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Vibration Analysis of Industrial Drive for Broken Bearing Detection Using Probabilistic Wavelet Neural Network

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ABSTRACT

A reliable monitoring of industrial drives plays a vital role to prevent from the performance degradation of machinery. Today's fault detection system mechanism uses wavelet transform 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 was used in our proposed work to detect broken bearing faults in induction machine. To generate an effective fault detection of industrial drives, Biorthogonal Posterior Vibration Signal-Data Probabilistic Wavelet Neural Network (BPPVS-WNN) system was proposed in this paper. This system was focused to reducing the current flow and to identify faults with lesser execution time with harmonic values obtained through fifth derivative. Initially, the construction of Biorthogonal vibration signal-data based wavelet transform in BPPVS-WNN system localizes the time and frequency domain. The Biorthogonal wavelet approximates the broken bearing using double scaling and factor, identifies the transient disturbance due to fault on induction motor through approximate coefficients and detailed coefficient. Posterior Probabilistic Neural Network detects the final level of faults using the detailed coefficient till fifth derivative and the results obtained through it at a faster rate at constant frequency signal on the industrial drive. Experiment through the Simulink tool detects the healthy and unhealthy motor on measuring parametric factors such as fault detection rate based on time, current flow rate and execution time.

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1. INTRODUCTION

Bearing fault detection is one of the most significant problems measured in the industrial drive. Early detection of fault in the bearing in induction motors helps to reduce not only the workflow in the industry but also degradation of machines can be reduced to a certain extent. Many researchers have concentrated on the early fault detection in industrial drive, but certain limitations were not addressed.

Basic Vibration Signal Processing (BVSP) [1] addressed the problems related to detection of faults in the bearing at an early stage applying amplitude modulation and Hilbert transform. One of the alternative methods was designed in [2] called as the Current Frequency Spectral Subtraction that regularly monitored the induction machine bearings using Fourier and Discrete Wavelet Transform. Though early detection was possible, automatic detection of fault in bearing was not addressed. A method using vibration signal analysis was structured in [3] using time domain techniques. However, measures were not included for periodic vibrations. One of the major machine failures is due to the occurrence of faults in bearing which has to be identified at an early stage in a planned manner rather than at the cost of machinery. A variable machine speed was applied [4] to identify the fault. However, the vibration data was not measured with respect to time. An online fault detection mechanism was designed in [5] using Fourier transform at varied time interval and also the impact of imbalances in power was also measured. But the mechanism was designed with the purview that neural network captures the nonlinear system dynamic. As a result, a method that could detect the fault at the start up period was designed in [6] called as Time Stepping Finite Element method by considering the spatial distribution of stator windings.

In the recent years, maintenance of machinery and induction motors has to be performed at a predictive rate with the increase in the cost and maintenance of machines. A method called Hilbert Huang Transform (HHT) [7] with the aid of Discrete Wavelet Transform (DWT) resulting in better suitability. However, the patterns were not clearer and the number of rotations was not taken into consideration. To obtain the faults at various speed with which the motors gets rotated, Gaussian-Enveloped Oscillation-type Wavelet [8] was used. This method proved to be efficient that in a way identified the faults at various rotating speed. A statistical analysis using mean, entropy and variance was applied in [9] to detect the faults in induction motors at varied rotational speed.

In order to identify and detect the faults occurred in induction motors, one of the most significant measures that can be taken is the monitoring of machines in an automatic manner. Common Vector Approach (CVA) [10] was used to detect the faults in induction motors using wavelet energy component. But, measures were not taken to vibration signals in database. One of the solutions was to disintegrate the vibration signal using Discrete Wavelet Transform (DWT) [11]. As a result, the fault size was identified and also provided a means for early detection of faults. In this paper, an effective bearing fault detection in induction motors using, Biorthogonal Posterior Vibration Signal-Data Probabilistic Wavelet Neural Network (BPPVS-WNN) is presented. The system BPPVS-WNN first identifies the transient disturbances by localizing time and frequency. From it the detailed coefficient is extracted until the fifth derivative form is achieved. Nest, Posterior Probabilistic Vibration Signal-Data Neural Network is applied for faster detection of final level of faults using fifth derivative form.

The rest of the paper has been organized as follows. Section 2 gives a brief model for fault detection of bearing in induction motors. Section 3 includes the review works related to induction motors in industrial drive and several fault detection mechanisms with their briefing and limitations. Section 3 presents the proposed system with neat architecture diagram and algorithmic described included with an elaborated description of the same. Section 4 present the experimental analysis and metrics considered for the design of the model whereas Section 5 includes simulation results. Section 6 concludes the work with concluding remarks.

2. RELATED WORKS

The improvement of reliability factor of mechanism system by diagnosing the faults of rolling element is highly significant as breakdowns on bearing are the most frequent problems related to rotating machinery. A hybrid model including Empirical Model Decomposition and Hilbert Huang Transform was included in [12] to diagnose the faults in bearing by applying varied load conditions. However, the life of the component was not considered. An intelligent method using Artificial Neural Network (ANN) was structured in [13] 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) [14] 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 [15] 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 [16] 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 in [17] for broken bearings in rotor bars fault detection.

Noise and sparseness of vibration signals are posing greater threat while detecting fault in the bearings in induction motors. In [18], efficient means for reducing noise and early fault detection was presented 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 [19] resulting in higher precision. A new method called as the Complementary Ensemble Empirical Mode Decomposition (CEEMD) [20] was designed to accurately identify the faults in bearings in induction motors.

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 Biorthogonal Posterior Vibration Signal Data Probabilistic Wavelet Neural Network is presented in detail.

3. BIORTHOGONAL POSTERIOR VIBRATION SIGNAL-DATA PROBABILISTIC WAVELET NEURAL NETWORK

Major industrial drive is interested in constructing the induction motor without any transient disturbance while speeding up the motor speed. The main goal in this work is to construct a Biorthogonal wavelet transform using the vibration signal-data of the industrial drive. The wavelet transform represent the vibration signal-data simultaneously at time ‘t’ with a frequency ‘f’. Biorthogonal analysis of the wavelets decomposes the vibration signal-data into frequency and also the time factor on which the frequency gets fluctuated. BPPVS-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 fifth derivative form. The Biorthogonal wavelet transform in BPPVS-WNN system is illustrated in Figure 1.

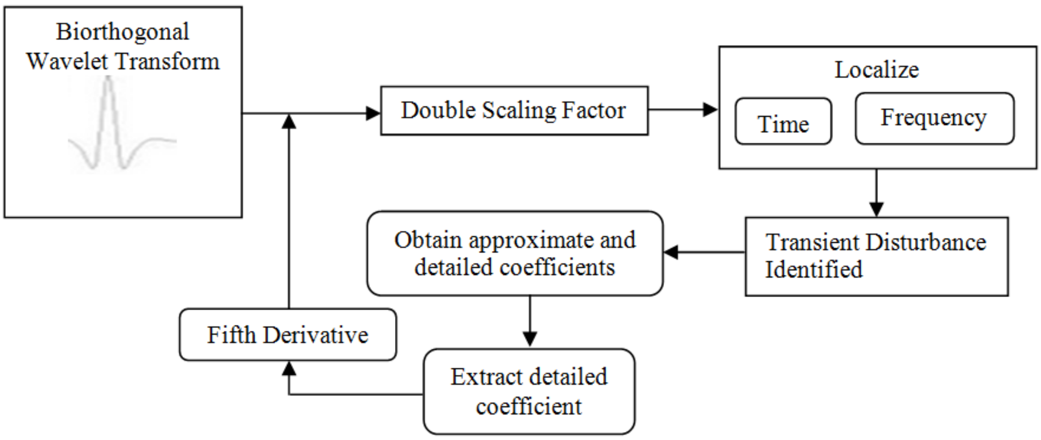

Figure 1. Procedural step of biorthogonal wavelet transform

The Biorthogonal 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 Biorthogonal Wavelet Transform. The overall diagrammatic form of proposed BPPVS-WNN system is illustrated in Figure 2. The overall structure of the Biorthogonal Posterior Vibration Signal-Data Probabilistic Wavelet Neural Network is presented. The vibration signal-data of induction motor is taken as the input parameter using the Simulink MATLAB code. The vibration data are analyzed through the Biorthogonal Wavelet Transform. The wavelet transform 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 induction motor is used on the industrial drive with maximal speed rate.

Biorthogonal Wavelet varies based on the frequency domain, and then the fault occurred on the induction motor is measured. The fault in the induction motor is measured based on the broken bearing using the Posterior Probabilistic Vibration Signal-Data Neural Network. The broken bearing detection through neural network in BPPVS-WNN System results in two coefficient values called the approximate coefficient and detailed coefficient. The detailed coefficient value is applied until fifth derivative is obtained. Posterior Probabilistic Wavelet Neural network combine the theory of the fifth derivative wavelets and neural networks into one to feed-forward neural network to identify the faults in the induction motor at a faster rate.

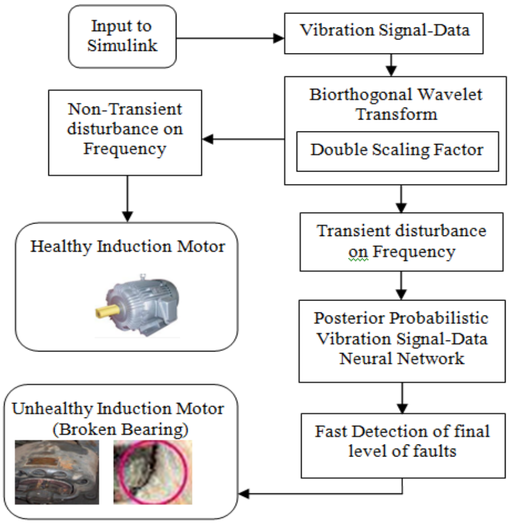

Figure 2. Proposed BPPVS - WNN system

3.1. Biorthogonal 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 Biorthogonal wavelet constructs the symmetric wavelet function using vibration signal-data. Biorthogonal wavelet transform generates the double scaling factors in BPPVS-WNN System differs with ‘A’ (i.e., Approximate coefficient) coefficient and ‘D’ (i.e., Detailed coefficient) values. Biorthogonal Vibration Signal-data Wavelet condition is formularized as,

$$BWT = \sum_{n=1}^{N} (A_N \, D_{N+2}) \tag{1}$$

The Biorthogonal Wavelet Transform ‘BWT’ initially obtains the approximated and detailed coefficient values. To obtain the fifth derivative (FD) form, our work proposed system uses the detailed coefficient value ‘D’. This ‘D’ value is iterated five times. The fifth derivative form is the final output obtained through BWT. In a similar manner, BPPVS-WNN system takes the approximated coefficient value once and detailed coefficient value with the fifth derivative form of ‘N’ induction motors of the industrial drive. Biorthogonal Transform using time and frequency wavelets and identify the faults. As a result, the dual scalar functions are interrelated and with this the faults of the induction motor are easily identified.

The Biorthogonal wavelets using the vibration signal-data are supported by symmetric wavelets of dual scaling factor. The detailed coefficients approximated values using FD of Biorthogonal Wavelet Transform is illustrated in Figure 3. The dual scaling factor uses the vibration Signal-Data on detecting the bearing broken faults of the induction motor. On part of the dual scaling, during first derivate form the coefficient valuesA_N generated by the low pass filter and the other part is the vibration signal-data D_Ngenerated approximated value by the high-pass filter is obtained. The detailed coefficient value from the first derivate is obtained and this value process is fed as input to the industrial drive resulting in approximated and detailed coefficient of second derivative.

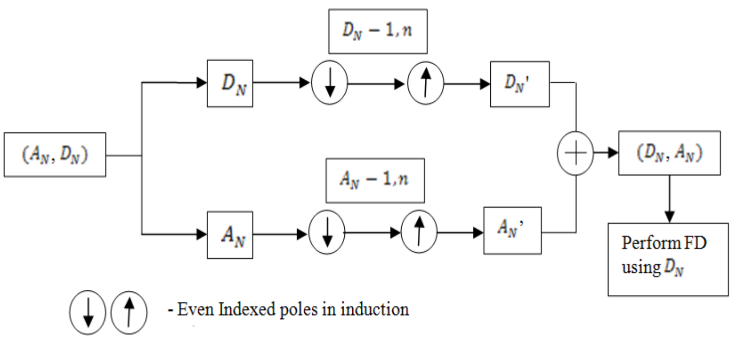

Figure 3. Biorthogonal wavelets with coefficient and approximated values

This process is continued until the fifth derivative form is obtained that helps in identifying higher number of faults at minimum time interval. In a similar manner, to all the cases, coefficients of approximated and detailed values are identified for ‘N’ induction motor. BPPVS-WNN System uses the original vibration signal-data to process and detect the faults of the industrial drive induction motor. BPPVS-WNN System solves the coefficients as described below:

$$Coeffcients\ Solver\ FD\ (z) = C_N\ (0) + \sum_{n=1}^{N}(C_N)z^n + (C_{-N}))z^{-n} \tag{2}$$

Evidently, Coeffcients Solver FD (z) corresponds to perform the fifth derivative filter and identify the breaked bearings on the induction motor. The coefficient solver in Equation (2) helps to easily identify the frequency range of the running induction motor. This is because the zero-phase characteristic on the coefficient solver $C_N(0)$ meets the requirement of symmetric wavelets. Symmetric wavelet helps to identify the time and frequency domain.

3.1.1 Algorithmic Procedure

The BPPVS-WNN System through dual scaling factor is formularized as:

Begin
Step 1: Vibration Signal-Data taken as input on Simulink
Step 2: Initialize zero factor on ideal state of induction motor
Step 3: Biorthogonal Wavelet transform obtain the dual scaling factor’
Step 3.1: Initial Scaling factor computes the coefficient solver to identify whether transient disturbance occurred or not
Step 3.2: Second scaling factor attain the approximation values i.e., Approximated coefficient and Detailed coefficient through low and high pass filter, detects faults on minimal time using FD
Step 4: Low and High pass association filter are symmetrical wavelets
Step 5: Identifies higher fault count on minimal execution time
Step 6: Biorthogonal wavelets used in fault detection of induction motor
End

The vibration signal-data used to measure the time and frequency domain for detecting the fault rate. The Biorthogonal wavelet vibration signal-data transform is interrelated with dual scaling factor to achieve higher speed rate of motor, by detecting faults at an earlier stage. The lesser rate of current flow leads to minimal fault on the industrial drive induction motor.

3.2. Neural Network Applied Based on Posterior Probabilities

Posterior Probabilistic Wavelet Neural network combine the theory of the wavelets and neural networks into one to feed-forward neural network to identify the faults in the induction motor at a faster rate. Posterior probability on wavelet neural network is the conditional probability of faults occurred in the induction motor with relevant evidence obtained with the help of the pervious operation. Posterior Probabilistic Wavelet Neural network consists of an input layer, fault detecting process layer and output layer. The activation function of neuron in Posterior Probabilistic Wavelet Neural network uses the detailed coefficient values of the Biorthogonal wavelet to detect the fault at faster rate. The activation function uses the probabilistic distribution function on the evidence of ‘X’ vibration signal-data is formularized as:

$$PDF = p(X|D_N) \tag{3}$$

The prior evidence of detected faults is used in the posterior probability Wavelet Neural network to attain faster fault detection rate using the detailed coefficient FD value. Posterior Probabilistic Wavelet Neural network through the activation function is described as:

$$Activation\ Function\ p(D_N|X) = \frac{p(X|D_N)}{\mathrm{p(X)}} \tag{4}$$

Wavelet Neural network uses the activation function on the industrial drive, where maximum likelihood of faults (i.e., broken bearing) is assessed. The assessed values are used to detect the faults in the wavelet neural network. The feed forward helps to utilize the vibration signal-data input on the fault detecting process layer to identify the unhealthy motor in the output layer. The FD of D_N Coefficient is used to identify the deep layer faults on the induction motor. The BPPVS-WNN System detects the faults using the specified criterion function,

$$Posterior\ Probability\ \alpha\ Activation\ Function * Prior\ Frequency\ Probability\ Range$$

The posterior probability uses directly the distinguished frequency probability range to identify broken bearings at a faster rate. The activation function uses the fifth derivative form of the detailed coefficient values using Biorthogonal wavelet to identify the unhealthy bearings.

4. EXPERIMENTAL EVALUATION

The experimental setup used using healthy motor and unhealthy motor for the proposed Biorthogonal Posterior Vibration Signal-Data Probabilistic Wavelet Neural Network (BPPVS-WNN) system is depicted in Figure 4. BPPVS-WNN detects the broken bearings using the harmonics obtained through the approximated and detailed coefficient values using healthy motor and unhealthy motor.

Figure 4. Experimental setup using healthy and unhealthy motor

In case if the industrial drive system is healthy then there does not occur any harmonic values. The modulation signal is created using the Biorthogonal Posterior Vibration Signal-Data Probabilistic Wavelet Neural Network. On the other hand, if there occurs broken bearing in the industrial drive then the harmonic values are obtained for motor running. During the first derivation, two coefficient values called as the approximated coefficient and detailed coefficient is obtained. The approximated coefficient values are not considered whereas the detailed coefficient value is used which is given as input. In this way the process is continued till fifth derivative form to obtain the resultant output. The system healthiness and faults are checked using BPPVS-WNN system and identify the actual failure rate of motor at an earlier stage. The constancy on the frequency domain is maintained as 50 Hz. If there is an occurrence of broken bearing, then the current flow rate get increased with varying frequency range. To evaluate the proposed system, the Biorthogonal wavelet transform is used on measuring the time and frequency domain.

Real time vibration data on industrial drives measure the speed ‘N’ of the induction motor. In BPPVS-WNN system, sampling frequency is set to 50 Hz on different length of vibration data signal. The motor was running for different set of time (i.e., of about 10 minutes) on every iteration. The generated result table is described in next section. Biorthogonal Posterior Vibration Signal-Data Probabilistic Wavelet Neural Network (BPPVS-WNN) system for detecting the induction motor faults is compared against existing Basic Vibration Signal Processing for Bearing Fault Detection (BVSP) and Current Frequency Spectral Subtraction (CFSS). Experiment conducted on factors such as fault detection rate based on time, current flow rate, execution time, speed of healthy and unhealthy induction motor, frequency signal range of healthy and unhealthy motor, voltage factor of healthy and unhealthy induction motor.

Parameters taken for the BPPVS-WNN system and their specification range are described in below table:

Table 1. BPPVS-WNN system parametric table

Parameters	Specification
Current Flow Rate	350mA
Voltage Rate	230 Volts
Fault Detection rate based on Time	600 seconds per iteration
Speed	1550 RPM
Frequency Range	50 Hz
Power rate on Execution	0.25 Hp

5. RESULTS ANALYSIS OF BPPVS-WNN

In this section, a detailed analysis of the proposed Biorthogonal Posterior Vibration Signal-Data Probabilistic Wavelet Neural Network is made with two other existing works, Basic Vibration Signal Processing for Bearing Fault Detection (BVSP) [1] and Current Frequency Spectral Subtraction (CFSS) [2] respectively. For experimental analysis, the values of Table 1 and the experimental setup in Figure 4 is used to analyse the results in an elaborate manner.

Table 2. Tabulation of execution time using healthy motor and unhealthy motor with respect to frequency

Healthy Motor				Unhealthy Motor			
Frequency (Hz)	Execution Time (ms)			Frequency (Hz)	Execution Time (ms)		
	BPPVS-WNN	BVSP	CFSS		BPPVS-WNN	BVSP	CFSS
50	0.123	0.135	0.165	25	0.205	0.213	0.277
100	0.147	0.159	0.189	75	0.219	0.257	0.300
150	0.152	0.164	0.194	125	0.234	0.262	0.406
200	0.182	0.194	0.214	175	0.244	0.292	0.326
250	0.175	0.187	0.217	225	0.257	0.285	0.329
300	0.205	0.217	0.247	275	0.315	0.367	0.359
350	0.220	0.232	0.262	325	0.330	0.342	0.374

The performance indices for the output execution time on healthy motor with respect to frequency are shown in Figure 5 and with that on unhealthy motor is shown in Figure 6. These statistical performance indices of execution time gives a precise picture of performance improvement for BPPVS-WNN system as compared to BVSP and CFSS and is lower than BVSP and CFSS showing that BPPVS-WNN system has improved performance results in transient manner at a steady state with respect to frequency. The quantitative values for these performance indices are tabulated in Table 2.

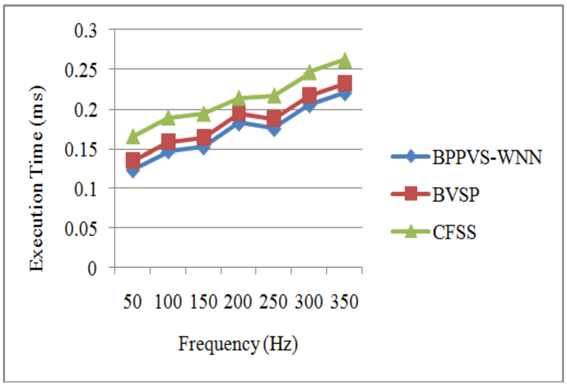

Figure 5. Measure of execution time with respect to frequency using healthy motor

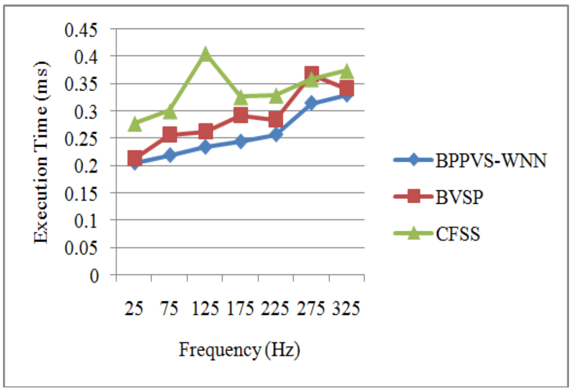

Figure 6. Measure of execution time with respect to frequency using unhealthy motor

In order to check the robustness of the proposed Biorthogonal Posterior Vibration Signal-Data Probabilistic Wavelet Neural Network (BPPVS-WNN) system, series of frequency is applied to the system. A two stage operation with a duration of seven cycles is applied at Frequency f = 50, 100, …, 350 on healthy motor and f = 25, 75, …, 325 on unhealthy motor. It shows that using the proposed BPPVS-WNN system though the minimum output execution time on healthy motor is at f = 350 Hz, comparatively and on unhealthy motor is at f = 25 Hz, optimization of execution time achieves at f = 200 Hz, with 6.59 % and

17.58 % improvement compared to BVSP and CFSS. In a similar manner using unhealthy motor, optimization of execution time is achieved at f = 125 Hz, with 11.96 % and 73.50 % improvement compared to BVSP and CFSS. A comparison of the results shows that BPPVS-WNN system has more performance improvement because the frequency range is maintained without any transient disturbance using doubling scale factor as compared to single factor, therefore, more suitable for the commercial systems.

Table 3. Tabulation of fault detection rate based on time using healthy motor and unhealthy motor

Time	Using Healthy Motor Fault Detection Rate based on time (%)			Time	Using Unhealthy Motor Fault Detection Rate based on time (%)		
	BPPVS-WNN	BVSP	CFSS		BPPVS-WNN	BVSP	CFSS
10.30 – 12.00	58.58	50.55	45.53	10.00 – 10.30	53.56	45.52	40.51
12.00 – 1.30	61.40	53.27	48.25	10.30 – 11.00	56.38	48.24	43.23
1.30 – 3.00	64.50	56.37	51.35	11.00 – 11.30	59.48	51.34	46.33
3.00 – 4.30	71.72	63.67	58.65	11.30 – 12.00	65.70	58.63	53.62
4.30 – 6.00	62.76	57.47	52.45	12.00 – 12. 30	57.75	52.45	47.42
6.00 – 7.30	71.45	65.37	60.35	12.30 – 1.00	66.44	60.33	55.31
7.30 – 9.00	74.62	70.46	65.44	1.00 – 1.30	69.60	65.42	60.43

Table 3 summarizes the simulation results of the proposed BPPVS-WNN system and elaborate comparison made with the existing methods BVSP [1] and CFSS [2] respectively with respect to differing time period from morning to evening.

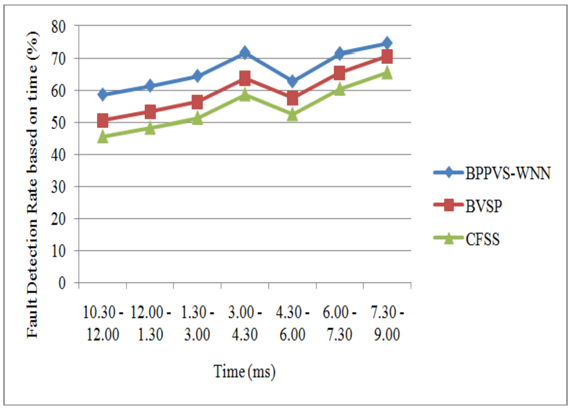

Figure 7. Measure of fault detection rate with respect to time using healthy motor

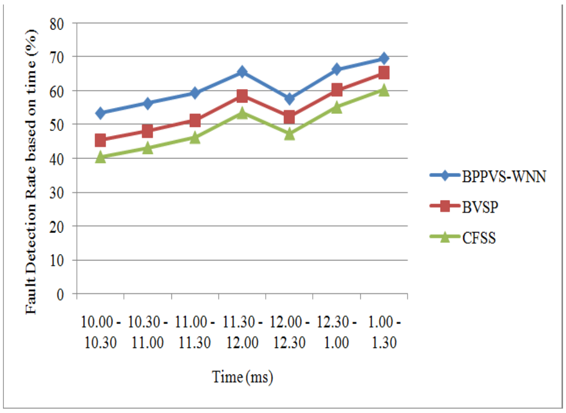

Figure 8. Measure of fault detection rate with respect to time using unhealthy motor

Figure 7 and Figure 8 show the fault detection rate of the proposed BPPVS-WNN system analyzed at different time intervals using healthy and unhealthy motors. Experiments are conducted at varying level of input time periods between 10.30 and 9.00 pm using healthy motor and between 10.00 and 1.30 pm using unhealthy motors and the fault detection rate are investigated. The test bed of the proposed biorthogonal wavelets with approximated and detailed coefficients value is depicted in Figure 3. The maximum fault detection rate of the proposed system is observed between time 10.30 am and 9.00 pm on healthy motor and 10.00 am and 1.30 pm using all the methods. But comparatively the fault detection rate is found to be higher with the proposed system that is measured as 74.62 % and it varies according to different time periods and the coefficient values using fifth derivative form. However, the maximum energy fault detection rate reaches to 71.72 % and 65.70 % using healthy and unhealthy motor which declines to 62.76 & and 57.75 % with the existing BVSP [1] and CFSS [2] respectively. This is because of the application of posterior probability Wavelet Neural network through the activation function uses the detailed coefficient FD value to identify the fault detection rate. This makes the system to increase the fault detection rate using Biorthogonal Wavelets with detailed and approximated coefficients 13.70 % and 22.27% better comparatively to the two other existing methods [1], [2] using healthy motors and 14.43 % and 23.32 % using unhealthy motors. It is therefore significant that the proposed BPPVS-WNN system provides a standard fault detection rate mechanism that manages voltage supply and power flows is an appropriate and flexible manner.

Table 4. Tabulation for current flow rate using healthy and unhealthy motor

Voltage in volts	Using Healthy Motor Current Flow Rate (Amperes)			Using Unhealthy Motor Current Flow Rate (Amperes)		
	BPPVS-WNN	BVSP	CFSS	BPPVS-WNN	BVSP	CFSS
205	0.112	0.122	0.144	0.232	0.243	0.276
210	0.118	0.126	0.148	0.235	0.247	0.270
215	0.125	0.133	0.155	0.242	0.254	0.288
220	0.133	0.139	0.161	0.248	0.252	0.295
225	0.128	0.133	0.155	0.240	0.255	0.288
230	0.136	0.145	0.167	0.252	0.266	0.294
235	0.145	0.161	0.172	0.263	0.283	0.302

Table 4 tabulated the current flow rate with respect to different voltages applied to the healthy and unhealthy motors using the proposed method and comparison is made with two other methods [1], [2] respectively using MATLAB for simulation purposes.

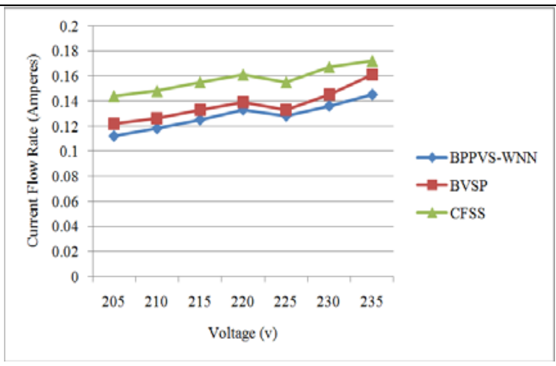

Figure 9. Measure of current flow rate with respect to voltage using healthy motor

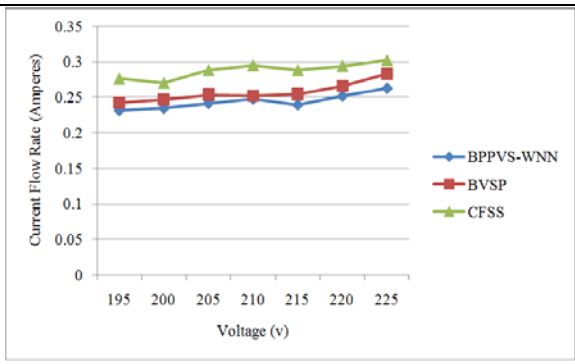

Figure 10. Measure of current flow rate with respect to voltage using unhealthy motor

Figure 9 and Figure 10 illustrate the current flow rate with respect to different voltages using healthy and unhealthy motor respectively. From both the figures it is evident that the current flow rate is reduced using both healthy and unhealthy motors is comparatively reduced with reverence to the two other existing methods. During the bearing fault detection using a stochastic program, detailed coefficient and approximated coefficient is significantly generated whereas the detailed coefficient is used as the by-product for detecting the bearing fault detection. In this way five derivative forms is applied and the resultant output is used to identify the fault that helps in minimizing the current flow rate using the proposed system. With the application of Posterior Probabilistic Wavelet Neural network that consists of an input layer, fault detecting process layer and output layer, the bearing fault detection rate efficiency is improved reducing the current flow rate. The overall probability distribution function on the evidence of 'X' vibration signal-data with respect to detailed coefficient values obtained until the fifth derivative form is reached. In this design, the current flow rate is minimized from 3 – 11 % and 18 – 28 % compared to the existing methods using healthy motors and 1 – 7 % and 14 – 20 % using unhealthy motors compared to BVSP [1] and CFSS [2] respectively. The results showed a healthy agreement using detailed coefficient with respect to fifth derivative form, which indicates that the performance of the BPPVS-WNN system is comparatively better than the existing BVSP [1] and CFSS [2].

6. CONCLUSION

This research provides an inclusive study of real time industrial drive vibration signal data for broken bearing detection using probabilistic wavelet neural network for increasing the fault detection rate and to handle larger power demand. The Biorthogonal vibration signal-data based wavelet transform is localized with the aid of time and frequency domain to minimize the current flow rate. A prototype of the healthy and unhealthy induction motor using starting and rated voltage rate was simulated and tested. A MATLAB environment with Simulink is used to calculate the result of effective fault detection rate. Simulation results show the optimal fault detection rate at different time zones reaches to 10.76 % observed at 11.30 and 12.00

pm using unhealthy motors and 11.22 % observed at 3.00 and 4.30 pm using healthy motors. The transient response test shows that the time taken to identify the fault in bearing reaches its zenith i.e., maximum at frequency range of 50 Hz and minimum is observed at frequency range of 350 Hz. The experimental measurements show that the Biorthogonal Posterior Vibration Signal-Data Probabilistic Wavelet Neural Network is an efficient method for identifying the harmonics using detailed coefficients applied at the rate of fifth derivative form. This in turn identifies the faults observed at bearing in industrial drive providing a standard power rate that manages the voltage profile and current flow rate among several voltage rate in order to provide an effective means to the industry by minimizing the degradation of machinery.

REFERENCES

[1] SA McInerny, Y Dai. Basic Vibration Signal Processing for Bearing Fault Detection. *IEEE Transactions On Education*. 2003; 46(1).

[2] El Houssin El Bouchikhi, Vincent Choqueuse, Mohamed El Hachemi Benbouzid. Current Frequency Spectral Subtraction and Its Contribution to Induction Machines' Bearings Condition Monitoring. *IEEE Transactions On Energy Conversion (CFSS).*

[3] Amit R Bhende, Dr GK Awari, Dr SP Untawale. Critical Review of Bearing Fault Detection Using Vibration Signal Analysis. *International Journal for Technical Research & Development*. 2012; 1(1).

[4] Jason R Stack, Thomas G Habetler, Ronald G Harley. Effects of Machine Speed on the Development and Detection of Rolling Element Bearing Faults. *IEEE Power Electronics Letters*. 2003; 1(1).

[5] Hua Su, Kil To Chong, R Ravi Kumar. Vibration signal analysis for electrical fault detection of induction machine using neural networks. *Springer Journal., Neural Computer & Applications.* 2011.

[6] Jawad Faiz, Bashir-Mahdi Ebrahimi. A New Pattern for Detecting Broken Rotor Bars in Induction Motors During Start-Up. *IEEE Transactions on Magnetics*. 2008; 44(12).

[7] Jose A Antonino-Daviu, M Riera-Guasp, M Pineda-Sanchez, Rafael B Pérez. A Critical Comparison Between DWT and Hilbert–Huang-Based Methods for the Diagnosis of Rotor Bar Failures in Induction Machines. *IEEE Transactions on Industry Applications*. 2009; 45(5).

[8] Tommy WS Chow, Shi Hai. Induction Machine Fault Diagnostic Analysis With Wavelet Technique. *IEEE Transactions on Industrial Electronics.* 2004; 51(3).

[9] Eduardo Cabal-Yepez, Arturo A Fernandez-Jaramillo, Arturo Garcia-Perez, Rene J. Romero-Troncoso, Jose M Lozano-Garcia. Real-time condition monitoring on VSD-fed induction motors through statistical analysis and synchronous speed observation. *International Transactions on Electrical Energy Systems Int. Trans. Electr. Energ. Syst.* 2014.

[10] Semih Ergin, Arzu Uzuntas, M Bilginer Gulmezoglu. Detection of Stator, Bearing and Rotor Faults in Induction Motors. *Elsevier, International Conference on Communication Technology and System Design.* 2011.

[11] S Khanama, N Tandona, JK Duttb. Fault size estimation in the outer race of ball bearing using discrete wavelet transform of the vibration signal. *Elsevier, 2nd International Conference on Innovations in Automation and Mechatronics Engineering, ICIAME 201*.

[12] George Georgoulas, Theodore Loutas, Chrysostomos D Stylios, Vassilis Kostopoulos. Bearing fault detection based on hybrid ensemble detector and empirical mode decomposition. *Mechanical Systems and Signal Processing, Elsevier.* 2013.

[13] Jafar Zarei, Mohammad Amin Tajeddini, Hamid Reza Karimi. Vibration analysis for bearing fault detection and classification using an intelligent filter. *Mechatronics, Elsevier*. 2014.

[14] Sukhjeet Singh, Amit Kumar, Navin Kumar. Motor Current Signature Analysis for Bearing Fault Detection in Mechanical Systems. *Elsevier, 3rd International Conference on Materials Processing and Characterisation (ICMPC 2014).*

[15] Milind Natu. Bearing Fault Analysis Using Frequency Analysis and Wavelet Analysis. *International Journal of Innovation, Management and Technology*. 2013; 4(1).

[16] A Moosavian, H Ahmadi, Atabatabaeefar. Journal-bearing fault detection based on vibration analysis using feature selection and classification techniques. *Control Engineering, Elixir International Journal.* 2012.

[17] El Houssin El Bouchikhi, Vincent Choqueuse, Mohamed Benbouzid, Jean Frederic Charpentier. Induction Machine Fault Detection Enhancement Using a Stator Current High Resolution Spectrum. *IEEE.* 2012.

[18] Hua-Qing Wang, Wei Hou, Gang Tang, Hong-Fang Yuan, Qing-Liang Zhao, Xi Cao. Fault Detection Enhancement in Rolling Element Bearings via Peak-Based Multiscale Decomposition and Envelope Demodulation. *Hindawi Publishing Corporation Mathematical Problems in Engineering.* 2014.

[19] Hongmei Liu, Xuan Wang, Chen Lu. Rolling Bearing Fault Diagnosis under Variable Conditions Using Hilbert-Huang Transform and Singular Value Decomposition. *Hindawi Publishing Corporation Mathematical Problems in Engineering.* 2014.

[20] Liye Zhao, Wei Yu, Ruqiang Yan. Rolling Bearing Fault Diagnosis Based on CEEMD and Time Series Modeling. *Hindawi Publishing Corporation Mathematical Problems in Engineering.* 2014.

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