbance on the frequency range (i.e., 50 Hz), then the healthy and unhealthy induction motor is used on the industrial drive with maximal speed rate.The fault in the induction motor is measured based on the broken bearing using the vibration signal through BP-WNN. The broken bearing detection through the proposed system results in two coefficient values called the approximate and detailed coefficients. The detailed coefficient value is applied until sixth level decompose data is obtained, then the Wavelet – Back Propagation Neural Network combine to identify the faults in the induction motor at a faster rate.

V Vibration Signal-Data Based Wavelet Transform

Let us consider the Vibration Signal data 'X' of the induction motor that provides higher degree of freedom on measuring the time and frequency domain. The wavelet constructs the symmetric wavelet function using vibration signal-data and generates the double scaling factors in proposed system differs with 'A' (i.e., Approximate coefficient) coefficient and 'D' (i.e., Detailed coefficient) values. Vibration signal-data wavelet transform is given as

$$WT = \sum_{i=1}^{n}(A_n, D_n) \tag{4}$$

The wavelet-packet method is a generalization ofwavelet decomposition that offers a richer range ofpossibilities for signal analysis. In wavelet analysis, a signal is divided into an approximation and a detail coefficient and then, the detail coefficient itself divided into a second- level approximation and detail and the process isrepeated [18] until sixth level and the targeted results are obtained. For n-level decomposition, thereare n+1 possible ways to decompose or encode the original signal. Wavelets and wavelet packetsdecompose the original signal, which is of no stationary or stationary in nature into independent frequencybands with multi-resolution. The wavelet transform is also known as multi scale decomposition process and shown in Fig. 4.

They form bases which retain many of the properties like orthogonality, smoothness and localization of their parent wavelets. The coefficient filter algorithm starts from a Signal (S) as shown in Fig.5 and two sets of coefficients are computed; that is, approximation coefficients cA_1 and detail coefficients cD_1. The vectors are obtained by convolving S with the low-pass filter Lo_D for approximation and with the high-pass filter Hi_D for detail, followed by dyadic decimation [19].

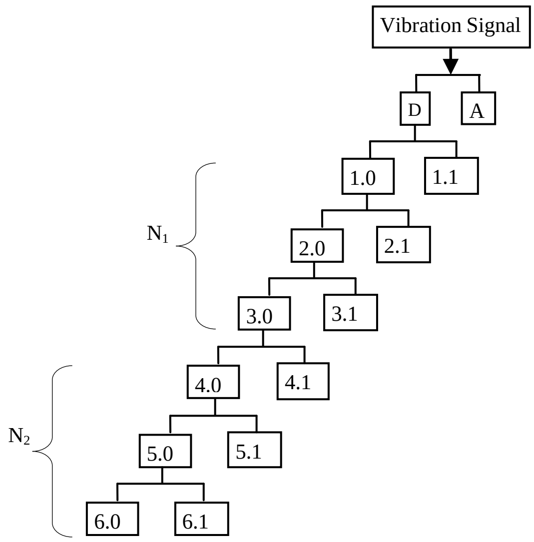


Fig. 4 Wavelet Pocket Decomposition

The length of each filter is equal to 2N. If n = length(s), then signals length *n+2N-1* and then the coefficients cA_1 and cD_1 are of length and floor for an illustration the wavelet packets decompose the signal into one low-pass filter and ($2l-1$) band pass filters and provide diagnosis information in two frequency bands [20]. A_j is the low-frequency approximation and D_j is the high-frequency detail signal. After decomposing the signal, the approximation signals A_1, A_2 .....A_j and D_1, D_2 ....,. D_j detail signals are obtained

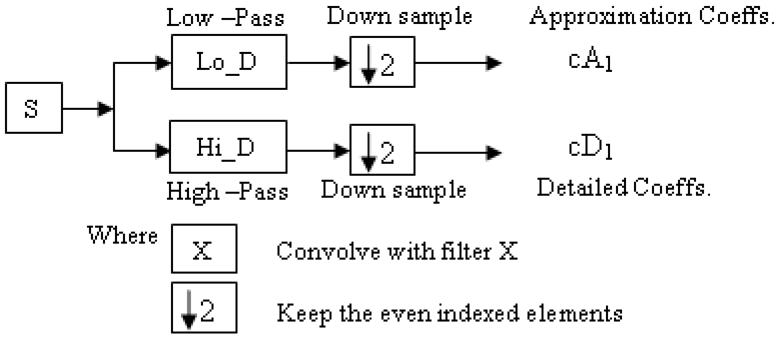


Fig. 5 Wavelet Coefficients with Filters

This process is continued until the sixth level decomposition and the coefficient obtained which helps in identifying higher number of faults at minimum time interval. Similarly, to all the cases the coefficients of approximated and detailed values are identified for such as healthy, unhealthy with one broken bearing and unhealthy with two broken bearing induction motor.

VI Back Propagation Algorithm

Back propagation neural network is the structure that involves in changing the weights and biases in the network, which means computing the partial derivatives. In order to compute those, we first present an intermediate quantity, which is the error in the i^{th} neuron in the j^{th} layer. It manipulates and give us a procedure to compute the error and then relate to the desired output. Back Propagation Algorithm (BPA) is a supervised method which maps the features of an electrical signal to a predefined classification category of failures [17]. The BPA learns the features using the steepest decent concept. The structure of the artificial neural network is designed as shown in Fig 6. The information flows from input layer to output layer through hidden layer.

Input Layer = 12 Nodes (a_1, a_2, a_3 ………. a_{12})
Hidden Layer = 2 Nodes (h_1, h_2)
Output Layer = 1 Node (y_1)

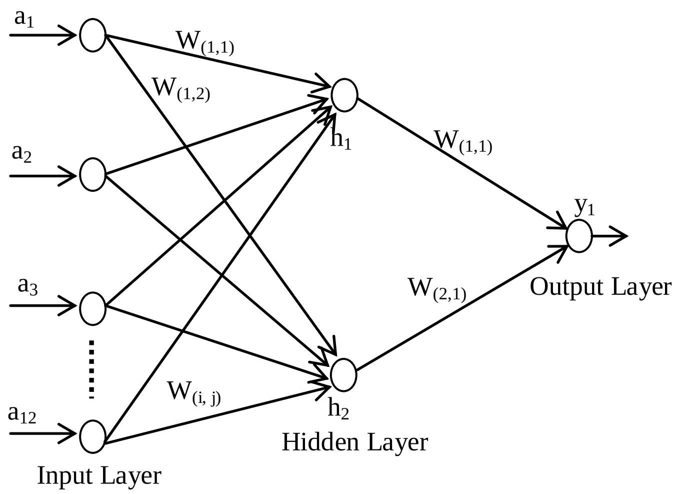


Fig. 6 Structure of Back Propagation Neural Network

The BPA is a supervised learning and it is implemented by weight updates from output layer to input layer through hidden layer. The training is stopped, when the desired value in the Mean Squared Error(MSE) is reached at the output layer. During forward propagation the weights of the network are initialized. The inputs and outputs of a pattern are presented to the network. The output of each node in the successive layers is calculated in the forward propagation. In the reverse process weights are updated between layers. This process is accounted to a one weight update. Then the second pattern is presented and the same sequences are followed for the second weight update. When all the training patterns are presented, it is considered that, a cycle of iteration or epoch is completed. The cycle of iteration is repeated, until the Mean Squared Error (MSE) is less than a specified value.

VII Algorithmic Procedure

The vibration signal-data used to measure the time and frequency domain for detecting the fault rate. The wavelet transform coefficients are interrelated with dual scaling factor to achieve to detecting faults at an earlier stage. Thelesser rate of current flow leads to minimal fault on the industrial drive induction motor.The BP-WNN System through dual scaling factor is formularized as,

Begin
Step 1: Feed the Input to the Input layer (12 features extracted from the Wavelet pocket decomposition)
Step 2: Initialize the weights and target.
Step 3: Calculation of hidden layer input and output
Step 3.1: Calculation of hidden layer input (from first node input to h_1)

$$h_1 = a_1 \times W_{11} \tag{5}$$

Step 3.2: Calculation of hidden layer output (output of h_1)

$$h_1 = \frac{1}{1 + e^{-(I/P)}} \tag{6}$$

Step 4: Calculation input and output of output layer
Step 4.1: Calculation of input to the output layer (output of h_1 to output layer)

$$Input\ to\ output\ layer = output\ of\ h_1 \times w_{11} \tag{7}$$

Step 4.2: Calculation of output for the output layer (output y_1)

$$y_1 = \frac{1}{1 + e^{-(I/P)}} \tag{8}$$

Step 5: Calculation of the error for the case Target output $\approx$ actual Output, which is more than precision value
Step 5.1: Error δ = Actual output ~ Target Output
Step 6: Calculation of new weight $W_{new} = W_{old} + \delta$
Step 7: Identifies higher fault count on minimal execution time
End

VIII Experimental Evaluation

The experimental setup incorporate healthy motor and unhealthy motor with one broken bearing and two broken bearing projected for Back Propagation - Wavelet Neural Network (BP-WNN) system as depicted in Fig.7. In order to measure the vibration signal data, a standalone module of digital signal processor TMS320F2812 is interfaced with computer. This module has a single chip parallel port to JTAG scan controller. Therefore, it could be operated without additional development tools such as an emulator and it is an excellent platform to develop, demonstrate, and run software.

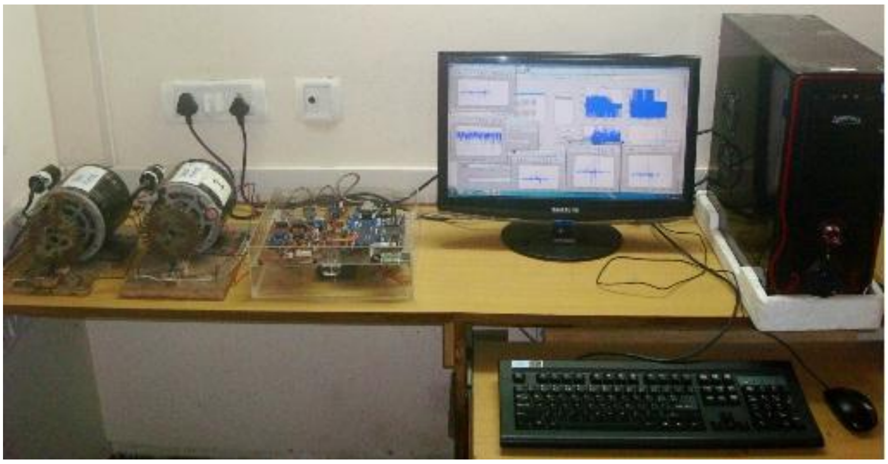


Fig. 8 Experimental setup using healthy and unhealthy motor

The BP-WNN detects the broken bearings using the harmonics obtained through the approximated and detailed coefficient values of a healthy motor and unhealthy motor. The industrial drive system is healthy, and then there does not occur any harmonic values. On the other hand, if there is a broken bearing in the industrial drive, then the harmonic values are obtained under running condition. During the first level, two coefficient values are extracted and called as the approximated and detailed coefficients. The approximated coefficient values are not considered whereas the detailed coefficient value is used to process for the second level of decomposition. In this way the process is continued till sixth level, form to obtain the resultant output of the vibration signal – data. The system healthiness and faultiness are checked using BP-WNN system and identify the actual failure rate of motor at an earlier stage. The dependability on the frequency domain is maintained as 50 Hz. If there is an occurrence of broken bearing, then the rate of flow of current is increased with varying frequency range and to evaluate the proposed BP-WNN system, the wavelet transform is used on measuring vibration signal – data in time and frequency domain.The motor was running for different set of time (i.e., of about 15 minutes) on every iteration.

Table 1. Induction Motor Specification

Parameters	Specification
Current	350 mA
Voltage	230 Volts
Fault Detection rate based on Time	600 seconds per iteration
Speed	1440 RPM
Frequency Range	50 Hz
Power rate on Execution	0.25 Hp

The Back Propagation Wavelet Neural Network (BP-WNN) system for detecting the induction motor faults is compared against existing Basic Vibration Signal Processing for Bearing Fault Detection (BVSP). Experiment conducted on factors such as fault detection rate based on execution time and time of operation of healthy and unhealthy induction motor. Parameters taken for the drive system specifications are given Table 1.

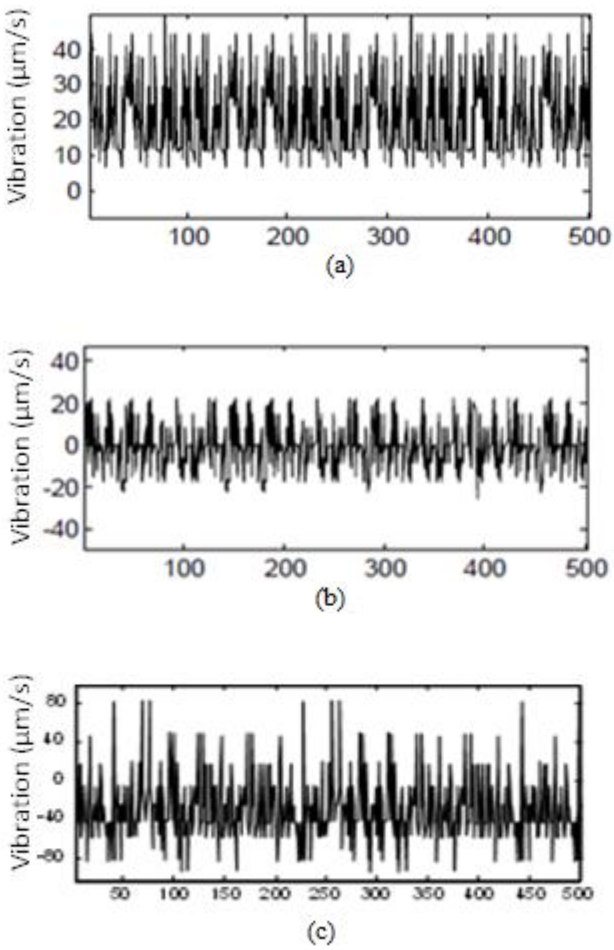


Fig. 9 Plot of Vibration Measured Experimentally (a) Healthy motor (b) Unhealthy motor (1BB) (c) (b) Unhealthy motor (2BB)

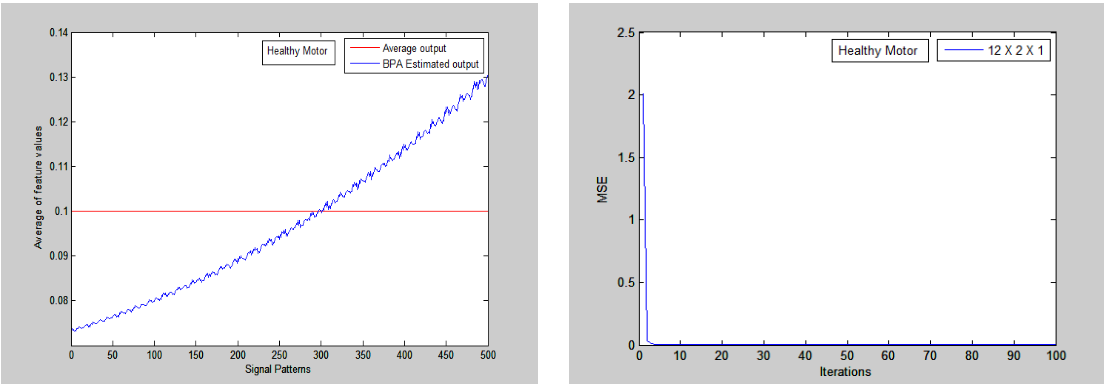
The broken or damaged bearing is analysed by identifying the harmonic components around the fundamental component of vibration. The vibration of healthy and unhealthy motor is measured experimentally and plotted as shown Fig. 9 and is observed that the magnitude of vibration plot of (a) healthy motor is almost constant and has fewer ripples, whereas the plot of (b) with one broken ball bearings (1BB) has more ripples and the plot of (c) with two broken ball bearings (2BB) has higher ripples compare to the other.

IX Result Analysis

The detailed coefficient extracted from the wavelet packet decomposition are grouped in to two set like N_1 (Level 1.0, 2.0, 3.0) and N_2 (Level 4.0, 5.0, 6.0). The features are created with coefficient group such as the first five features are Norm, SD, Mean, Max, Min of N_1, the second five features are Norm, SD, Mean, Max, Min of N_2, last two features are Norm and SD of Energy. The twelve features were fed as input to back propagation neural network and trained the network for 50 patterns and tested with 500 patterns the results are tabulated in Table 2.

Table 2 Result of Back Propagation Neural Network

Drive Condition	No. of pattern used for training	No. of patterns used for testing	Execu - tion Time (sec)	Target output	Range of BPA Estimated Output	% of Fault identification	% of Error
Healthy Motor	50	500	1.97	0.1	0.065-0.132	96.70	3.30
Unhealthy Motor-1BB	50	500	2.15	0.2	0.158-0.224	94.80	5.20
Unhealthy Motor-2BB	50	500	2.35	0.3	0.246-0.404	92.80	7.20

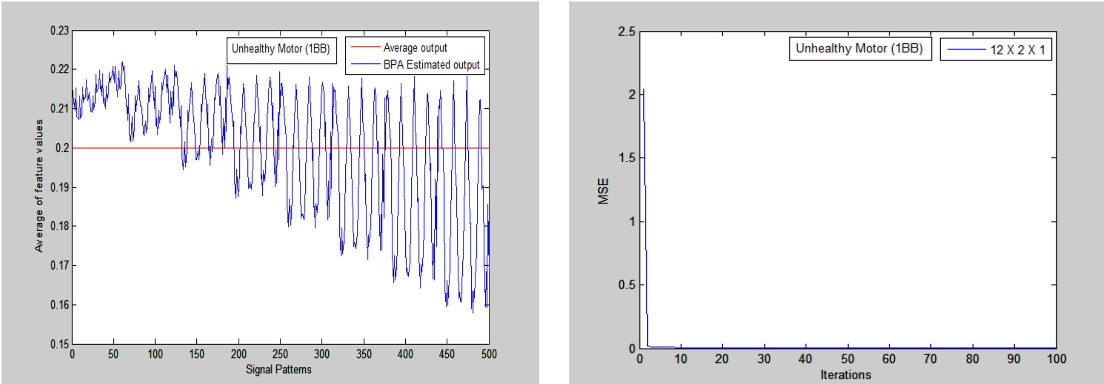


(a) Estimated Output (b) Mean Square Error

Fig. 10 BPA Results of Healthy Motor

The back propagation results for healthy motors are shown in Fig. 10 (a) and (b). The Fig.10 (a) shows the estimated output and the average output of healthy motor, the range estimated output is between 0.06 – 0.132 with the target value of 0.1. It is clearly observed that, first 300 signal pattern closer to the target value and remaining patterns slightly higher, the overall deviation is ± 0.035 which is satisfactory range compared to the targeted value. The output is obtained within 1.96

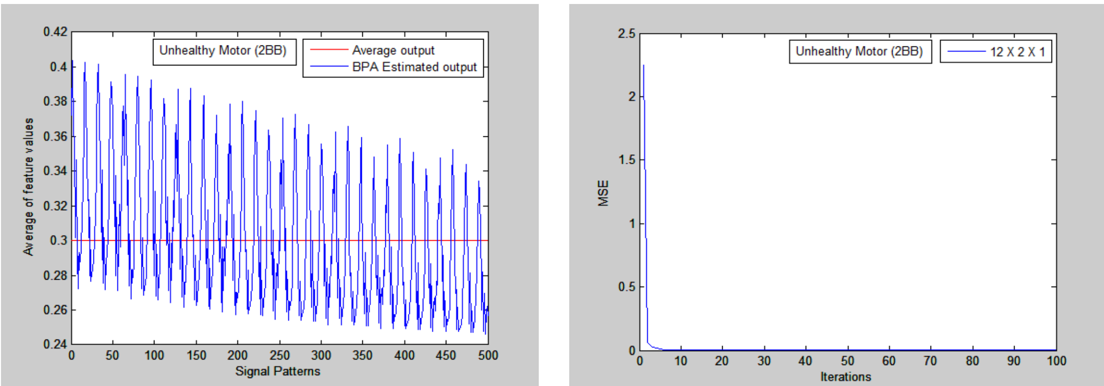
second of execution time for 50 training pattern. The Fig.10 (b) shows the Mean Square Error against the number of iterations. The MSE for the healthy motor has been reduced near to zero within9 iterations and takes 100 iterations to complete the weight updation.



(a) Estimated Output (b) Mean Square Error

Fig. 11 BPA Results of Unhealthy Motor (1BB)

The Fig. 11 (a) shows the estimated output and the average output of unhealthy motor (1BB), the range estimated output is between 0.158 – 0.224 with the target value of 0.2. It is clearly observed that, the estimated output not properly approaches the target value, the deviation structure is not like as healthy motor and after 400 signal pattern follows uniform structure and closer to the target value and the overall deviation is ± 0.042 which is unsatisfactory range compared to the healthy motor. The output is obtained within2.15 second of execution time for 50 training pattern. The Fig. 11 (b) shows the Mean Squared Error against the number of iterations.



(a) Estimated Output (b)Mean Square Error

Fig. 12 BPA Results of Unhealthy Motor (2BB)

The MSE for the healthy motor has been reduced near to zero within 12 iterations and takes 100 iterations to complete the weight updation. The Fig. 12 (a) shows the estimated output and the average output of unhealthy motor (2BB), the range estimated output is between 0.246 – 0.404 with the target value of 0.3. It is clearly observed that, the estimated output not properly approaches the target value, the deviation structure is not like as healthy motor and after 400 signal pattern follows uniform structure and closer to the target value and the overall deviation is ± 0.054 which is unsatisfactory range compared to the healthy motor. The output is obtained within 2.15 second of execution time for 50 training pattern. The Fig. 12 (b) shows the Mean Squared Error against the number of iterations. The MSE for the healthy motor has been reduced near to zero within 15 iterations and takes 100 iterations to complete the weight updation.

X Conclusion

In this work, wavelet transform has been used to obtain feature such as approximate and detailed coefficients at 6^{th} level decomposition and these features are used as training and testing data for the BPA network. Based on the number of samples considered in a frame, the accuracy of the feature value varies. The 6^{th} level decomposed detailed coefficients are grouped as N_1 and N_2. The 12 features are Norm, Min, Max, Mean, SD of N_1 and N_2, Norm and SD of energy of all detail coefficients. The back propagation neural network has structured and developed an algorithm to train 50 patterns. The weights have been update during training and the network produced the targeted output. The target output is fixed as 0.1, 0.2 and 0.3 for healthy motor, for unhealthy motor (1BB) and for unhealthy motor (2BB) respectively. Then the test carried out for 500 patterns, the BPA estimated output received from the network, the output for healthy motor ranged between 0.065 – 0.132 which is very close to target value and it identifies the condition of the drive by 96.7% with a minimum error of 3.3%. The other cases such as one broken bearing and two broken bearing are tested with same 500 patterns and the percentage of fault identification is 94.8% and 92.8% respectively with a satisfactory error. Also the MSE is almost reached zero with 9, 12 and 15 iterations in all three cases respectively and updated the weights with 100 iterations. These results show that the wavelet transform – back propagation neural network (BP – WNN) functions satisfactorily with minimum execution time and it has to be compared to designate the still better algorithm.

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