Outer Race Bearing Fault Identification of Induction Motor based on Nonlinear Signal Detection and Time Frequency Representation

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Abstract **- Paper presents outer race bearing fault detection system in an induction motor based on nonlinear decomposition and Time frequency representation. Overall life of any machine is based on its timely identification of fault scenario and the appropriate corrective action taken for it. The paper referrers to timely identification of bearing fault behavior of an induction motor using stator current analysis. It is the combination of regular stator current, noise and required component of faulty bearing signature. The fault signature is carried out by comparing a set of two bearings mainly healthy and faulty bearing on the same machine. Testing is carried out for obtaining dataset of currents for healthy and faulty bearing operated for different load conditions. This detection is inscrutable as change in the obtained current wave is very small for different energy levels as well as frequency. Separating noise pattern and fault pattern is critical. Using Hilbert Vibration Decomposition (HVD) method Current wave is decomposed into number of mono components keeping phase information intact. For accelerating further process of identification, time information of decomposed components should be unchanged. Smoothed Pseudo Wigner-Ville distribution (SPWVD) with reassignment is applied to decomposed components for localizing fault zone in current wave. As a next step, feature extraction is followed by localization of fault part. At last training is obtained for the features extracted from the wave and for this process, Support Vector Machine (SVM) classifier is used for training dataset. In testing phase the system gives binary output i.e. faulty or non-faulty bearing. The result analysis shows that the proposed method can detect bearing fault correctly. Performance analysis of proposed method demonstrates accuracy rate of as high as 95%.**

Keywords—Induction motor, stator current signature, Hilbert Vibration Decomposition (HVD), Smoothed Pseudo Wigner-Ville distribution (SPWVD), Support vector Machine (SVM)

I. INTRODUCTION

The use of induction motor in all various fields is predominant compare to any other type of machines in the electrical field. This is because of the characteristics of this machine. Induction motor specifically characterized as robust, maintenance free, spark less and salient machine. It can be used for varied conditions like outdoor, indoor, hermetically sealed, hazardous areas and also flame proof areas industrial zones. It is the best reliable option for agricultural usage of machines even can be used underwater conditions. These all advantages maximized the overall applications of this machine to 90 to 95 percent of al`l types. One can easily focus on the importance of this machine and its operations. The total cost involved in down time of any machine is enormous. One can always plan for routine maintenance, but a breakdown of any machine put lots of pressure on every system element. Looking at the overall faults of induction motor, major fault occurrence probability of mechanical faults is huge. As per IEEE faults reported in the machines of higher ratings, 185 machines out of 380 are of mechanical in nature. Even more out of all these mechanical faults, 166 faults were bearing faults. It means that, bearing fault occurrence is roughly 40 percent of all other faults [1].
In the development of strategies for identification of these mechanical faults following diagnostic systems were used.

- Vibration monitoring
- Thermal monitoring
- Chemical monitoring
- Acoustic noise monitoring

In most of the above methods data collection needs some type of sensor and these sensors are to be inserted in the machine at appropriate place for collection of the data. These are called are invasive type of sensors. These are specialized and are expensive. Insertion of these sensors in routine machine is another task and also required planning in the working system. Another solutions can be adopted in the recent trend of analysis are various techniques such as motor current signature analysis (MCSA) [3] and space vector angular fluctuation (SVAF) [4]. In these types of investigation advantage of noninvasive sensing is available. Data can be collected by simply collecting the current or voltage samples of the supply of the motor. Few online current monitoring systems also work satisfactorily. [5] Once the samples are collected, using advance signal processing technique, condition of the motor can be monitored effectively. MCSA method of diagnostic gives the advantage

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of low cost and simplicity.

Induction motor works on the principal of rotating magnetic field having supply frequency on the stator and speed related frequency in the rotor. By collecting current samples side bands around the supply frequency in the stator current is monitored. After applying and analyzing these samples using specific digital signal processing technique the various faults are analyzed [6].

It is a different world of signal processing where so many feature extraction methodologies and different classifier techniques can be used for accurate analysis of faults. In the paper various methods and approaches in the digital signal processing era are discussed.

Digital signal processing technique can be implemented in various paradigms such as Time domain, frequency domain and Time-frequency domain. [7]

It is quite significant that which method is applied to specific fault. Mechanical imbalance or misalignment can be handled very well using motor current signature analysis (MCSA) and vibration analysis but less significantly handled by Extended Park's Vector Approach (EPVA). Bearing faults can significantly handle by Vibration analysis but using Wavelet on current it can be handled less significantly. Very low significance is observed in the methods like EPVA and Instantaneous Power Signature Analysis (IPSA). It is also observed that coupling and load mechanical faults can be handled very well using vibration but less significantly handled by MCSA, EPVA and IPSA.[8]

In this paper for feature extraction Hilbert Vibration Decomposition (HVD) method with SWVD is used. Once fault condition is characterized it can be detected by training the processor. Artificial intelligence (AI) is more helpful in this process. [9] Human interface can be reduced by this type of fault diagnosis. Large set of readings are used for training.

II. THEORY OF CURRENT SIGNATURE

1.

Induction motor works on the principle of rotating magnetic field. Stator carries windings which are displaced by each other mechanically and also electrically by providing phase difference in the two windings. Each winding produces alternating power frequency flux and a combination of all different phase flux creates a rotating magnetic field. Process is similar to Mexican wave produced in the football stadium. This rotating magnetic field induces emf in the rotor winding. As per lenses law it try to oppose the cause that is speed of field noting but synchronous speed. Air gap flux as resultant produces voltage harmonics. Reciprocate the same in the stator current harmonics.

Most of the motors in the electrical side use some component like bearings. Bearings are used in outer and inner race which reduces friction. A fault occurred in the load provides increased periodic variation of the induction machine load torque. This can happen due to fault in load part of the drive system, load imbalance, shaft misalignment, gearbox faults, or bearing faults.

If we consider the various suffixes used are: 1 is for stator, 2 for rotor, s for slot, st for deviation due to static eccentricity, dy for deviation due to dynamic eccentricity. N1 & N2 is the number of stator and rotor slots respectively. ω_2 is rotor angular speed used in the equation.

Resultant of an air gap flux density in term of required frequency harmonics: [10]

$$f_{dy} = f_1\left(n \pm \frac{(1-s)}{p}\right) \tag{1}$$

$$f_{2s} = \left|f_1\left(n \pm \frac{N_2(1-s)}{p}\right)\right| \tag{2}$$

$$f_{dy} = f_n \pm f_2 \tag{3}$$

$$f_{2s} = |f_n \pm N_2 f_2| \tag{4}$$

Let f1 be the supply current frequency and considered as fundamental. Frequency f_n is the nth harmonic supply current frequency. These equations can be used for finding the side bands due to dynamic eccentricity f_{dy}.

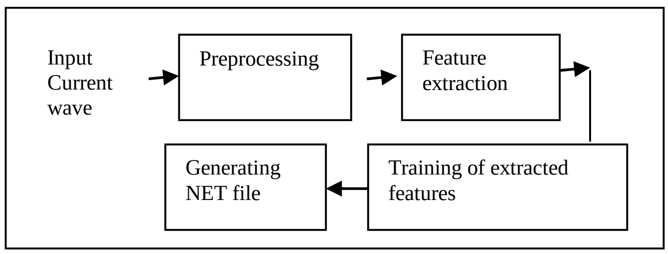
For specific bearing fault, occurred in the system, it causes a change in its vibrations and hence translates its vibration frequency. It is different than the known rotor frequency component. For specific rolling component bearing in the machine, corresponding change in the eccentricity flux can be calculated using following equation.

$$f_{bearing} = |f1 \pm mfbc| \tag{5}$$

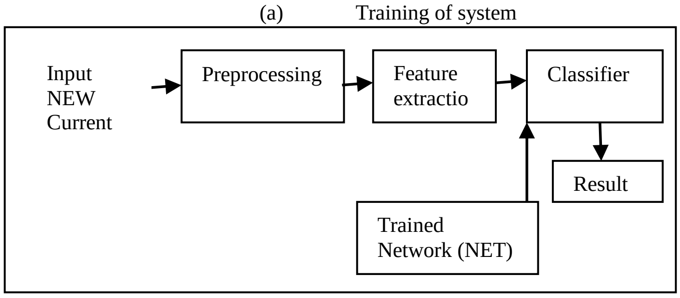
Using its fbc, the bearing characteristic vibration frequency, the equation gives characteristics frequency for bearing fault. With the specific bearing specifications, its characteristics frequency related to inner race, outer race and also for a ball defect can be found out. Specific defect will define the time of occurrence of that fault and repetitiveness.

III. SYSTEM OVERVIEW

Total system is divided in to two phases. Training of signal database for faulty and non-faulty conditions Refer fig – 1 (a). Testing of NEW incoming signal and produce result about bearing fault detected or not. Refer fig – 1 (b).



(a) Training of system



(b) Testing

Fig. 1: - Block diagram of total system

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Fig – 1(a) depicts training phase of system. Input current wave is preprocessed and given to feature extraction block. Fig – 2, shows detailed description of feature extracting procedure. Database of current waves is created. It will have two categories of current waves i.e. with bearing fault and without bearing fault under different load conditions. Program will input database signals and train the system using Support Vector Machine (SVM). [11] Training network typically generates .NET structure. The same will be used for testing system performance.

In testing phase one can apply current wave taken in real time working condition. Current wave will be preprocessed and given to feature extraction block. SVM classifier will have now two inputs, one is new feature set from real time system and other feature set from trained network (.NET). Output of classifier will announce about positive or negative report of bearing.

Refer Figure 2. Input to the system is current waveform captured using hall sensor. Database is created taking into consideration different load conditions with faulty bearing. To decompose a signal Hilbert Vibration Decomposition (HVD) is applied. [12] It gives N number of sub components. In HVD phase information is intact for all the N sub components. Decomposed component sum and original signal, for both, Normalized root mean square error (NRMSE) and correlation values are calculated. These two parameters will decide value of N. NRMSE and N is inversely proportional. Typically value of N $\leq$ 4 provides good results. Smoothed Pseudo Wigner Ville Distribution (SPWVD) is applied to all the decomposed components for analyzing time frequency energy. Peak of the energy is used as a feature.

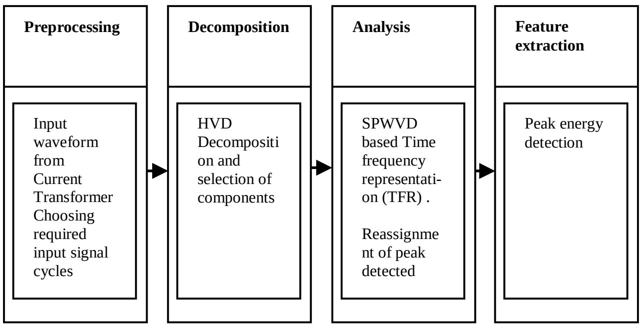

Fig. 2: - Block diagram representing feature extraction steps

IV. PROPOSED METHODOLOGY

Accuracy level of any signal processing depends upon quality extraction of dominant features of the signal. The proper extraction technique will decide the accuracy of the method. The mathematical analysis and theoretical calculations of typical used bearing will give the range of the values of fault frequency. The fault for which this analysis is carried out, that is, outer race bearing fault, calculated fault frequency for typical bearing is in the range of 60 to 90 Hz. It is expected that the greater energy of signal is obtained in this region for faulty bearing. Selecting typical sample frequency (fs) for sampling the input current is 48 KHz. Thus this signal combines the original signal and fault signal in it.

From the Fig.3 it can be clearly visible that, one can easily obtain the fault signature marked in the red circle for outer race bearing fault. Outer race fault creates the time base interference in the rotational air gap flux due to obstruction in the speed element. Bearing fault on outer race superimposes time base fault signature on stator current.

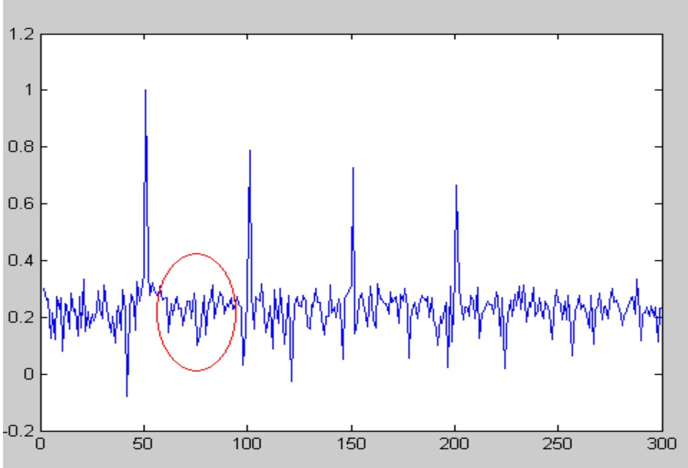

Fig. 3: - Amplitude of max peak, Higher value indicates fault (red circle)

For extracting this fault signature three major steps are

- Hilbert Vibration Decomposition (HVD)
- Smoothed Pseudo Wigner-Ville Distribution (SPWVD) based time frequency analysis
- Peak energy calculation.

Step by step method description is given as follows.

A. Decomposition - discrimination

Applying HVD on input signal decomposes it into N number of mono components. Instantaneous frequency (IF) and amplitude slowly varies in mono component. Discrimination process keeps phase information unaltered which keeps time space information intact.

Decomposed mono components represented as

$$S_{decomp}(t) = \sum_m A_m(T)\cos(\int \omega_m(t)dt) \qquad (6)$$

$$A_m(T) = instantaneous\ amplitude\ m^{th} component$$
$$\omega_m(t) = instantaneous\ frequency\ m^{th} component$$

Mono component has different amplitude and oscillatory frequency. HVD being an adaptive method it extracts component using low pass filter in each iteration. Completion of iteration output low energy component. Decomposition is done on following assumptions:

1. Signal is a formation of superposition of Quasi Harmonic function (QHF)
2. QHF may or may not have DC offset which is slowly varying and is a periodic
3. IF and an envelope of each mono component varies

Points are suitable for characteristics of current signature signal. IF estimation, synchronous detection and signal separation, are the steps involved in HVD. Refer Fig.4,

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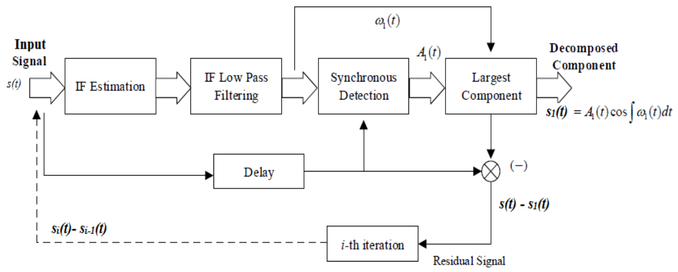

Fig.4:- HVD block diagram

B. *Analysis*

As input signal is nonlinear and non-stationary Time Frequency Representation (TFR) is adopted. A powerful method SPWVD is used in proposed work. Bearing defect after many energy conversions gets reflected in current waveform. Changes in the current waveforms will be very small, not large enough to track the fault lucidly. System should track sensitive and minute changes of signal in the time domain. SPWVD found effective in current wave analysis. It's an improvement over basic Wigner Ville distribution (WVD). In TFR gives high resolution.

WVD general definition is as follows.

$$W_s(t,\omega) = \int_{-\infty}^{+\infty} s(t+\tfrac{\tau}{2})\, s^*\left(t+\tfrac{\tau}{2}\right) e^{j\omega\tau}\, d\tau \qquad (7)$$

$$s\left(t+\frac{\tau}{2}\right) s^*\left(t+\frac{\tau}{2}\right) = instantaneous\ autocorrelation$$

Unwanted terms generated by WVD are filtered out by SPWVD. It uses different window function and performs double convolution along frequency and time directions. Thus SPWVD is 2D filtering of basic WVD method.

$$W_h(t,\omega) = g(t)H(-\omega) \qquad (8)$$

$$H(\omega) = Fourier\ transform\ of\ the\ window\ function\ h(t)$$

$$g(t) \rightarrow Reduces\ frequency\ domain\ cross\ terms$$

$$H(\omega) \rightarrow Reduces\ time\ domain\ cross\ terms$$

SPWVD method gives progressive and independent control to WVD using $g(t)$ *and* $h(t)$.

$$SPW_s(t,\omega) = \int_{-\infty}^{+\infty} h(\tau) \int_{-\infty}^{+\infty} g(S-t)\ s(S+\tfrac{\tau}{2})\, s^*\left(S+\tfrac{\tau}{2}\right) e^{j\omega\tau}\, dS\, d\tau \qquad (9)$$

Due to correlation of $g(t)$ *and* $h(t)$ in the time frequency domain smoothness increment directly degrades the resolution performance. But combined effect of equation (13) and (14) will be delimiting specific time frequency regions near the neighbourhood of point (t,ω). SPWVD Values' weighted average is taken in those regions. In this particular application it is necessary to get exact time index of higher energy or peak energy regions. Reassignment is part of SPWVD in case exact time index is expected. Before reassignment the point which is supposed to be geometrical centre of a region e.g. point(t,ω) around that point certain values are not symmetrically distributed so point$(t,\omega)$is not exact representation of centre of gravity. Reassignment relocates present point(t,ω) to new point(t_N,ω_N) which is having all the values symmetrically distributed around. Following equations shows reassignment.

$$SPW_s^R{}_s(t_N,\omega_N\,; g,h) = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} SPW_s(t,\omega; g,h)\ \delta\big(t - \hat{t}(s;t,\omega)\big)\ \delta\big(\omega - \widehat{\omega}(s;t,\omega)\big) dt\, d\omega \qquad (10)$$

Here,

$$\hat{t}(s;t,\omega) = t - \frac{SPW_s(t,\omega,\tau_g,h)}{2*\pi*SPW_s(t,\omega,g,h)} \qquad (11)$$

$$\widehat{\omega}(s;t,\omega) = \omega + j\,\frac{SPW_s(t,\omega,\tau_g,h)}{2*\pi*SPW_s(t,\omega,g,h)} \qquad (12)$$

Thus process of reassignment improvises readability of TFR. Finally exact time index for a particular peak is achieved.

C. *Peak detection*

After reassignment for getting the area under curve the output array is converted to binary array using threshold technique. When motor is running without any fault in the bearing still some harmonics with less amplitude are present. While analysing system for bearing fault, these harmonics should not give wrong results. Threshold suppresses effect of such harmonics. It allows only dominate energy for detecting bearing fault. To broaden the required area and to remove isolated region operations like dilation erosion is used considering binary array as an image input. At this stage dominant peaks with their area are available for next stage i.e. training.

V. EXPERIMENTAL SET UP

Looking at an objective of this exercise, basic aim is to identify the typical outer race bearing fault of the Induction motor. Induction motor is selected such a way that one can change its bearing and replace it with same type of faulty bearing easily. For observing various changes in the fault frequency and variance in the speed torque of the machine, motor is coupled to a separate loading arrangement. For loading induction machine a typical indirect loading arrangement is used. In the indirect loading arrangement machine is coupled to another dc machine working as a generator as shown in **Fig 5.** By assuming efficiency of that generator mechanical load on the motor can be obtained in terms of electrical power. Fig.5 induction motor and D.C. generator coupled set is used for this test.

Initial test is carried out on healthy bearing. Test on this healthy bearing is carried out for different loading conditions. For another set of readings of faulty bearing, it is replaced. Outer race fault is created by drilling a hole on the outer race as shown in Fig 6. (b) Once again a similar set of readings are obtained for same load conditions.

Main supply current is to be obtained and required to sample at prescribed rate. This is done by using a separate Hall Effect current sensor (Fig. 6.) (a) The output of the Hall Effect current sensor is rectified and converted to voltage signal. The voltage obtained from the sensor is an overall signal reference to input current. National instruments data acquisition card USB 6009 is used with proper signal modulation for extracting these signals. Stored signals from data acquisition card can be obtained in suitable Mat lab files. Two sets of Mat lab file readings for healthy and faulty bearing are obtained with different load conditions for further analysis.

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Fig. 5 - Test set up; Induction Motor # DC shunt Generator# Tacho Generator

Specification	Rating
Induction Motor	
Voltage	190/250V
Frequency	50Hz.
Current	4Amps.
Power	750W
Speed	1200RPM
1 Ph. Cap Start & run	5µF

Table 1: - Induction Motor and Generator set

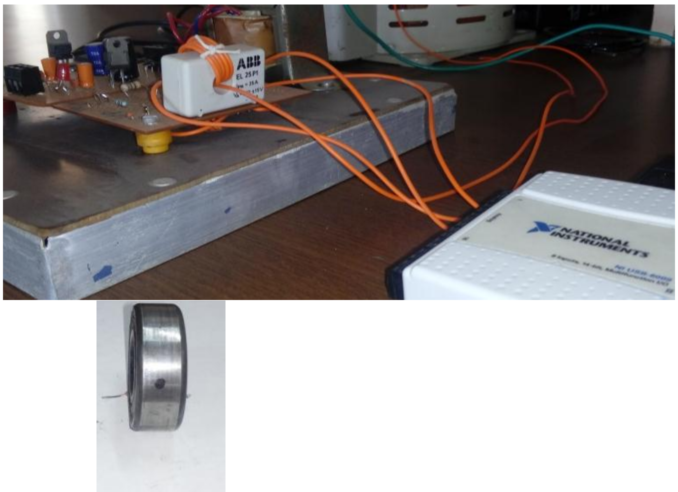

Fig. 6: - (a) Data acquisition and Hall current sensor set up
(b) Bearing with fault on outer race.

Specification	Rating
Bearing Type skf 6203-z	
No. of balls (z)	8
Pitch diameter(D)	29.75mm
Ball diameter (d)	6.35 mm
Angle of contact(α)	(Typically taken as 0°)

Table 2: - Bearing specification

Fundamental frequency outer race f_{oc}

$$f_{oc} = \frac{f_2}{2}\left[1 - \frac{d}{D}\cos\alpha\right] \tag{13}$$

Ball-pass frequency of outer race f_{boc}

$$f_{boc} = \frac{zf_2}{2}\left[1 - \frac{d}{D}\cos\alpha\right] = \frac{zN}{60}\left[1 - \frac{d}{D}\cos\alpha\right] \tag{14}$$

Where f_2 be the rotor frequency, z is the number of balls, d be the ball diameter, N be the motor speed in RPM, and D be the pitch diameter of bearing.

VI. EXPERIMENTAL METHODOLOGY

Testing is carried out for different load conditions of the motor. Following are the table depicts few samples of different load conditions. For every set of reading the stator current samples are saved using data acquisition card. The values for each case is obtained as a MATLAB file and used for creating database for both, faulty and healthy (no fault) condition.

Speed RPM	Motor AC Voltage	Motor AC current	Motor Power	Load DC Vtg	Load DC Current	Power reading M.F.= 4
RPM	Volts	Amp	Watts	Volts	Amps	
1490	220	1.2	164	7	0	41
1446	220	1.45	348	180	0.9	87
1407	218	2.2	500	170	1.6	125
1349	218	3	680	155	2.5	170
1270	217	3.9	880	140	3.25	220

Table – 3: Bearing fault readings

Speed RPM	Motor AC Voltage	Motor AC current	Motor Power	Load DC Vtg	Load DC Current	Power reading M.F.= 4
RPM	Volts	Amp	Watts	Volts	Amps	
1493	220	1	148	10	0	41
1449	220	1.34	340	183	0.9	87
1414	218	2.1	492	172	1.62	125
1359	218	2.97	680	157	2.5	170
1277	216	3.9	888	140	3.3	220

Table – 4: Healthy Bearing readings

Total database consists of 100 waves with different load conditions with and without fault. Features are extracted for 40% of database. Remaining database used for testing purpose. Support vector Machine (SVM) is used for training dataset.

A. *Training Phase*

A successful feature extraction technique should exactly identify the difference between healthy and faulty condition of the outer race fault. Actual faulty bearing signal obtained from stator current using current sensor is used for analysis Fig. 7. These stator current parameters are stored in terms of MATLAB code. It formulates the current signature for the fault. Out of this signal for training purpose first 5 cycles are taken into consideration. For better comparison and analysis signal is normalized, which creates standard reference. Negative portion in the signal is converted in to positive half by shifting it using dc offset. DC shifted is Waveform as shown in Fig 8.

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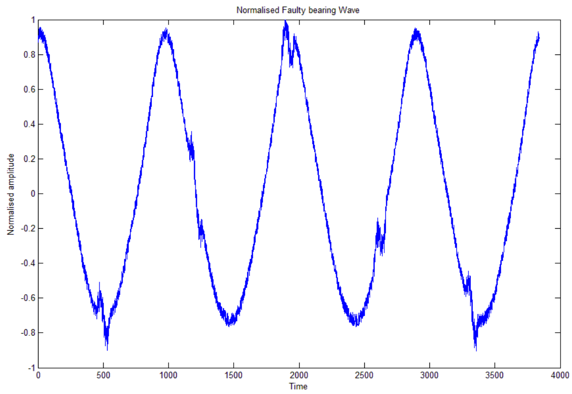

Fig.7:- Captured test signal for faulty bearing

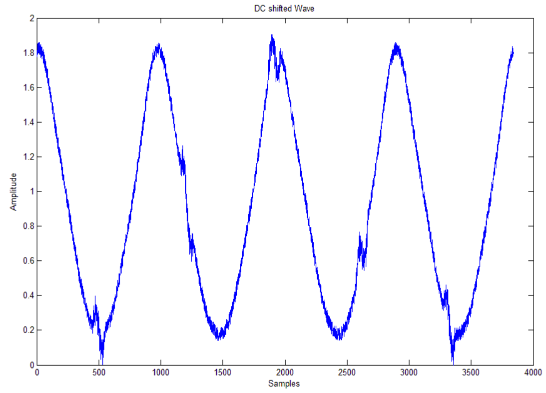

Fig.8:- DC shifted Captured test signal for faulty bearing

After this dc shift mono component of Hilbert vibration decomposition (HVD) is find out. This is done by finding maxima and minima with usage of SPLINE function. In this type of interpolation in which the interplant is a special type of piecewise polynomial called a spline.

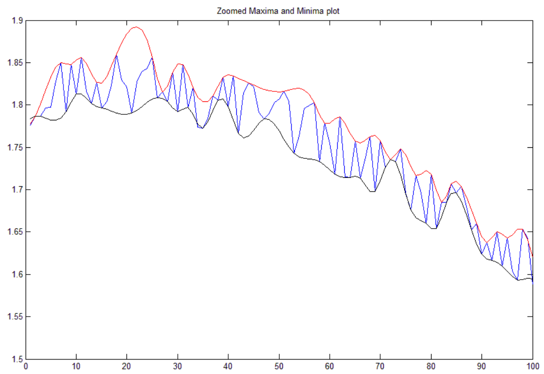

Fig. 9:- 1st iteration [Zoomed view]

In the Fig.9 and Fig.10 it gives the iteration of order 1st and 2nd. In the 1st mono component maxima minima difference is more. Red and black lines are plotted using SPLINE function. One can easily observe the smoothness in the 2nd iteration. Over number of iterations, function becomes smooth as it filters out component.

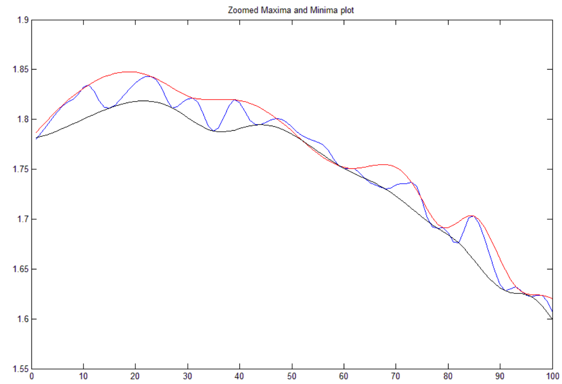

Fig. 10:-- 2nd iteration [Zoomed view]

Further to obtain mono component after each iteration average of maxima and minima is calculated and then it is subtracted from the original wave. Fig – 8, shows 1st component.

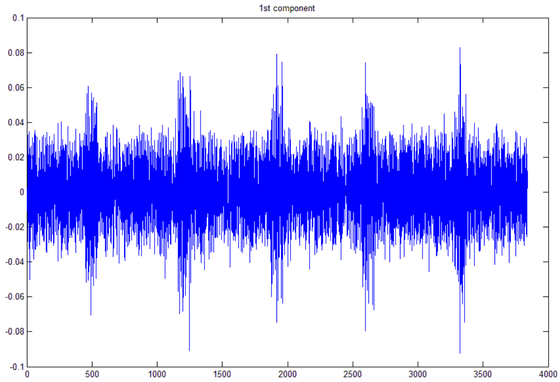

Fig. 11:- 1st component of HVD

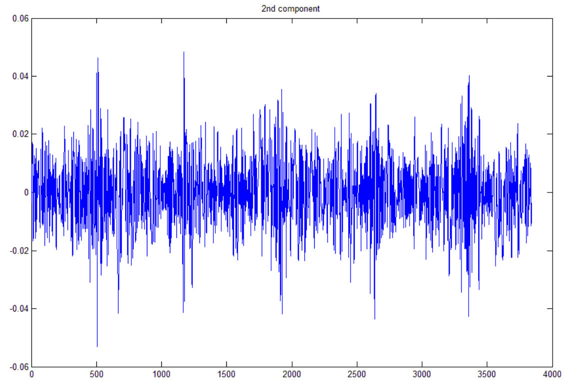

Fig. 12:- 2nd components of HVD

After applying Hilbert vibration decomposition, next step is to obtain mono component by applying SPWVD. Window size is selected and FFT is performed piecewise. Fig.13 and Fig.14 indicates the 3D plot of SPWVD output. It is obtained for 10 iterations of both the components of HVD.

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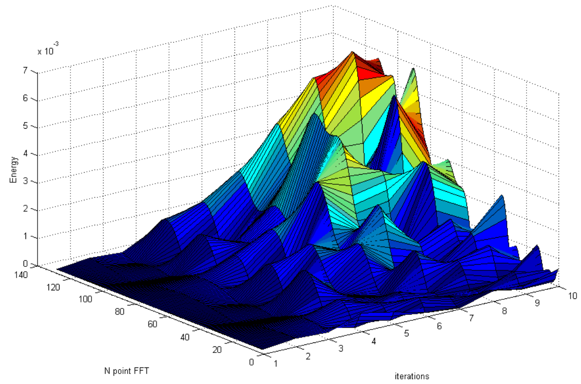

Fig. 13:- SPWVD output of 1st component

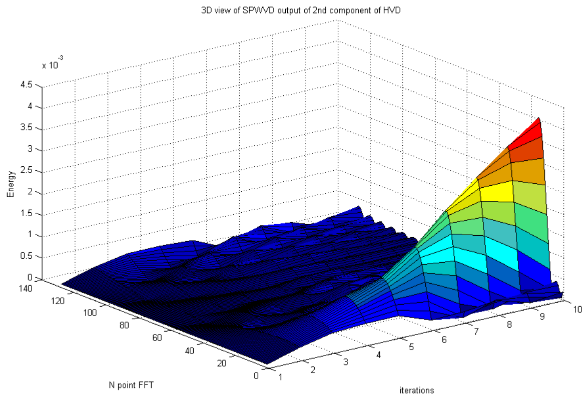

Fig. 14:- SPWVD output of 2nd component

From SPWVD output maxima is found out. It is for both the components. For calculating area under peak, maximum value with threshold is taken to filter out the values below the product. These values are part of features used for training the system. For proper representation of the array, it is shown as an image, where white dots correspond to binary 1.

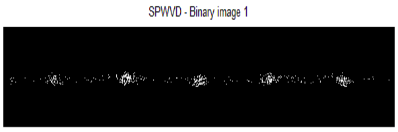

Fig. 15:- SPWVD output after Threshold – Bearing Fault

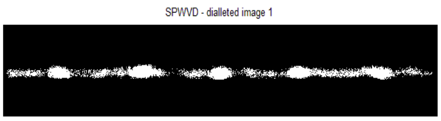

Fig. 16:- SPWVD output after dilation operation - Bearing Fault

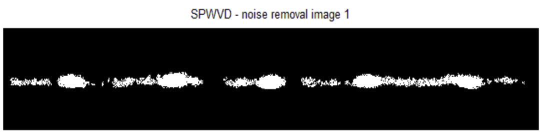

Fig. 17:- SPWVD output after removing noise pixels - Bearing Fault

As observed in Fig. 14, the peaks are been seen as highlighted spots. For clear understanding let us observe the condition where there is no bearing fault and the case is as represented in fig. 18 to 20. Compare this condition with bearing having the fault as represented in fig. 15 to 17. Thus it indicates that in the condition of bearing fault, the pattern is fairly constant. It is seen as a standard noise pattern. But with bearing fault after particular interval SPOTS are highlighted representing high noise pattern. Area of such high noise SPOTS is a feature used for training system.

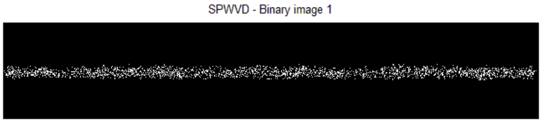

Fig. 18:- SPWVD output after Threshold – No Bearing Fault

Fig. 19:- SPWVD output after dilation operation - – No Bearing Fault

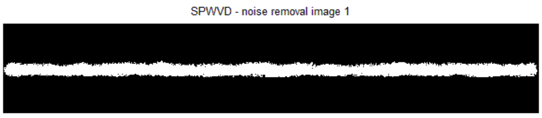

Fig. 20:- SPWVD output after removing noise pixels - – No Bearing Fault

B. Testing Phase

Non-trained current wave form is used as a input to the classifier. This non trained waveform input is used for testing purpose. After analyzing the performance it is compared with the performance of trained classifier. The input signal will go through the same steps of feature extraction. These features will be provided as an input to a classifier. Classifier is already trained. Classifier will compare input feature with the database of trained feature. Output will be of binary type representing fault or No fault condition.

VII. CONCLUSION

In this method of non-invasive motor current signature analysis not any additional costly sensors required for testing hence it can be easily adopted for any industrial machine. It is also proved that Characteristic frequency is proportional to the characteristic of bearing fault. It is also observed that energy of fault frequency increases with the load. From all above methodology and analysis, following conclusions can be drawn.

1. Hilbert Vibration Decomposition HVD method accurately bifurcate frequency components present in the signal.
2. Smoothed Pseudo Wigner-Ville Distribution SPWVD is efficient time frequency presentation technique for bearing fault detection.
3. Support vector Machine SVM classifier is also very selective and proven to be better in this condition.

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