Combination of FFT & ICA methods for Faults Analysis of Rotating Machine

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ABSTRACT

The vibration analysis using Fast Fourier Transform FFT is a common and widely used method, because of the similarity between faults signatures in this analysis a question is raised to what is the most effective ways to distinguish between different faults. In order to overcome this difficulty other method combined with the FFT was used. In this paper, a new combination will be present to overcome this situation. Independent Component Analysis (ICA) is used in combination with FFT to identify faults in rotating machines. The vibration is measured through multi-channel vibration data acquisition system. The signals are then analyzed using ICA and finally, FFT is applied on ICA components. The extraction features give the best signature to identify each fault from others. This method is used for detecting more general faults occur in rotating machine (bearing fault, misalignment, unbalance, shaft fatigue), and can identify the similarity between faults. The interaction between different types of faults can be solved effectively by using ICA.

KEYWORDS

Vibration analysis, Fast Fourier transform (FFT), Independent component analysis (ICA), Multi-fault features.

1 INTRODUCTION

The recognition of fault location in rotating machines is a very important task in industrial applications. The most powerful way to detect such faults is vibration monitoring and analysis [1]. The monitoring process is normally based on some type of vibration transducer. One of the most common transducers for such application is an accelerometer.

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Using one of the vibration analysis techniques one can eliminate many problems that can arise from improper maintenance or insulation [2]. The unbalance of rotating machines in addition to misalignments are considered as 80% of the most important faults [3]. Other problems may include bearing faults, rotating shafts, gears, couplings, and other rotating machine problems.

One common way to analyze vibration is the Fast Fourier Transform. Many faults can be determined using this technique. As an example when the rotating machine has shaft unbalance then K*Fr harmonics normally present [2]. Where Fr stands for shaft rotation and K is the harmonic number. The same signature for bent shaft and misalignment are presented so in combined faults required to separate these faults and determine accurately the type of faults it had the same difficulties. With a single or an insufficient number of vibration analyses, these signatures do not appear clearly and also with the various development in recent years many methods were proposed for not more than three combined faults by also no more than three methods of faults analysis the combined faults produce different features [3]. [4] Used Independent component analysis (ICA) to find a structure in a large amount of multivariate data. ICA can be employed as a measurements data compression where several channels can be reduced to a smaller number of channels [5]. ICA techniques were adopted to decompose free vibration data into Modal Components [6]. Used ICA first to fused the information take from multi-channels of induction motor, then also used ICA by Fast ICA algorithm to find the independent component from the measurement data set, they note this method enhances the fault diagnosis routine, to identify the fault type of the aircraft engine [7] used Fast ICA blind source separation algorithm, which has fewer iteration times, low computing complexity, the separation effect, and stability is good. Because of the weakness of signal coming from rub-impact, it's difficult to separate it from vibration signal including noise and background signal by using straight forward empirical mode decomposition so[8] proposed the ICA-EMD to obtain much better decomposition performance, then by these decomposition can extract feature for rotor with rub- impact, also [9] utilized similar approach which applied to the rotating machine, resulting components are further processed Welch's power spectrum density, which used to separate machine vibration from interfering vibration sources. The similarity between different faults signature were still challenging. In this paper, a method is proposed to use ICA method and further applying FFT to the resulting components, the decomposition of time history vibration measurements to reduce the size of measured response data and filtered unwanted measurement noise [10]. Vibration signature analysis, as usual, begins by defining the baseline vibration signature of the component before damage occurs. If a new measurement of vibration signatures varies from the original baseline signature, then the machine estimated to have a fault.

In this work, two methods were used to detect the faults in rotating machines. The first, used the traditional FFT method. The second used the advanced ICA method, this method is more than the first method in detecting the faults because it separates all the basic components. After the use of ICA, the signal analysis chart was very clearly to indicate the types of faults. Also, ICA is an effective method to fault detection process, which gives detection results of 96.8 % about the statement of machine operation condition, either it is worked normally or faulty.

2 SIGNAL PROCESSING TECHNIQUES IN VIBRATION ANALYSIS

In order to understand the working condition of any type of rotating machinery and the initiation of defects and prediction can be done through the study of resulting vibration form theses machines which can include the reference to the defect and therefore study and analysis of this signal can be early detection of errors, extract the failure features or initial symptoms of vibration signals are essential. However, the vibration signals of rotating machines offer a nonlinear, curvy and unstable character, whose extraction is a difficult problem in this area. Thus, a new method of extracting parameters (FFT and ICA) is proposed for vibration signals of rotating machines by combining independent component analysis (ICA) with FFT. First, signals from multiple vibration sensors were separated into a statistically independent component by ICA. Afterwards, each component of independent statistics was analyzed using a self-correlation analysis method to eliminate background noise interference. Finally, all independent components of the statistics were analyzed using FFT, and the defect feature signals were obtained by assembling and reconfiguring all components of the common channel. The results of the simulation and application example show that this method can extract effective initial symptoms, weak signals, transient signals and other fault signaling signals. Compared to other methods, this method is an effective way of practical projects.

2.1 Frequency Domain Feature Parameters

Analysis or display of vibration signal depended on the frequency described the frequency domain. Application of Fourier transform to time domain signal will yield frequency domain by FFT which is powerful technique since it can successfully identify most of the machinery faults [12], usually in the form of fast Fourier Transform (FFT), we shall take the basic relationship of the discrete Fourier transform:

$$X(k) = \sum_{n=0}^{N-1} x[n] e^{-\frac{i2\pi kn}{N}} \qquad (1)$$

Where $X(k)$ is the kth harmonic (k=0…N-1).

The features selected for the purpose of faults diagnosis are the maximum frequencies in the frequency region and their trend with different faults.

2.2 Independent Component Analysis

ICA is a method to construct a set of independent signals from a set of measured signals. The measured signals are assumed to be a linear combination of the independent signals. The measured and independent signals are to be equal. As an example, Fig.1 shows two measured and independent signals. ICA is also known as source separation. Its power leads to its application in many research fields [13].

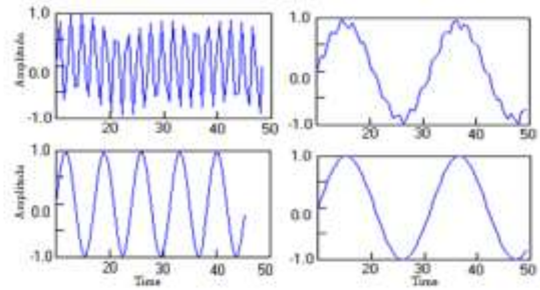

Figure 1: These graphs show the measured signals X1 and X2 on the top, and the independent signals S1 and S2 on the bottom.

2.2.1 Objective of ICA

ICA is a technique used to find the (statistically) independent components, s (t) from observable data, x (t) consisting of linear mixtures of independent components. Specifically, ICA addresses the following issue.

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$$x_i(t) = \sum_{j=1}^{N} a_{ij}\, s_j(t) \quad 1 < i \leq m \qquad (2)$$

Here, the independent components are mixed linearly by the elements of the mixing matrix a_{ij}. To make the time dependence implicitly and writing in matrix notation, the above equation can be written as [13],

$$X^{(m\times 1)} = A^{(m\times n)}\, S^{(n\times 1)} \qquad (3)$$

Where the dimensions have been placed in the superscript. The objective of ICA is to estimate both the mixing matrix, A, and the vector of independent components, S from the observed data X. Due to the number of variables involved, this task requires a characterization of the independent components S. Specifically, we need to define what it means to be an independent component in the most general way possible. ICA requires each component S_i to be statistically independent with respect to each other. Is more Invites compact forward to consider the inverse relationship (3).

$$S^{(N\times 1)} = W^{(n\times m)}\, X^{(m\times 1)} \qquad (4)$$

Here W is the (generalized if necessary) inverse of the mixing matrix A. Estimating W and S is now the major task. The n independent components to be estimated; it is essential to have adequate independent observations. This requires $m \geq n$ and the rank of A is n. If $m = n$, then (3) is a deterministic issue for A. If $m > n$, then (3) is an overdetermined issue, and A can be solved in the least squares sense. However, if there are only n independent components then, in the nonexistence of noise, only n of the observations will be independent. Then $m - n$ equations will be redundant and an exact solution exists for S. It can be seen that the number of independent components n, must be deduced from the observed data X in a similar fashion as is done in modal identification.

2.2.2 Algorithm for Multiple Unknown Signals Extraction.

Many algorithms based on second-order statistics such as Algorithm for Multiple Unknown Signals Extraction (AMUSE) assume that:

1- The mixing matrix A is of full column rank.
2- Sources are spatially uncorrelated with different autocorrelation functions but are temporally correlated (colored) stochastic signals with zero-mean.
3- Sources are static signals and / or non-fixed second-order signals, i.e. their variations change over time.

The AMUSE algorithm is outlined below:

1- Centering the data simply involves removing the mean value from each time series X_i.

$$X = X_i - \sum X_i \quad (5)$$

2- Whitening or sphering of the data involves transforming the data X into a new vector $\tilde{x}$ such that the covariance matrix of $\tilde{x}$ is the identity matrix:

While the covariance matrix can be estimated as:

$$C_x = \frac{1}{N}\sum_{K=1}^{N} \tilde{x}(k)\, \tilde{x}^T \quad (6)$$

Whitening can be accomplished by:

$$\tilde{x} = ED^{-\frac{1}{2}}E^T x \quad (7)$$

Where E is the orthogonal matrix of eigenvectors of $E\{xx^T\}$

$$E\{xx^T\} = ED \quad (8)$$

and D is the diagonal matrix of its eigenvalues.

Then to perform other ICA steps,

3- Select a random vector for de-weighting matrix w with $||w||=1$
4- Calculate an arbitrary function Y which is a potential independent signal found by mixing measured signals

$$Y = w^T\tilde{x} \quad (9)$$

5- Perform Negentropy approximation to estimate non-Gaussianity; [14] identify statistically independent and non-Gaussian sources from a linear mixture of such sources. where the independent component tends to be as non-Gaussian as possible, the function which is non-linear that describes the case of super-Gaussian distribution is usually set as [15]:

$$G(Y) = \mathrm{Tanh}(Y) \quad (10)$$

Negentropy is also a measure of the distance of normality can be defined by:

$$J(Y) = H(Y_{gauss}) - H(Y) \quad (11)$$

But there is difficult to compute negentropy equation (11), so Hyvärinnen & Oja [15] have proposed the following approximation:

$$N(V) = E\big(\emptyset(V)\big) - E\big(\emptyset(U)\big)^2 \quad (12)$$

6- Compute

$$w^+ = E(\tilde{x}G(Y) - E\big(G(Y)\big)w \quad (13)$$

7- Normalize by: $w = \frac{w^+}{||w^+||}$
8- Repeat the above step until $w^T w$ is converging to 1.

In the same way, multiple columns can be estimated, but need to prevent each column from converging with the same solution, so each row must be decorrelated at each step using the Gram-Schmidt algorithm which orthonormalize each vector with the previously obtained.

After each iteration, w_{k+1} can be made orthonormal to $w_1, \ldots, w_k$ by subtracting off the projections $w_{p+1}\, w_i\, w_i$, $1 \le i \le p$. then w_{k+1} can be renormalized [9].

9- Compute

$$w_{p+1} = w_{p+1} - \sum_{i=1}^{p} w_{p+1}^T w_1 w_i \quad (14)$$

10- Compute $$w_{p+1} = \frac{w_{p+1}}{\sqrt{w_{p+1}^T w_{p+1}}} \quad (15)$$

11- Get all independent components s_j
12- Applied FFT on each component s_j.

3 EXPERIMENTAL WORK

In this section, the experiments of different faults on the test bench figure 2 where the experiments of rotor unbalance fault severities, the bearing fault severities, misalignment fault, while shaft fatigue is accomplished on the second test rig figure 3.

Figure 2: Test Rig

Figure 3: Fatigue Test Rig

This machine demonstrates the fatigue failure of materials when subject to alternating stresses, based on Wohler's design, in this experiment the accelerometers are mounted in the position shown to take the vibration data. These experiments are carried out to test the feasibility of the proposed method as shown in the test scheme of figure 4 the data acquisition system DAQ was proposed as used in [16].

4. FAULT PROGNOSIS SCHEME

The scheme for faults prognosis is shown in figure 5. The vibration data are read by data acquisition system, then these Data are passed to two signal processing methods, First is FFT in this the frequency domain features are estimated.

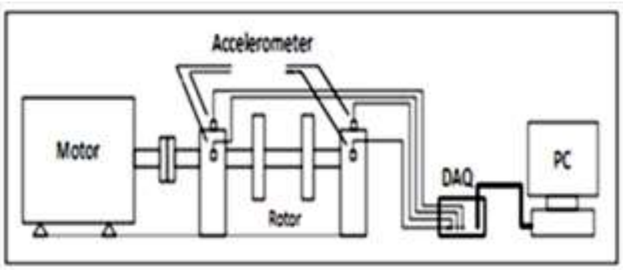

Figure 4: Test Scheme of the experiments

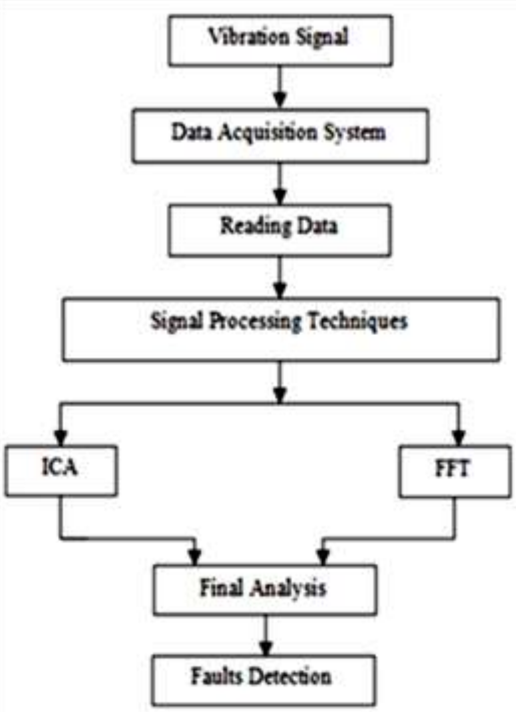

Figure 5: Fault Prognosis scheme

These data also passed to ICA to obtain the independent components of signals, then the output of ICA are returned to FFT these two properties are then passed through filtration method to choose the best features that effect in the prognosis of the fault it has the ability to detect the machine defect type, such as unbalance, misalignment, shaft fatigue, and bearing defects.

4.1 Vibration response of rotor unbalance

In a real-world application of rotating machinery, when the rotor unbalance occurs, the severities of which various, in this experiment, the vibration signals of the simulation test bench under the working conditions of 2700 RPM for four simulated conditions are

C1: Normal

C2: Rotor unbalances small mass

C3: Rotor unbalances medium mass

C4: Rotor unbalances large mass

The working condition C1-C4 in three cases of rotating speed are achieved by adding screws with different mass in one of the tapped holes in the rotor disks in the middle edge respectively. The mass adds as mention above.

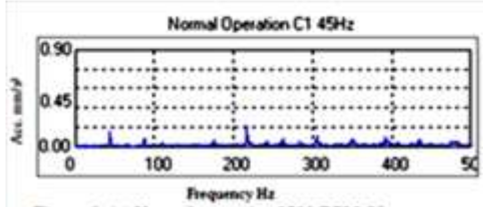

Figure 6: (a) Normal operation 2700 RPM C1

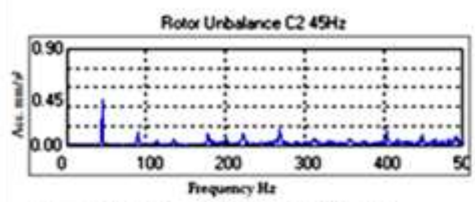

Figure 6: (b) Rotor unbalances 2700 RPM C2

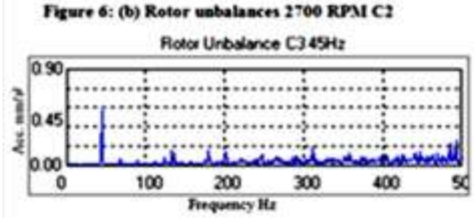

Figure 6: (c) Rotor unbalances 2700 RPM C3

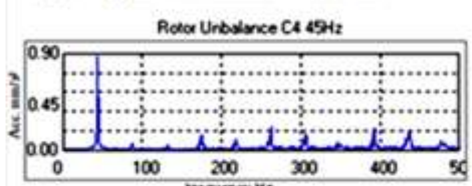

Figure 6: (d) Rotor unbalances 2700 RPM C4

The rotor unbalance response as figure 6 shows the unbalance in the case of the rotation speed of 2700 RPM and response frequency in the horizontal or lateral plane. the vibration motion can be seen as a synchronous and growing at the top of the frequency spectrum is good value and in this case strongly the 1X and a sufficient amount of the nX harmonics also exist adequately when using FFT, while when using the ICA, it gives a clarity of the signal frequency response at 1X and also gives clarity to the incidental response, as well as the resulting signal to noise ratio. Figure 7 shows the unbalance responses for different independent components. It is clear through the figures that ICA Showed that the use of 1X and the output of the analysis of the FFT remains the most accurate indicator of this fault type.

4.2 Vibration response of shaft Fatigue

Vertical vibration signal spectrum analysis of a shaft rotating until failure due to fatigue is presented in this experiment. In this case, the characteristics of the response are the non-linearity of flexibility and its change during crack propagation, as well as the changing of the internal structure of the shaft until to failure.

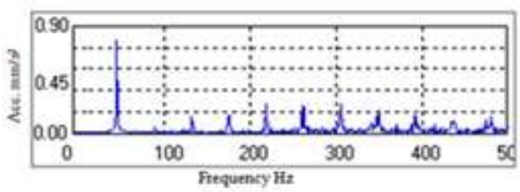

Figure 7: (a) Rotor unbalances 2700 RPM ICA1 of C2

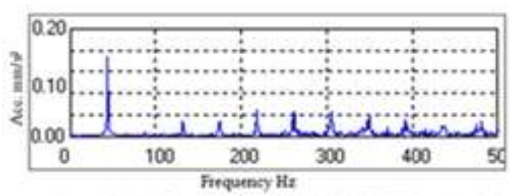

Figure 7: (b) Rotor unbalances 2700 RPM ICA2 of C2

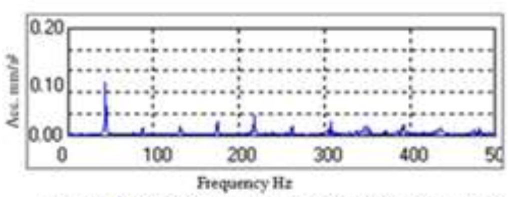

Figure 7: (c) Rotor unbalances 2700 RPM ICA3 of C2

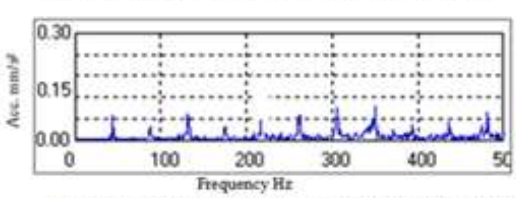

Figure 7: (d) Rotor unbalances 2700 RPM ICA4 of C2

All that leads to the change of the vibration signal and the change of the length of the peak. These changes are evident in figures 8 and 9. The study of FFT alone does not give enough diagnosis features in order for this failure. So, using ICA combined with FFT can give a better method to the diagnosis of this fault as shown in figure 10.

One can note that the spectrum will change with the number of the revolutions until failure, especially before fracture takes place, 1X and 2X still the dominates spectra in FFT analysis. When using the ICA, the spectrum vibration at 2X be dominant and this is the exact index for the crack in the shaft which leads finally to get a failure.

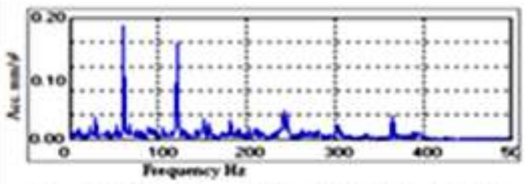

Figure 8: Shaft fatigue at 3600RPM with load 56 N in Vertical

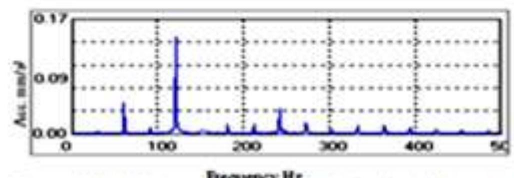

Figure 9: Shaft fatigue at 3600RPM with load 46 N in vertical

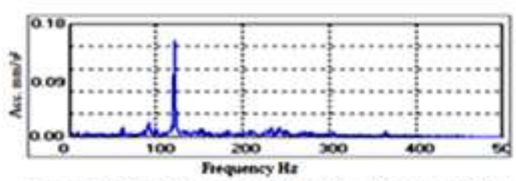

Figure 10: Shaft fatigue at 3600 RPM with load 46 N ICA1

4.3 Misalignment Vibration Signatures

Parallel misalignment (0.4 mm), is introduced in the horizontal direction, to the rotor, which rotates at 2700 RPM. The vibration spectrum in the horizontal direction is obvious than in the vertical direction and that is because of the effect of preload on the direction of the initial misalignment and often show that 2X is the higher harmonics in the vibration response. Figure 11 used FFT method only for the analysis of this situation. When using ICA the higher harmonics may appear to give extra fault feature to identify it from that of shaft fatigue. The 5X also appear as a dominate spectrum figure 12 and 13 also the normal operation condition (figure 14) used to explain the using of ICA separation method.

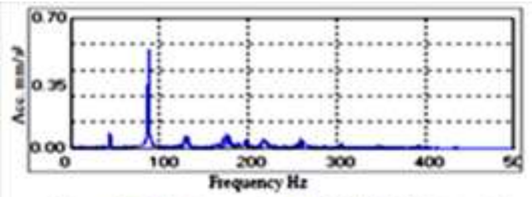

Figure 11: Misalignment at 2700 RPM in Horizontal

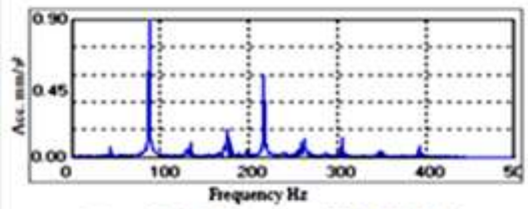

Figure 12: Misalignment at 2700 RPM ICA1

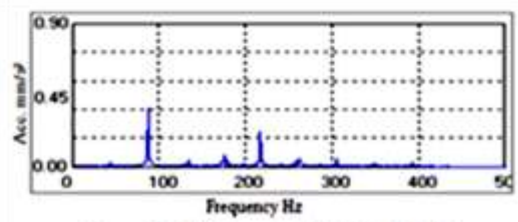

Figure13: Misalignment at 2700 RPM ICA2

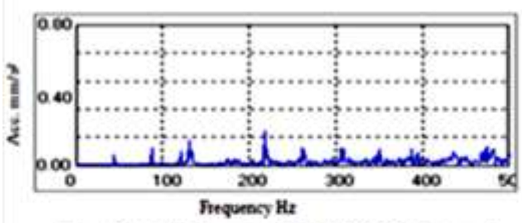

Figure14: Misalignment at 2700 RPM ICA3 normal

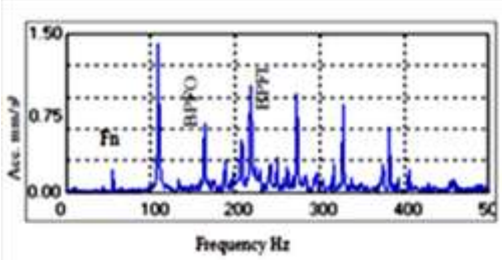

Figure 15: Bearing Fault outer Race Vertical

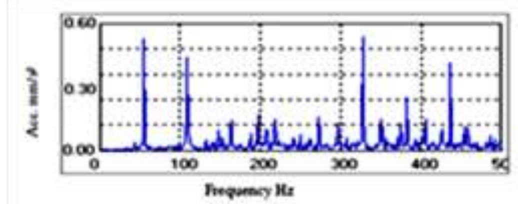

Figure 16: Bearing Fault outer Race Horizontal

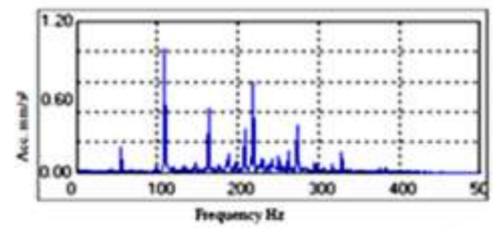

Figure 17: Bearing Fault outer Race ICA1

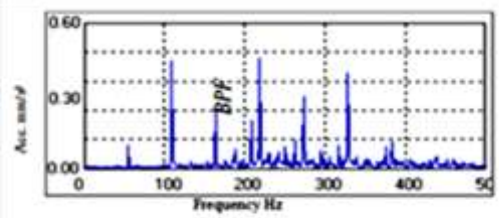

Figure 18: Bearing Fault outer Race ICA2

4.4 Bearing Fault vibration Response

In Bearing outer race defect the more dominate vibration frequency is 2X and the multiple harmonics of the outer race which is clearly identified in both vertical and horizontal direction, the use of ICA technique shows these characteristic frequencies. Figure 15 and 16 analyze this fault using FFT. While figures 17 and 18 shows the response using ICA. Using FFT these fundamentals frequencies besides the motor rotational frequency which made a confusion in the detection of the bearing fault from that of shaft fatigue. In the horizontal direction the vibration analysis of the faulty bearings cases, the vibration at 2x is prevalent in addition to the spectrum of 1x and this is similar to the case of the shaft fatigue. This failure analysis by using FFT. When using the ICA method combined with FFT, the vibration frequency of 2x disappears, the frequency vibration at 1x which accompanying the rotational speed of the rotor. Also, these figures show that the multiple harmonics of the outer race defect which represent the ball pass frequency of outer and inner race beside the fundamental frequency of bearing Fn.

5. CONCLUSION

On using the FFT method in the prognosis of faults of rotating machinery a similar feature of different faults arises, that makes the prognosis difficult. Analysis of vibration with other methods for separating different faults from each other with high accuracy requires the use of more adaptive methods of analysis to show the characteristics of each fault individually. High accurately of prognosis through direct observation and without the use of methods of intelligence to follow the case of vibration and other comparable standard cases may not lead to the detection of faults exact path.

As the frequency of vibration at 1X is used widely to detect the state of unbalance in rotating machines in both horizontal and vertical directions there is also another fault shows 1X as the largest component of it, such as rotor rub. The use of FFT may not meet the purpose of the distinction between such types of faults, so the use of more accurate analysis methods such as ICA would distinguish between those ambiguities through the analysis of other features hidden in all signal components, which show a clear distinction between each failure. The ICA method, therefore, can be used in conjunction with the FFT to resolve such obscurity. In addition to that, there are other faults showed the more dominant component at 2X which remained widely used to indicate the occasional case of misalignment, there are other errors may exhibit the same indicator at 2X such as fatigue crack, as well as in case of asymmetry of stiffness, etc. This study solves this ambiguity. In unbalance mass fault the two analysis method give the same indicators but in the cases of fault, ICA gives more advantage in faults identification than that FFT. As a conclusion the used of ICA combining with FFT give the advantage to distinguish between different Faults.

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