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Condition Monitoring of Low Speed Slewing Bearings Based on Ensemble Empirical Mode Decomposition Method

EEMD법을 이용한 저속 선회베어링 상태감시

W. Caesarendra*, J. H. Park**, P. B. Kosasih* and B. K. Choi†
와휴 캐서렌드라, 박진희, 코사시, 최병근

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Key Words : Condition Monitoring(상태감시), Low Rotational Speed(저속회전), Slewing Ring Bearing(선회베어링), Ensemble Empirical Mode Decomposition(EEMD)

ABSTRACT

Vibration condition monitoring of low-speed rotational slewing bearings is essential ever since it became necessary for a proper maintenance schedule that replaces the slewing bearings installed in massive machinery in the steel industry, among other applications. So far, acoustic emission(AE) is still the primary technique used for dealing with low-speed bearing cases. Few studies employed vibration analysis because the signal generated as a result of the impact between the rolling element and the natural defect spots at low rotational speeds is generally weak and sometimes buried in noise and other interference frequencies. In order to increase the impact energy, some researchers generate artificial defects with a predetermined length, width, and depth of crack on the inner or outer race surfaces. Consequently, the fault frequency of a particular fault is easy to identify. This paper presents the applications of empirical mode decomposition(EMD) and ensemble empirical mode decomposition(EEMD) for measuring vibration signals slewing bearings running at a low rotational speed of 15 rpm. The natural vibration damage data used in this paper are obtained from a Korean industrial company. In this study, EEMD is used to support and clarify the results of the fast Fourier transform(FFT) in identifying bearing fault frequencies.

요 약

대부분의 철강산업 기계 등에 설치되어 사용되는 선회베어링은 교체를 위한 정확한 정비계획이 필요하기 때문에 저속회전체의 선회베어링에 대한 진동 상태감시가 매우 중요하게 되었다. 지금까지 음향방출(AE)법이 저속베어링의 상태감시에 가장 많이 사용되는 기술이고 몇몇의 경우는 진동을 사용한다. 음향방출을 사용하는 일반적인 이유는 저속에서 구름요소와 결함위치 사이의 충격에 의하여 발생되는 신호가

† Corresponding Author ; Member, Department of Energy and Mechanical Engineering, Gyeongsang National University
E-mail : bgchoi@gnu.ac.kr
Tel : +82-55-772-9116, Fax : +82-55-772-9119
* School of Mechanical, Materials and Mechatronic Engineering, Faculty of Engineering, University of Wollongong
** Department of Mechanical and Automotive Engineering, Pukyong National University

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약하고 때때로 노이즈나 다른 간섭 주파수에 결함신호가 묻혀 검출이 어렵기 때문이다. 따라서 쉽게 특정 결함에 대한 결함주파수의 동정을 위하여 몇몇 연구자들은 충격에너지를 증가시키기 위하여 인위적으로 미리 정해진 길이, 넓이와 깊이의 결함을 베어링의 내, 외부 레이스에 인가하기도 한다. 이 논문에서는 15 rpm에서 운전하는 저속 선회베어링의 진동신호에 EMD와 EEMD를 적용하였고 논문에서 사용한 진동결함 신호는 국내 산업체에서 공급받은 것이다. 이 논문에서는 베어링결함 주파수 동정을 위하여 EEMD를 사용하여 결함신호의 FFT처리 결과를 입증하고 설명하였다.

1. Introduction

Most published articles on the topic of slewing bearings are frequently concerned with using the finite element method for analysis(1~5); there is also a small amount of work done in oil analysis(6,7), and even less in vibration monitoring techniques(8). A recent article about slewing bearings as related to vibration analysis is presented by Žvokelj(9,10). The method used in Refs. (9), (10) is the ensemble empirical mode decomposition (EEMD) combined with multi-scale principal component analysis(MSPCA). An artificial fault is introduced on the inner ring of the slewing bearing as presented in Refs. (9), (10). As signal from artificial single fault is easier to identify than more realistic multiple fault damage the method is yet to be proven for practical application. Another report in the literature used EEMD to study high-speed rolling element bearings(2100 rpm) with seeded faults(19) albeit the artificial damage is not representative of real conditions. In this paper, slewing bearing data without artificial defects are used. EEMD, which is an improved method of empirical mode decomposition(EMD), is employed to support and clarify the results of the fast Fourier transform(FFT). Moreover, two bearing frequencies, BSF and BPFO, that do not appear in the FFT are identified using EEMD.

2. EMD and EEMD

EMD was first introduced by Huang et al.(11). EMD has been demonstrated to be adaptable in a wide variety of applications for extracting signals from data generated in noisy nonlinear and non-stationary processes(see, for example, Huang and Shen(12) and Huang and Attoh-Okine(13)). In the rolling element bearing case, the rolling elements contact each other and generate different mode oscillations, which synchronize simultaneously. The main purpose of EMD is to decompose these signals into intrinsic mode functions(IMFs), some of which are bearing fault signals. The EMD method decomposes the bearing signal $x(t)$ into IMFs, c_j, by

$$x(t) = \sum_{j=1}^{n} c_j + r_n \tag{1}$$

where n is the number of IMFs, c_j represents the IMFs, and r_n the final residue of data. IMFs are defined as oscillatory functions with varying amplitude and frequency. The frequencies of the IMFs range from high to low. According to Ref. (11), an IMF is a function that satisfies the two following conditions:

(1) Throughout the length of a single IMF, the number of extrema and the number of times the function crosses zero must either be equal or differ by one at most.

(2) At any data location, the mean value of the envelope is defined by the local maxima and the envelope defined by the local minima is zero.

The process of decomposing a signal into IMFs is called the sifting process.

One of the main demerits of the original EMD is the problems with modes mixing. Mode-mixing is defined as a single IMF either consisting of a signal with widely disparate scales or a similar signal that resides in different IMF components(14). The mode-mixing problem is associated with signal intermittency. Moreover, the intermittency could cause aliasing in time-frequency distributions, making the individual IMF lack physical meaning. To prove the existence of intermittency, Huang et al.(15) conducted an intermittence test. They found that the intermittency can be avoided by subjectively selecting appropriate scales. With this subjective intervention, the EMD ceases to be fully adaptive. Thus, to overcome the scale separation issue without the interference of a subjective intermittent test, Wu and Huang(16) proposed a noise-assisted data analysis (NADA) method, namely, EEMD.

In practice, the low-speed slewing bearing signal has a low signal-to-noise ratio(SNR). This is due to the impact energy between the rolling element and the defect spots, which is generally weak. This weak vibration signal is buried in noise and difficult to identify. Hence, EEMD, which can be used to cancel out this noise and extract the bearing signal, is employed in this study. The term "ensemble" in EEMD refers to the repeated trial of added noise with a finite amplitude into the original time series signal. The true IMF results are computed from each trial by taking the mean value of the corresponding IMFs. The basic principle of cancelling out the noise from the bearing signal $x(t)$ is as follows. The added white noise distributes uniformly to the time-scale or time-frequency space with the constituent components of different scales. The added noise in this case works as a uniform reference frame in the time-frequency space. When the bearing signal is added to this uniform reference frame, the bits of the bearing signals of different scales are automatically projected onto proper scales of reference. Certainly, each individual trial, which consists of the signal and the added white noise for its decompositions, may produce noisy results. Because the noise is different for separate trials, it is cancelled out in the ensemble mean of a large enough number of trials. In other words, the only persistent part that survives in the averaging process is the signal, which is then treated as the true result(17). The principle of EEMD is described in Ref. (16) as follows.

(1) A collection of white noises cancels out in an ensemble mean; therefore, only the signal can survive and persist in the final noise-added signal ensemble mean.

(2) White noise is necessary to force the ensemble to find all possible solutions; the white noise makes the different scale signals reside in the corresponding IMFs and renders the resulting ensemble mean more meaningful.

(3) The decomposition with a truly physical meaning of EMD is not without noise; it is designated to be the ensemble mean of a large number of trials including the noise-added signal.

According to Wu et al.(16) and based on the principle of EEMD above, the EEMD decomposition algorithm of the original signal $x(t)$ can be summarized in the following steps:

(1) Add the white noise series to the bearing signal. Note that the number of data points of added noise is equal to the bearing signal.

(2) Decompose the amalgamation data(the bearing signal plus the white noise) into IMFs until the smallest frequency is reached. This individual decomposition is obtained by using the original EMD method.

(3) Repeat step 1 and step 2 continuously with a different white noise series.

(4) Obtain the(ensemble) means of the corresponding IMFs of the decomposition as the final result.

The above steps are illustrated in Fig. 1 and Appendix A.

To apply EEMD, two parameters should be determined: (1) the number of ensembles notated by E and (2) the amplitude ratio between the added noise and the bearing signal, which is denoted as α.

2.1 Number of ensembles

The relationship among the ensemble number, the amplitude of the added noise, and the effect of the added noise can be represented by the following equation, which
has been derived by Wu and Huang[17] :

$$\varepsilon = \frac{a}{\sqrt{N}} \tag{2a}$$

or

$$\ln \varepsilon + \frac{a}{2} \ln N = 0 \tag{2b}$$

where N is the ensemble number, a is the amplitude of the added white noise, and ε is the standard deviation of the error, which is defined as the difference between the input signal and the corresponding IMFs. Eqs. (2a) and (2b) imply that a small error can be achieved by decreasing the added noise amplitude or by increasing the ensemble number. In an exceptional case, i.e., when the signal to be analyzed has a large gradient, if the error is small, it may cause a change of extrema for each IMF.

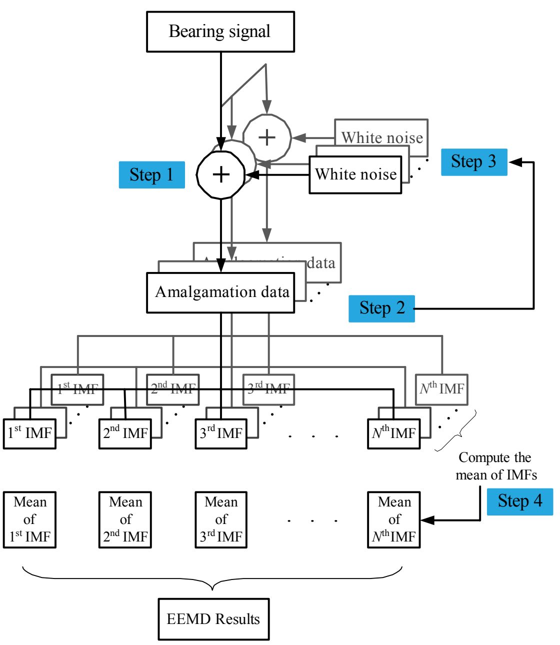


Fig. 1 Illustrations of the EEMD method

2.2 Amplitude ratio

In order to demonstrate how to select the amplitude ratio and study the effect of the amplitude ratio on the decomposition results, Wu and Huang[16] used different amplitude ratios that were 0.1, 0.2, and 0.4 in standard deviation from the investigated signals. The ensemble number for each case was 100. The results showed that the synchronization between cases of different added-noise levels is remarkably good, except for the case wherein no noise was added.

More decomposition of two different data sets was also conducted. The results reveal that increasing noise amplitudes or ensemble numbers insignificantly alters the decomposition if the added noise has moderate amplitude and the ensemble number is large enough. Wu and Huang[16] suggested that for most cases the amplitude of added noise is approximately 0.2 standard deviations from the data.

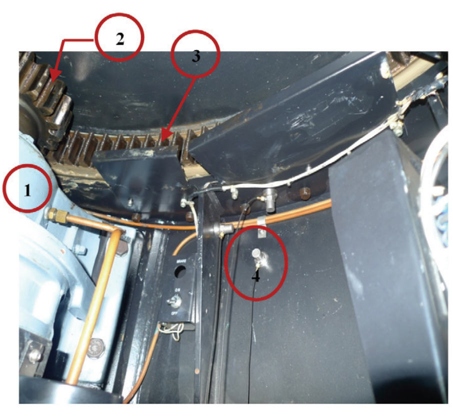
The selected ensemble number and the amplitude of added noise, as discussed in Ref. (16), is not always the proper value. Generally, when the signal is dominated by high-frequency components, the noise amplitude should decrease or the ensemble number should increase. On the contrary, when the signal is dominated by low-frequency components, the noise amplitude should increase or the ensemble number should decrease[18]. However, there is no basic guideline or a specified equation reported in the literature to select the noise amplitude or ensemble number yet. Thus, different noise levels and ensemble numbers should be tried for an investigated signal in order to select the appropriate one. This is the “uniqueness” of the EEMD method.

3. Data Acquistion and Results

The vibration data used in this paper is acquired from an industrial company in Korea. The Wilcox accelerometer used during the data acquisition has a sensitivity of 100 mV/g. This sensor is installed on the radial direction of the slewing bearings, as shown in Fig. 2. The slewing bearing is a single-row Koyo from Japan with an inner and outer diameter of 1093 mm and 1107 mm, respectively. The bearing runs continuously in one direction at a rotational speed of 15 rpm. The 15 rpm is obtained from a gear reducer mechanism. The driving motor rotational speed is 1800 rpm, and the gear ratio is 17:1. The output shaft speed of the driving motor is 106 rpm. The gear motor has 18 gear teeth, and the slewing bearing has 123 gear teeth. Therefore, the slewing bearing speed is also 15 rpm. This bearing has been used for seven years. The maintenance engineer of the bearing company says that it must be changed after six years use. Therefore, these data are treated as bearing damage data, supposedly including outer or inner race faults or ball faults. If there is a fault in the outer race, inner race, or even in the rolling element, the bearing fault frequencies should be appear in the FFT. The bearing frequencies were calculated and are presented in Table 1, where the gear mesh frequency is denoted by GMF.

Table 1 Bearing frequencies

FTF	0.24 Hz	GMF	30 Hz
BSF	5.16 Hz	2x GMF	60 Hz
BPFO	11.31 Hz	3x GMF	90 Hz
BPFI	11.87 Hz	Bearing speed	0.24 Hz



(1) Driving motor (2) Motor gear
(3) Slewing bearing gear (4) Sensor placement(radial)

Fig. 2 Slewing bearing and sensor placements

Four data sets were acquired on May 26, 2010; December 7, 2010; July 19, 2011; and November 1, 2011. These data are acquired within 1.6 s with a sampling frequency *fs* of 20480 Hz. Thus, they contain a discrete signal with a length *N* of 32768. Simple arithmetic is used to calculate the frequency resolution by

$$\begin{aligned} Frequency\ resolution &= \left(\frac{1}{N}\right) * fs \\ &= \frac{1}{32768} * 20480 = 0.625\,Hz \end{aligned} \quad (3)$$

According to the frequency resolution, the bearing fault frequencies should be able to be identified, except the FTF frequency(0.24 Hz),which is lower than 0.625 Hz. The four different data sets from the years 2010 and 2011 are selected subjectively to study the degradation conditions of the bearing. In the 2011 data, the bearing has been running for seven years. The FFTs of the four data sets are presented in Fig. 3. According to Fig. 3(a), the GMF is approximately 30 Hz, and the GMF harmonics appear and are valued as follows: 2x GMF is 60 Hz, 3x GMF is 90 Hz, and 4x GMF is 120 Hz. Enlarging the amplitude scale(y-axis) from 0.01 g to 0.006 g enables this to be seen more clearly. A comparison of Fig. 3(a) and 3(d) shows that the GMF and the GMF harmonics amplitudes on May 26, 2010 and November 1, 2011 are different. The amplitude of the 1x GMF on November 1, 2011 is smaller than on May 26^{th} 2011 the amplitude of the 1x

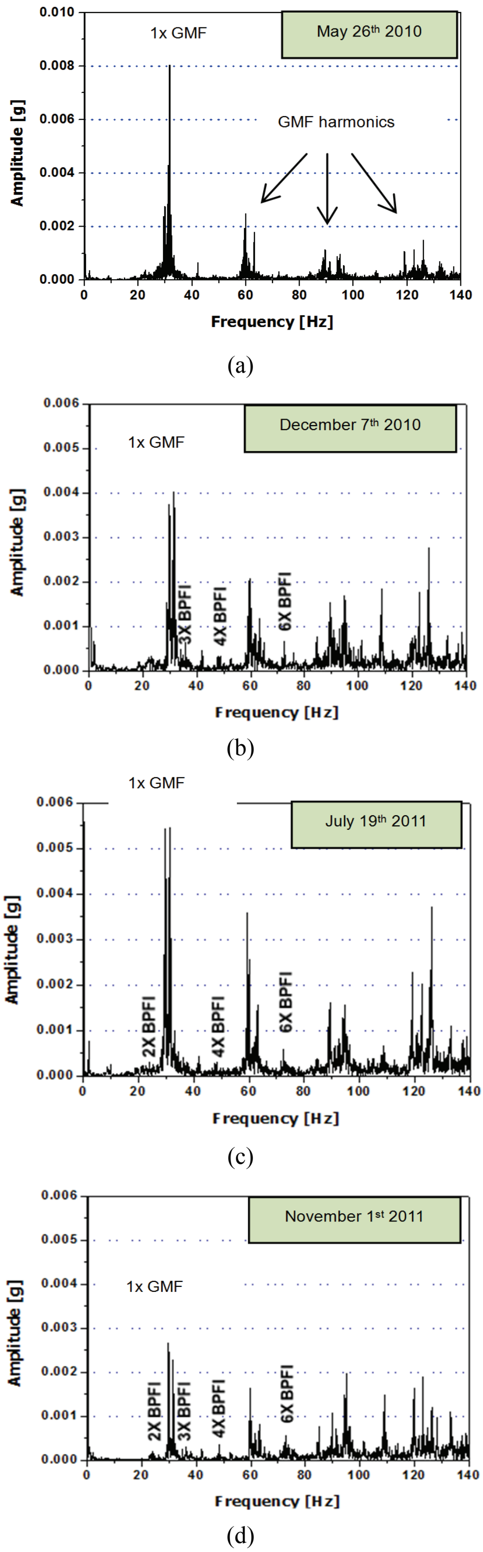


Fig. 3 FFT of four data samples

GMF and other GMF harmonics on November 1, 2011 is relatively flat. This indicates that the GMF is no longer dominant when the bearing is close to failure.

In Fig. 3(a), the frequencies are dominated by the GMF and its harmonics; from Fig. 3(b) to 3(d) only BPFI and its harmonics are identified, among three fault frequencies. Even though the BPFI frequency and its harmonics appeared, the amplitude is weak, indicating BPFI is not a dominant frequency even when the bearing is close to failure. Based on the result in Fig. 3, the bearing condition is assumed to be in a normal condition. Moreover, this FFT information renders maintenance engineers unsuccessful in determining the maintenance schedule. Hence, another signal analysis technique is needed to support the FFT results.

The November 1, 2011 data are subject to the EEMD method to reveal the information related to the fault frequencies. As explained in chapter 2, there is no basic guideline or specified equation reported in the literature to select the noise amplitude or ensemble number yet. Thus, different noise levels and ensemble numbers should be evaluated for an investigated signal in order to select the appropriate one. First, we use the added noise amplitudes of 0.1, 0.2, and 0.4 of the bearing signal. The ensemble number for each case is 100. The results(not shown here) did not produce any fault frequencies. More decomposition was then carried out, with an increase in the ensemble number to 500. The result(also not shown here) is the same as the result for the ensemble number of 100. Finally, with an ensemble number 1000, one fault frequency(BSF) of 5.178 Hz appears, as shown in Fig. 4(result 12). In this case, the BSF is identified when the added-noise amplitude is 0.2 of the bearing signal. Two frequencies close to 1x GMF and 2x GMF also appear in Fig. 4 (result 8 and 9, respectively). Naturally, the low-frequency signal will be modulated by the high-frequency signal. Hence, the reconstruction of signals can be accomplished by adding several EEMD decomposition results. In this case, we assumed that the BPFI frequency is modulated by a GMF frequency and another neighboring frequency. The reconstructed signal is the addition of signals of results 7 to 10(see Fig. 4), where results 8 and 9 are the GMF frequencies. The original EMD is used to decompose the reconstructed signal and the result is shown in Fig. 5. Figure 5 reveals a frequency of 11.25 Hz, which approximates BPFO. This frequency appears in result 7 using the EEMD method. The reconstruction results allow different amplitudes of added noise to be tested. Next, identical work using EEMD is conducted with α=0.4 and the same ensemble number of 1000. Calculating the decomposition of the reconstruction signal(results 6~9), the frequency close to BPFI emerges in result 7, as shown in Fig. 6.

There is no scientific rule reported on how to determine the ratio of the noise amplitude to the ensemble number. Thus, this study provides a comparison of these parameters with respect to the nearest value error. In general, the nearest-value error is calculated based on the root-mean-square error between the bearing fault frequencies (including its harmonic frequencies) and the selected EEMD results. The results are shown in Fig. 7.

First, the EEMD results are sorted. The selected EEMD results refer to any values between a pre-

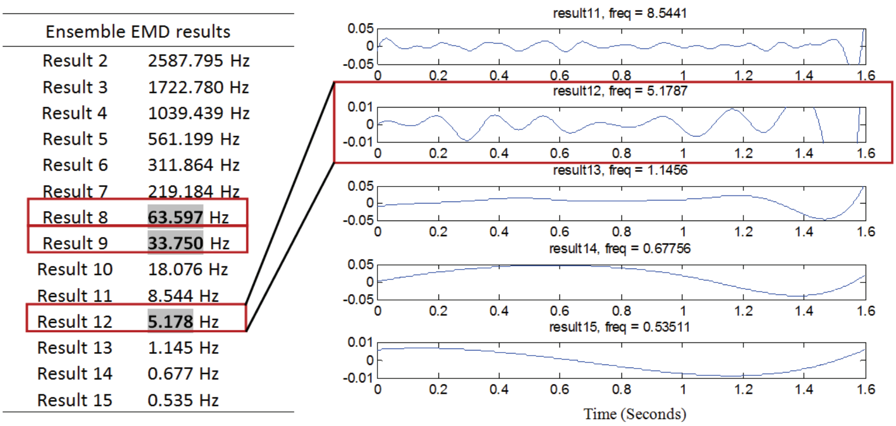


Fig. 4 EEMD results(α=0.2, E=1000)

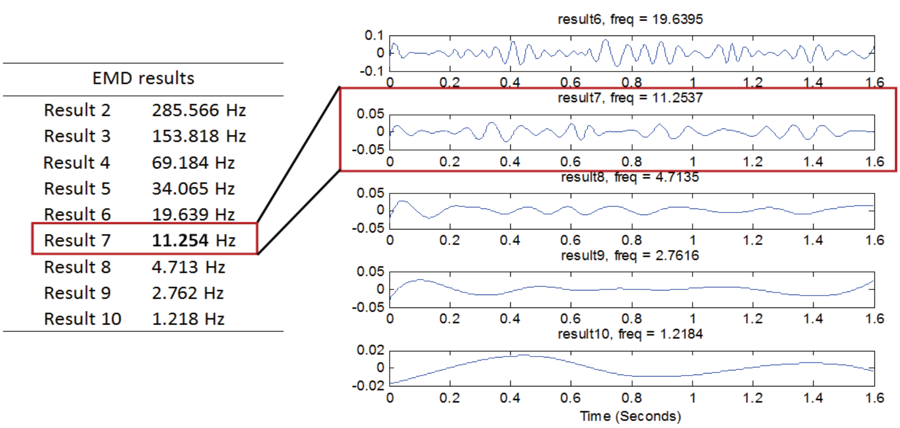


Fig. 5 EEMD of reconstruction signal(α=0.2, E=1000)

EMD results	
Result 2	325.579 Hz
Result 3	177.311 Hz
Result 4	84.272 Hz
Result 5	39.353 Hz
Result 6	22.839 Hz
Result 7	**11.641 Hz**
Result 8	6.874 Hz
Result 9	3.725 Hz
Result 10	2.448 Hz
Result 11	1.192 Hz
Result 12	0.600 Hz

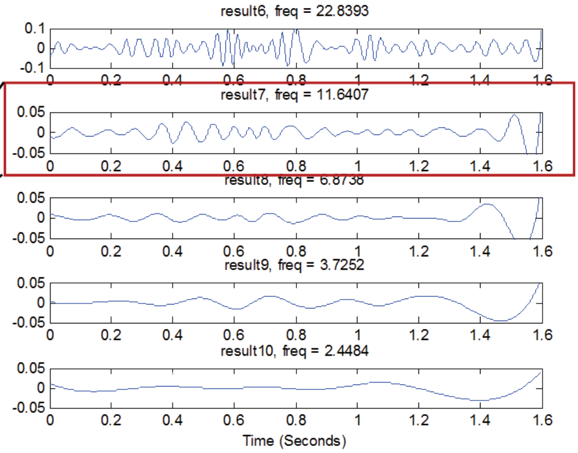


Fig. 6 EEMD of reconstruction signal(α=0.4, E=1000)

defined range. The predefined range for each fault frequency is given as follows:

$$\begin{aligned}
&\text{BSF}:\\
&(1xBSF-5\%*BSF)\le\boldsymbol{\lambda}\le(6xBSF+5\%*BSF)\\
&\text{BPFO}:\\
&(1xBPFO-5\%*BPFO)\le\boldsymbol{\lambda}\le(6xBPFO+5\%*BPFO)\\
&\text{BPFI}:\\
&(1xBPFI-5\%*BPFI)\le\boldsymbol{\lambda}\le(6xBPFI+5\%*BPFI)
\end{aligned} \tag{4}$$

where, $\boldsymbol{\lambda}=(\lambda_1,\lambda_2,\dots,\lambda_n)$ is the vector of the selected EEMD results, n is the data length, and 5 % is obtained based on 100 % being the confidence interval of 95 %.

Second, the ratio of n and the selected fault frequencies below the value of λ_i are defined as

$$f_i=\frac{n}{\begin{pmatrix}1x\sigma\\2x\sigma\\3x\sigma\\4x\sigma\\5x\sigma\\6x\sigma\end{pmatrix}\le\lambda_i} \tag{5}$$

where i is a real number in the range 1, 2, ⋯, n and σ denotes the fault frequency mode(BSF, BPFO, and BPFI). This process continues until n, the data length, is achieved and is saved as a vector f.

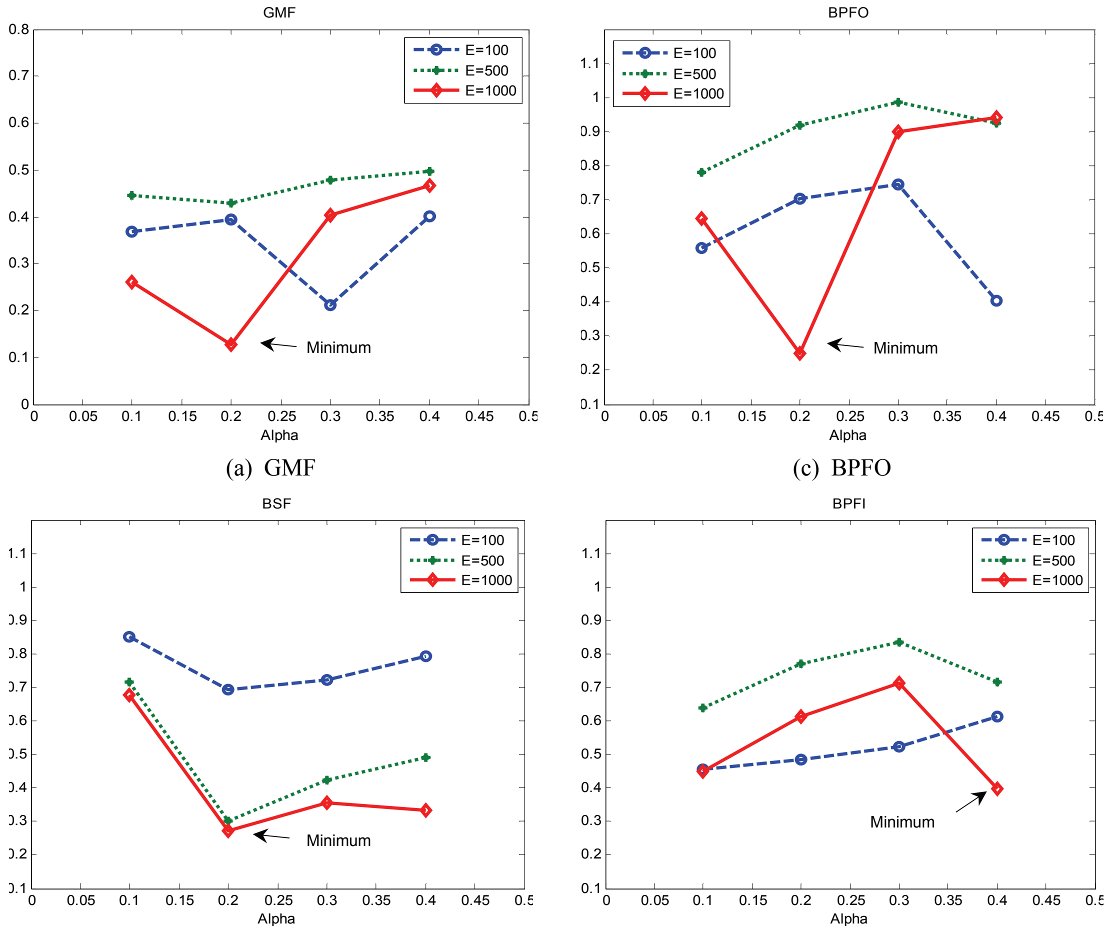
Third, the ratio between the selected EEMD results, λ_i, and the selected fault frequencies below the value of λ_i are calculated as

$$g_i=\frac{\lambda_i}{\begin{pmatrix}1x\sigma\\2x\sigma\\3x\sigma\\4x\sigma\\5x\sigma\\6x\sigma\end{pmatrix}\le\lambda_i} \tag{6}$$

This process continues until n data points are reached and is then saved as a vector, g.

Fourth, the root-mean-square error of vectors f and g are the nearest-value errors and are plotted in Fig. 7. Finally, the above algorithm is applied for different amplitude ratios: 0.1, 0.2, 0.3, and 0.4.

Figure 7(a~d) depicts the results of different amplitude ratios and ensemble numbers for three different fault frequencies(BSF, BPFO, and BPFI) and the GMF. Based on the results from Fig. 7, the proper amplitude ratio and ensemble are selected for this study. According to Fig. 7(a), the minimum nearest value error is achieved when the amplitude ratio is 0.2 and the ensemble number is



(a) GMF (c) BPFO

(b) BSF (d) BPFI

Fig. 7 Effect of added noise ratio on nearest value error for different ensemble numbers

1000. This indicates that using an amplitude ratio of 0.2 and an ensemble number of 1000 approximately identifies the GMF and its harmonics. Fig. 7(b) shows similar results as Fig. 7(a), where the minimum nearest value error occurs when the amplitude ratio is 0.2 and the ensemble number is 1000. These two results support the result in Fig. 4, where the 1x GMF, 2x GMF, and 1x BSF are identified closely using the EEMD method with an amplitude ratio of 0.2 and an ensemble number of 1000. For BPFI, the minimum nearest value error is obtained when the amplitude ratio is 0.4 and the ensemble number is 1000.

Other slewing bearing data with a frequency resolution of 0.31 Hz are utilized. This data is acquired with a sampling frequency of 640 Hz within 3.2s. Thus, the total number of data points produced was 2048 samples. Eq. (3) was used to calculate the frequency resolution to be 0.31 Hz. The FFT is shown in Fig. 8(a); the FFT is plotted every 25 Hz to better resolve the BPFO and BPFI harmonics, as shown in Fig. 8(b~d). The detailed values of the BPFO and BPFI harmonics are presented in Table 2.

Using a frequency resolution of 0.31 Hz, which is lower than the difference between BPFO and BPFI(0.56 Hz), we normally can identify both BPFO and BPFI. Unfortunately, this is not possi-

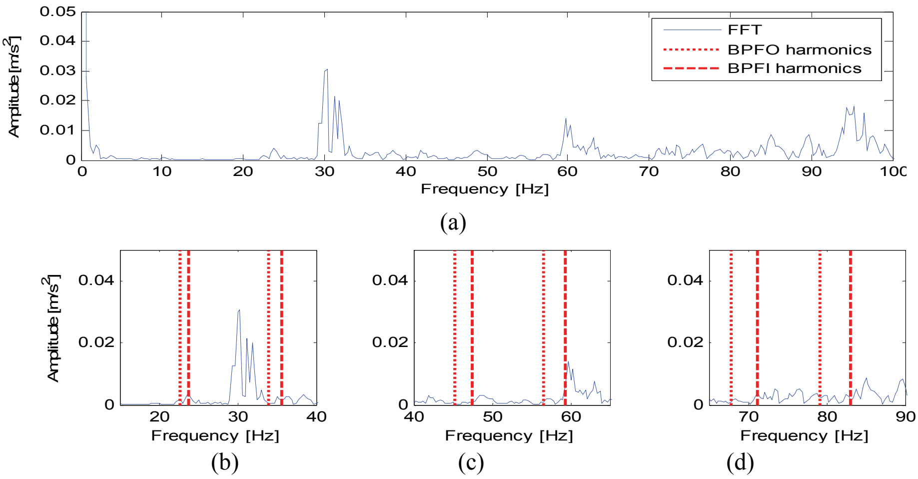


Fig. 8 FFT of vibration data(with a frequency resolution of 0.31 Hz) and BPFO and BPFI harmonics(see Table 2)

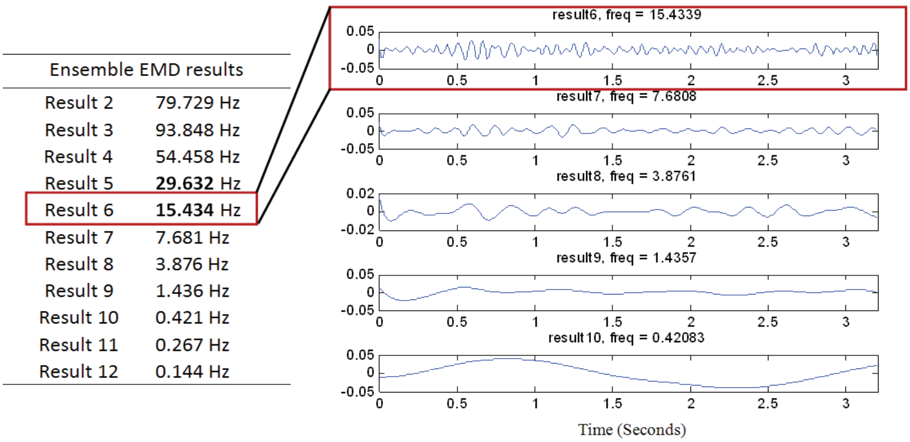


Fig. 9 EEMD results of vibration data with a frequency resolution of 0.31 Hz(α=0.2, E=1000)

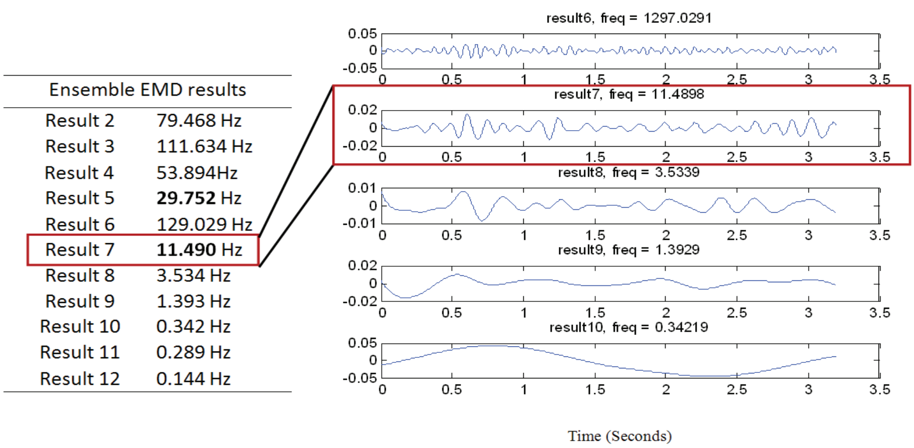


Fig. 10 EEMD results of vibration data with a frequency resolution of 0.31 Hz(α=0.4, E= 1000)

ble for the slewing bearing case. Low-rotational speeds produce weak signals; therefore, the fault frequency is difficult to identify using FFT, as shown in Fig. 8 and Table 2. BPFI still can be identified, although with a low amplitude. This result is similar to the data with the 0.625 Hz frequency resolution, where the only fault frequency that can be detected is BPFI, as presented in Fig. 3. In this particular case, EEMD is necessary to support the FFT results. This data is then analyzed using the EEMD method with an identical ensemble number of 1000 and an amplitude ratio of α=0.2. The result is shown in Fig. 9. Figure 9 shows that the 1x GMF appears in result 5 and the frequency of 15.43 Hz, which is close to the 3x BSF frequency, also appears in result 6. Another EEMD result is shown in Figure 10 with an ensemble number of 1000 and an amplitude ratio of α=0.4. The 1x GMF frequency is still identified in result 5, and the frequency near BPFI is appears in result 7.

4. Conclusion

In cases when FFT requires another method to support its result in identifying fault frequencies, EEMD, a relatively new and improved method, has potential. This paper has discussed the use of EEMD and EMD for analyzing real slewing ring bearings with natural damage. The selection of the amplitude ratio and the ensemble number is empirical. Different data may have different proper amplitude ratios and ensemble numbers. These two parameters are selected subjectively based on the suggestions of Wu and Huang(16). In particular cases, the desired frequency is still concealed in individual IMFs. Therefore, this paper used a reconstruction technique to extract more bearing fault signals from the EEMD results.

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Appendix A: EEMD Algorithm

Ensemble empirical mode decomposition

for $i = 1,...,E$ do

White noise

$n(t)^{(i)} = w(t)^{(i)}\ \alpha$, $i = 1,...,E$

Add white noise to the original data (step1)

$y(t)^{(i)} = x(t)^{(i)}\ n(t)^{(i)}$, $i = 1,...,E$

for $j = 1,...,d$ do

Decompose $y(t)^{(i)}$ using EMD into IMFs (step2)

Result $imf_{(i)}^{(d)}$, $i = 1,...,E$

end for

Repeat step1 and step2 for $i = 2,...,E$ (step 3)

$$\mathbf{IMF} = imf_{(i)}^{(d)} + imf_{(i+1)}^{(d)} + ... + imf_{(E)}^{(d)}$$

end for

Obtain the ensemble means (step4)

$result = mean\,(\mathbf{IMF})$

E is the ensemble number; t, the data length of the original signal $x(t)$; α, the ratio of the standard deviation of white noise, $w(t)$, to the original signal $x(t)$; and d, the number of decompositions or IMFs. d can be calculated by $d = \log 2(t) - 1$.

ByeongKeun Choi is an Associate Professor at the Department of Energy Mechanical Engineering at Gyeongsang National University in Korea. He received his Ph.D. in Mechanical Engineering from Pukyong National University, Korea, in 1999. Dr. Choi worked at Arizona State University as an Academic Professional from 1999 to 2002. Dr. Choi's research interests include vibration analysis and optimum design of rotating machinery, machine diagnosis, and prognosis and acoustic emission. He is listed in Who's Who in the World, among others.

Wahyu Caesarendra is a lecturer in the mechanical engineering department of Diponegoro University, Semarang, Indonesia since 2007. He received his B.Eng degree in mechanical engineering from Diponegoro University in 2005 and his M.Eng degree in Mechanical Design Engineering from Pukyong National University, Busan, South Korea in 2010, with his research interest in machine condition monitoring and fault diagnosis and prognosis. Currently, he is the recipient of the University Postgraduate Award(UPA) and International Postgraduate Tuition Award(IPTA) from the University of Wollongong, Wollongong, NSW, Australia, for doing his Ph.D. at the School of Mechanical, Materials and Mechatronic Engineering. His Ph.D. topic is Condition Monitoring and Prognosis of Large Slow-Speed Reversible Slewing Bearing with Online Monitoring System.

Jin Hee Park received his B.Eng in Automotive Engineering from Pukyong National University, Busan, South Korea. Currently, he is pursuing his M.Eng in the same department and university. His research focuses on machine condition monitoring and fault diagnosis.

Dr Buyung Kosasih received his Ph.D. in 1993 from the University of Wollongong in Mechanical Engineering in Tribology of Fluid Film Bearing. He is currently Senior Lecturer at the Faculty of Engineering, University of Wollongong, Australia. He actively carries out research in several areas including wind- and hydro-current-based renewable energy generation devices, tribology of aqueous lubricant for sustainable metal forming, and condition monitoring of slew bearing.