Journal of Engineering and Applied Sciences 13 (10): 3587-3593, 2018
ISSN: 1816-949X

Bearing Health Monitoring and Diagnosis Using ANC Based Filtered Vibration Signal

Sudarsan Sahoo and Jitendra Kumar Das
School of Electronics Engineering, KIIT University, Bhubaneswar, India

Abstract: Continuous monitoring of the condition of a rotating machine is an important and required task for engineers and researchers in industry. For any rotating machinery bearing is the core element. For that reason health monitoring of bearing in a rotating machinery is very important. Vibration is one of the most widely used signature used for the health monitoring of the bearings. In this research, the experiment is executed in two stages. As the vibration signal acquired from the bearing set-up is in general noisy in nature, so in the first phase of the experiment, the noise present in the vibration signal is removed to improve the SNR. This noise filtering is done using the ANC (Adaptive Noise Cancellation) technique. Initially, three ANC techniques are employed on the vibration signal acquired from the experimental set-up. The performance of the ANC techniques are compared. From the comparison EMD is found better. So, EMD algorithm is used for the implementation of the adaptive noise cancellation in the preprocessing of the vibration signal and then the filtered signal is used in the next phase of the experiment for further analysis to detect the bearing defect. As the time domain (static analysis) or frequency domain analysis alone may not provide the precise information about the defect, so in the second phase of the experiment the static analysis and the frequency domain analysis along with the time-frequency analysis is done on the filtered vibration signal to identify the defect in the bearing.

Key words: Condition monitoring, bearing fault, Adaptive Noise Cancellation (ANC), LMS, EMD, wavelet transform

INTRODUCTION

Every rotating machine generates its own vibration signal which is known as its vibration signature. This vibration signature gets changed by any defective component of the machine. A proper technique may be used to identify this change in vibration signature to monitor the health of the components of the rotating machinery. As bearing is one of the important component of a rotating machinery, so, the health monitoring of bearing is very essential. This research focuses on to identify the bearing defect using the vibration signature. Various techniques have been followed in different researches for the bearing defect identification.

In some literature it is observed that the vibration signature is used for detecting the defect in the bearings (Kankar *et al*., 2011; Ergin *et al*., 2012; Kunli and Yunxin, 2011).

In some literature it is found the application of wavelet transfer to analyze and to detect the defect (Al-Badour *et al*., 2011; Peng and Chu, 2004; Kankar *et al*., 2011). Kankar *et al*. (2011) showed the application of continuous wavelet transfer to analyze the defect using the vibration signature. It can also be found that the wavelet packet is used for the defect identification using current signature (Eren and Micheal, 2004; Thomson and Fenger, 2001). Lin and Qu (2000) highlighted on application of morlet wavelet for feature extraction and analysis. Liao and Lin (2007) shows the use of wavelet and HMM for the fault diagnosis of ball bearing. So, it can be concluded that the wavelet transfer analysis is one of the most promising method of time-frequency analysis.

In literature it can be found that though a lots of research has been done to identify the defect in the bearing of a rotating machine still lots of scope is there in the vibration signal processing. One of the challenge is to remove the background noise present in the vibration signal before its analysis for the defect identification. Adaptive noise cancellation is one of the best solution for this purpose. Also, the best ANC method is to be followed which can give better SNR.

Initially three ANC techniques are employed on the vibration signal acquired from the experimental set-up which is in general noisy in nature. The ANC techniques employed for the comparison are LMS, EMD and wavelet de-noising. The performance of the ANC techniques are compared on the basis of the Signal to Noise Ratio (SNR) and the Mean Square Error (MSE). From the comparison EMD is found better. So, EMD algorithm is used to implement the Adaptive Noisem Cancellation (ANC) in the preprocessing (filtering) of the vibration signal.

Corresponding Author: Sudarsan Sahoo, School of Electronics Engineering, KIIT University, Bhubaneswar, India

As stated earlier this research is implemented in two phases. In the first phase the signal to noise ratio of the acquired vibration signal is improved by employing the adaptive noise cancellation technique. The EMD algorithm is used for this purpose. In the second phase the time, frequency and time-frequency (wavelet transform) analysis of the filtered vibration signal is done to identify the defect.

Adaptive noise cancellation: Adaptive noise cancellation is used for the pre processing of the vibration signal. vibration signals are always contaminated with noises and other external interferences which must be removed or filtered from the original vibration signature before further processing and analysis.

LMS de-noising: The Least Mean Square (LMS) algorithm is used to update the filter coefficients as:

$$w_1(n+1) = w_1(n)+\mu x(n\text{-}1)e(n) \quad (1)$$

The ANC steps using the least mean square algorithm is explained briefly as follows (Liao and Lin, 2007; Troparevsky and Attellis, 2004):

- The selection of the step size μ and the filter Length L is made
- The output of the adaptive filter is calculated as:

$$y(n) = \sum_{l=0}^{L\text{-}1} w_l(n)x(n\text{-}l)$$

- The error signal is calculated as e(n) = d (n)-y(n)
- The coefficients of the adaptive filter is updated by using the following equation:

$$w_1(n+1) = w_1(n)+\mu x\,(n\text{-}l)\,e(n)$$

where, l = 0.1, ..., 1 1 L-1. The selection of the step size value is very important as it affects the convergence speed. The proper selection of filter length is also very important (Troparevsky and Attellis, 2004).

Empirical mode decomposition: This is another adaptive algorithm used for noise cancellation. This is suitable when the noise is non-stationary in nature. This algorithm is based on empirical basis functions. The original signal x(t) is decomposed into the set $\{r_J, c_{J,J\text{-}1}, ..., c_1\}$ where c_J, j = 1, ..., J represent Intrinsic Mode Functions (IMF) and r_J are residual terms:

$$x(t)=\sum_{J=1}^{J} C_J(t)+r_j(t) \quad (2)$$

The empirical mode decomposition is an adaptive method to recognize oscillations from the signal x(t). Like discrete wavelet transfer, EMD method decompose a signal into so-called Intrinsic Mode Functions (IMF).

Wavelet de-noising: This technique is one of the most popular and efficient techniques for the filtering of the noise. It starts with the decomposition of the signal into successive approximation and details. Wavelet de-noising performs correlation analysis. The expected value of the output turn out to be maximum if the input noisy signal looks a lot like the picked mother wavelet function. As the wavelet transform is linear it researches best for the additive noise.

Time domain study: In time domain analysis the statistical features are computed from the vibration signature. By comparing these statistical features the faults in the system can be identified. The statistical parameters used for the time domain analysis are RMS, skewness, mean, peak value, crest factor, kurtosis, standard deviation, clearance factor, impulse factor and shape factor.

Frequency domain study: In time domain analysis some information may not be revealed, so, frequency domain can is used to reveal those information which is not possible in time domain. The signal in time domain is basically converted to frequency domain by employing the fourier transform. In this analysis, the vibration signal peak is displayed in the frequency spectrum and provide the information in frequency domain. The characteristic fault frequencies can be calculated by the following equations:

$$\text{ORF (Outer Race Fault)} = \frac{N}{2}\omega_n\left(1\text{-}\frac{d}{D}\cos\alpha\right) \quad (3)$$

$$\text{IRF (Outer Race Fault)} = \frac{N}{2}\omega_n\left(1\text{-}\frac{d}{D}\cos\alpha\right) \quad (4)$$

Time-frequency study: In some cases, time or frequency analysis alone may not give adequate information about the fault in the rotating machine. So, time-frequency analysis is needed for this purpose to give better analysis of the fault. Wavelet transform is used for this purpose. The signals are processed by the wavelet transform to generate the two dimensional map of WT coefficients to get the required time frequency information. It provides the information simultaneously both in time and scale. In time-frequency methods of fault detection the contour plots are visually observed. The fault can be detected by visually monitoring the changes that occurred in the features of the distribution in the contour plots.

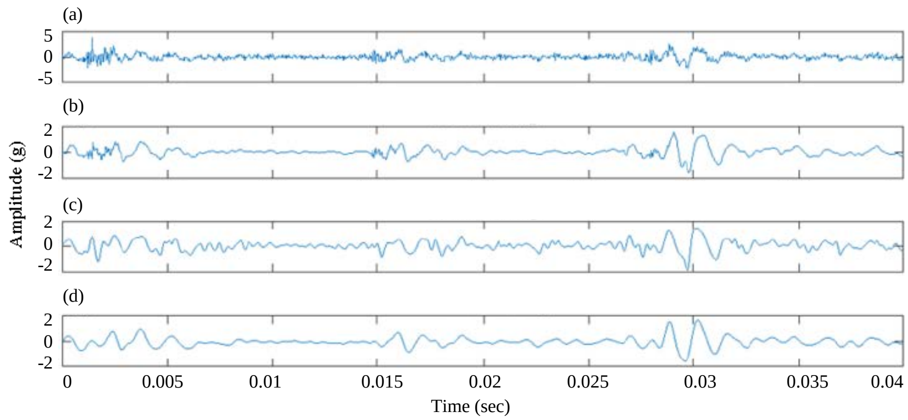

Fig. 1: Comparison of ANC techniques: a) Acquired vibration signal; b) LMS denoising; c) EMD denoising and d) Wavelet denoising

Table 1: Parameters comparison for ANC techniques

ANC techniques	SNR	MSE
LMS	11.068	0.0283
EMD	14.863	0.0210
Wavelet	13.061	0.0264

Performance evaluation of ANC techniques: In this study, the performance of the ANC techniques are compared. The comparison is made on the basis of Signal to Noise Ratio (SNR) and MSE (Mean Square Error).

The filtration of the Vibration signal acquired from the experimental setup is done with the implementation of the ANC techniques. The acquired noisy vibration signal and the filtered vibration signals obtained by different ANC techniques are shown in Fig. 1. Their performance based on SNR and MSE is compared and shown in Table 1 above. From the comparison table EMD is found better. So, in the preprocessing the EMD adaptive noise cancellation technique is used for the filtering of noise from all the acquired vibration signals.

MATERIALS AND METHODS

To implement the proposed technique for detection of fault in the bearing an experimental setup is made. The model of the experimental setup and the real experimental setup is shown in Fig. 2 and 3, respectively.

The experimental setup consists of an induction motor which is a single phase motor of 0.5 hp. The speed of the motor is 1400 rpm at no load with 230 V and 50 Hz supply. The bearing under test is mounted on the rolling shaft of the motor.

The accelerometer (PCB 325c-03 Accelerometer) is used to sense the vibration. To acquire the vibration data a 4-channel data acquisition system is used. For this purpose the NI 9234 DAQ card along with a PC with LabVIEW Software is used. In the experiment two deferent types of defected bearings are used named as type-1 and type-2 defect bearing. The healthy bearing used in this experiment is shown in Fig. 4 and the type-1 defect bearing and the type-2 defect bearing used in this experiment is shown in Fig. 5. The data acquisition is done in three different stages. In first stage the healthy bearing is mounted and the corresponding data is acquired. Then in second stage the type-1 defect bearing is mounted and the data is acquired. In third stage the type-2 defect bearing is mounted and the corresponding data is acquired. For all the acquired vibration signal the adaptive noise cancellation is implemented and the filtered vibration signals are shown in Fig. 6.

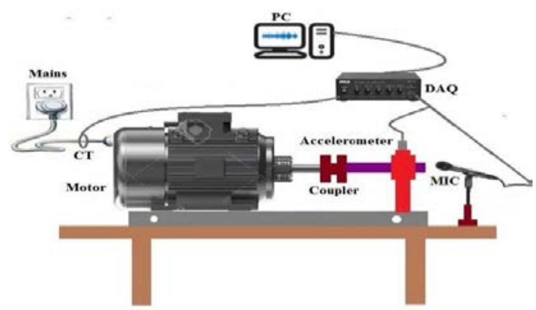

Fig. 2: Model of the experimental setup

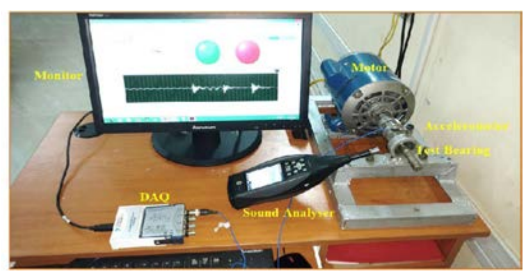

Fig. 3: Experimental setup

Fig. 4: The healthy bearing

Fig. 5: The type-1 and 2 defect bearing

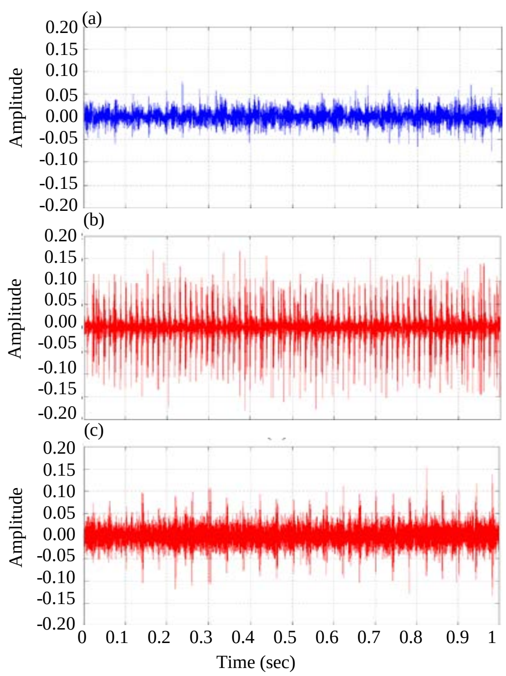

Fig. 6: Filtered vibration signal: a) Healthy bearing; b) Type-1 defect bearing and c) Type-2 defect bearing

RESULTS AND DISCUSSION

This study shows the time domain (static), the Frequency domain (FFT) and the Time-Frequency domain wavelet) analysis of the vibration signal to monitor the condition of bearings. This is done in comparison with a healthy bearing.

Table 2: Time domain parameter comparison

Time domain parameters	Healthy bearing	Type-1 defect bearing	Type-2 defect bearing
Root Mean Square (RMS)	0.0134	0.0261	0.0203
Mean	6.4463 e-004	4.4736 e-004	4.3398 e-004
Peak value	0.0773	0.1734	0.1432
Crest Factor	5.7737	6.6469	7.0564
Skewness	-0.0052	-0.2564	0.1228
Kurtosis	3.8532	9.0461	5.7542
Variance	1.7868 e-004	6.8005 e-004	4.1148 e-004
SD	0.0134	0.0261	0.0203
Clearance factor	716.0322	665.9750	624.7892
Impulse factor	7.4381	10.7450	9.4580
Shape factor	1.2883	1.6165	7.4381

Time domain analysis: The statistical parameters such as kurtosis, skewness, crest factor, RMS, peak value, variance, standard deviation, clearance factor, impulse factor, shape factor is computed and it is tabulated in Table 2. From the tabulation it can be clearly observed that the statistical parameters are changed when the bearing is in the defective condition in comparison to the healthy condition.

Frequency domain analysis: The Fast Fourier transform is used for the frequency analysis of the vibration signal. The Bearing Characteristic Frequency (BCF) also known as the Outer Race Defect Frequency (ORDF) is calculated by using the geometric configuration of the bearing and is used in the frequency analysis. The frequency spectrum comparison of the vibration signature of the healthy and type-1 defect bearing is shown in Fig. 7. The comparison at the Bearing Characteristic Frequency (BCF) is also shown in Fig. 8. Then the frequency spectrum comparison of the healthy and the type-2 defect bearing and its comparison at BCF is shown in Fig. 9 and 10, respectively.

Time-frequency analysis: For this analysis morlet wavelet is used as the mother wavelet. The 2D scalograms based upon the morlet wavelet are plotted for the vibration signals acquired from the healthy, type-1 defect and type-2 defect bearings and is shown in Fig. 11-13, respectively. The corresponding value of scale with respect to BCF or ORDF for type-1 and 2 defect bearing are presented in the figure. The difference can be easily visible from the scalogram.

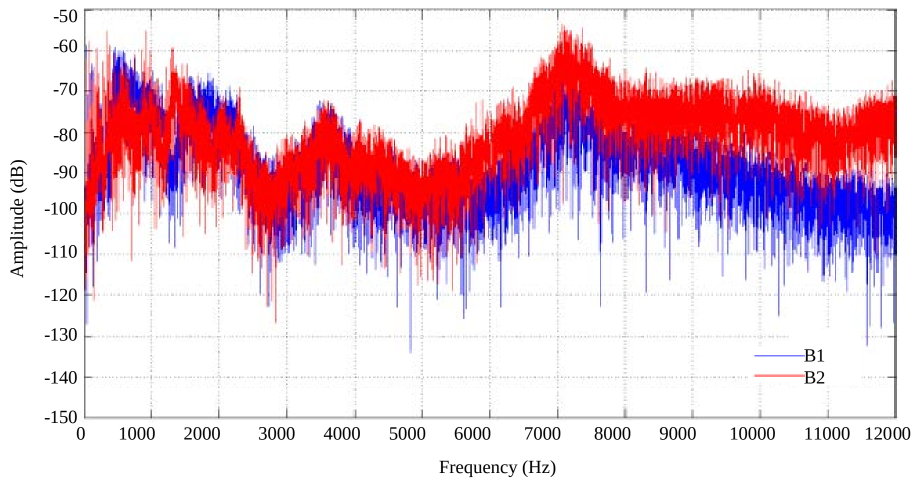

Fig. 7: FFT of healthy (B1) and type-1 defect Bearing (B2)

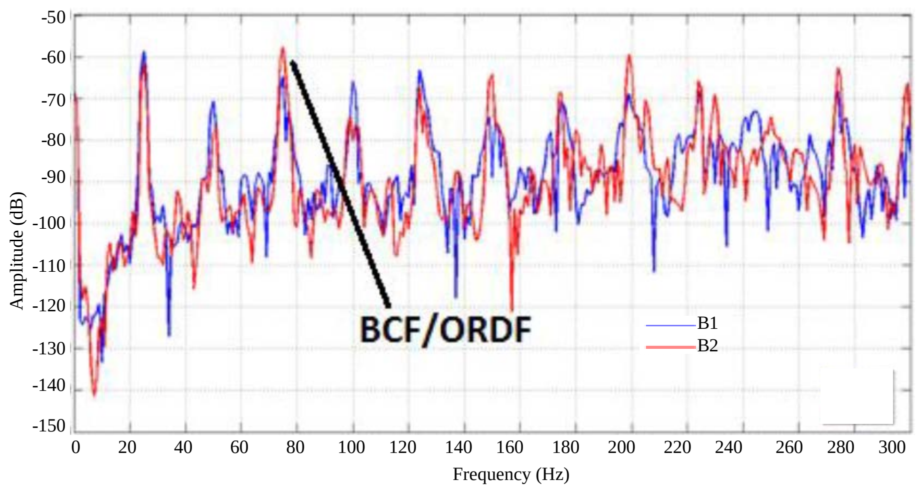

Fig. 8: FFT comparison of healthy (B1) and type-1 defect Bearing (B2) at BCF

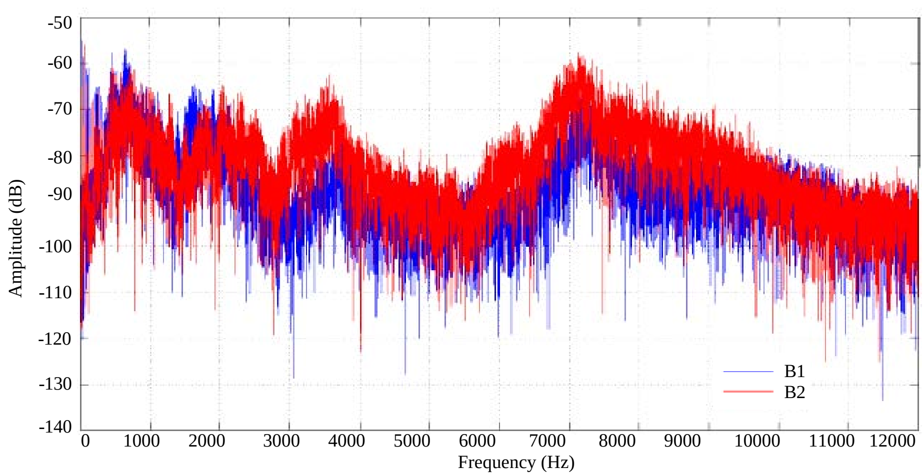

Fig. 9: FFT of healthy (B1) and type-2 defect Bearing (B3)

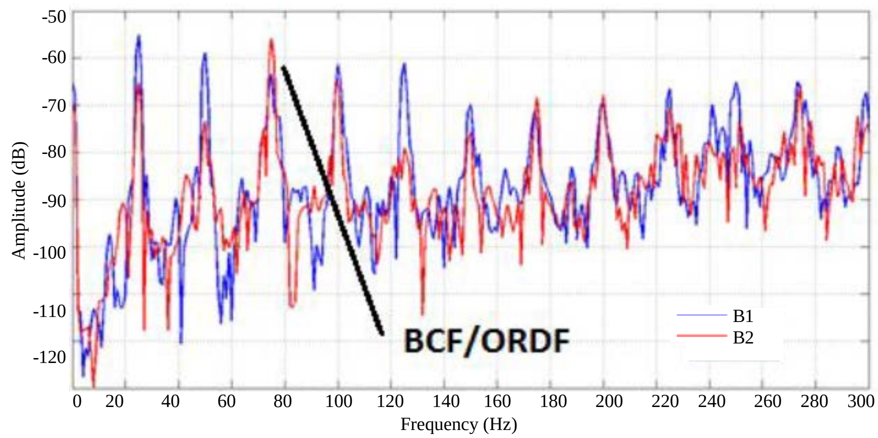

Fig. 10: FFT comparison of healthy (B1) and type-2 defect Bearing (B3) at BCF

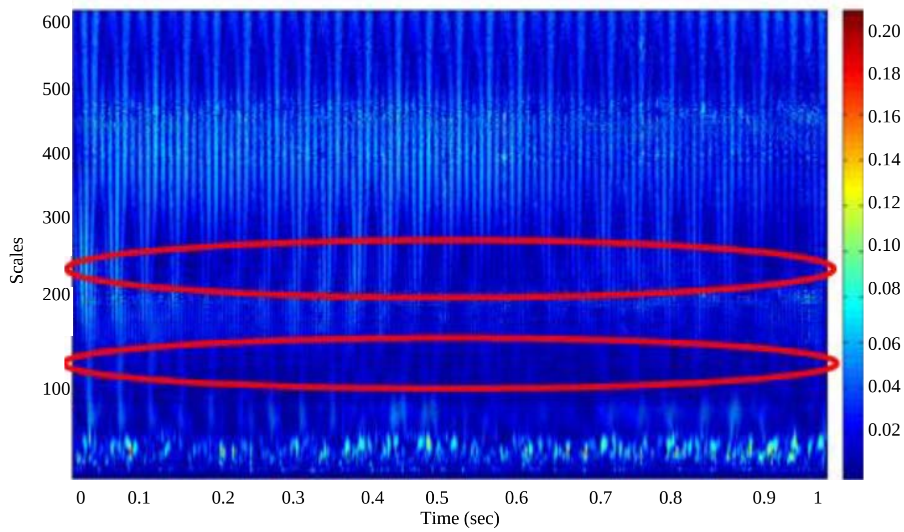

Fig. 11: Scalogram for the vibration signal of the healthy Bearing (B1)

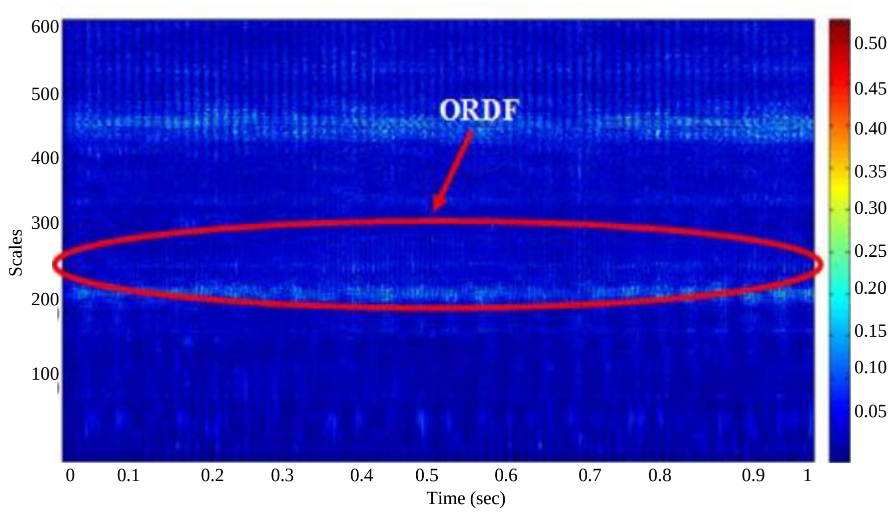

Fig. 12: Scalogram for the vibration signal of the type-1 defect Bearing (B2)

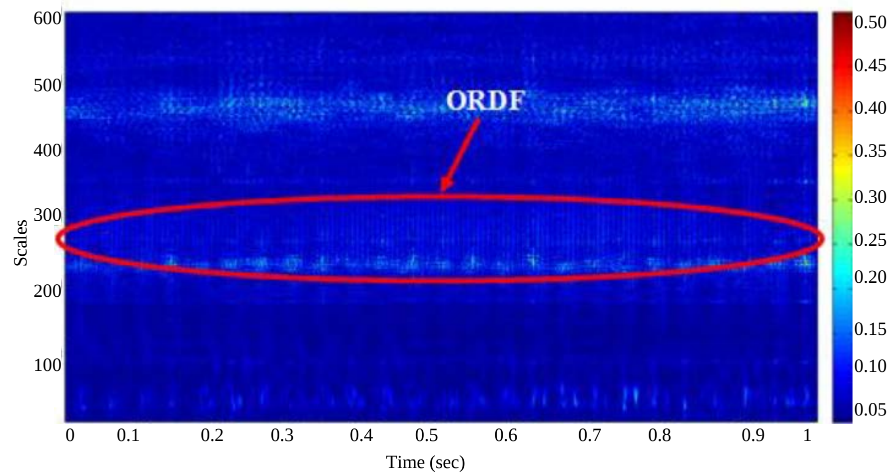

Fig. 13: Scalogram for the vibration signal of the type-II defect bearing (B3)

CONCLUSION

This present experimental research shows the application of the adaptive noise cancellation technique (ANC) for the filtration of the vibration signature to improve its Signal to Noise Ratio (SNR). Then this filtered vibration signature is used for the statistical and the wavelet analysis to identify the defects in the bearing. The statistical analysis though suitable to identify the defect but the wavelet analysis is more informative and give the information in time scale as well as in frequency scale. The precise information about the defect is obtained from the scalograms of the wavelet transform.

REFERENCES

Al-Badour, F., M. Sunar and L. Cheded, 2011. Vibration analysis of rotating machinery using time-frequency analysis and wavelet techniques. Mech. Syst. Signal Process., 25: 2083-2101.

Eren, L. and M.J. Devaney, 2004. Bearing damage detection via. wavelet packet decomposition of the stator current. IEEE. Trans. Instrum. Meas., 53: 431-436.

Ergin, S., A. Uzuntas and M.B. Gulmezoglu, 2012. Detection of stator, bearing and rotor faults in induction motors. Procedia Eng., 30: 1103-1109.

Kankar, P.K., S.C. Sharma and S.P. Harsha, 2011. Fault diagnosis of ball bearings using continuous wavelet transform. Appl. Soft Comput., 11: 2300-2312.

Kankar, P.K., S.C. Sharma and S.P. Harsha, 2011. Rolling element bearing fault diagnosis using wavelet transform. Neurocomput., 74: 1638-1645.

Kunli, M. and W. Yunxin, 2011. Fault diagnosis of rolling element bearing based on vibration frequency analysis. Proceedings of the 3rd International Conference on Measuring Technology and Mechatronics Automation (ICMTMA'11) Vol. 2, January 6-7, 2011, IEEE, Shangshai, China, ISBN:978-1-4244-9010-3, pp: 198-201.

Liao, C.W. and J.Y. Lin, 2007. New FIR filter-based adaptive algorithms incorporating with commutation error to improve active noise control performance. Autom., 43: 325-331.

Lin, J. and L. Qu, 2000. Feature extraction based on morlet wavelet and its application for mechanical fault diagnosis. J. Sound Vibrat., 234: 135-148.

Peng, Z.K. and F.L. Chu, 2004. Application of the wavelet transform in machine condition monitoring and fault diagnostics: A review with bibliography. Mech. Syst. Signal Process., 18: 199-221.

Thomson, W.T. and M. Fenger, 2001. Current signature analysis to detect induction motor faults. IEEE. Ind. Appl. Mag., 7: 26-34.

Troparevsky, M.I. and C.E. D'Attellis, 2004. On the convergence of the LMS algorithm in adaptive filtering. Signal Process., 84: 1985-1988.