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PULSATION SIGNALS ANALYSIS OF TURBOCHARGER TURBINE BLADES BASED ON OPTIMAL EEMD AND TEO

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ABSTRACT

Turbocharger turbine blades suffer from periodic vibration and flow induced excitation. The blade vibration signal is a typical non-stationary and sometimes nonlinear signal that is often encountered in turbomachinery research and development. An example of such signal is the pulsating pressure and strain signals measured during engine ramp to find the maximum resonance strain or during engine transient mode in applications. As the pulsation signals can come from different disturbance sources, detecting the weak useful signals under a noise background can be difficult. For this type of signals, a novel method based on optimal parameters of Ensemble Empirical Mode Decomposition (EEMD) and Teager Energy Operator (TEO) is proposed. First, an optimization method was designed for adaptive determining appropriate EEMD parameters for the measured vibration signal, so that the significant feature components can be extracted from the pulsating signals. Then Correlation Kurtosis (CK) is employed to select the sensitive Intrinsic Mode Functions (IMFs). In the end, TEO algorithm is applied to the selected sensitive IMF to identify the characteristic frequencies. A case of measured sound signal and strain signal from a turbocharger turbine blade was studied to demonstrate the capabilities of the proposed method.

Keywords: urbocharger turbine blades, pulsation signals analysis, ensemble empirical mode decomposition, Teager energy operator, correlation kurtosis

INTRODUCTION

As one of the critical systems of marine diesel engine, turbocharger plays an important role in ensuring the power for ship's propulsion provided sustainably and stably by diesel engine , and reducing the impact of exhaust gas emission on the environment. Turbine blades are an important component of the turbocharger, which suffer from periodic vibration and flow induced excitation. Knowing the amplitude of blade vibration is critical to the safe operation of turbochargers, and for this purpose, strain gauge and sound signals may be employed. These signals are often non-stationary and sometimes nonlinear. One such example is the pulsating sound and strain signals measured during engine ramp mode to find the maximum resonance of turbine blades or during engine transient mode. Because the signal frequency is proportional to engine speed it changes when the speed varies. Traditionally, such signals are analyzed by using Fast Fourier Transformation (FFT) [1]. The Fourier Transformation (FT) is a weighted sum of any signal decomposed into sinusoidal signals each of which corresponds to a fixed frequency. It simply treats the signal as an integral over time. Therefore, it is very effective in analyzing stationary signals which do not change with time. But for non-stationary signals which vary with time, FT is powerless. To overcome this weakness, Yeung used a piecewise FFT to process the compressor pressure pulsation signal. It could accurately detect the precursor signal of compressor instability in the experiment. Although the piecewise FFT was effective for the instability induced by the slowly developed modal wave, it had a limited effect on the instability caused by the sharp spike pulse [2]. Short Time Fourier Transform (STFT) is a FT with a window that can be varied to improve the treatment to non-stationary signals. However, once the window function is selected the size and shape of the time frequency window are fixed, and the time resolution and frequency resolution of Heisenberg function cannot be optimized at the same time [3]. Wavelets transform (WT) can transform the signal through the scalable and translational wavelets to achieve the localization of time-frequency analysis [4]. However, the WT requires to select an appropriate basis function, and its basis function is fixed and cannot change with the signal. The limited length of the wavelet basis function will also cause the leakage of the signal energy. The WT is essentially a FT with an adjustable window, and the signal in its wavelet window must be stationary, so that it does not get rid of the limitation of Fourier analysis.

Empirical Mode Decomposition (EMD) has been intensively investigated and applied to signal processing. It no longer treats the basis of a signal as sinusoidal, but a function called the intrinsic mode function (IMF) [5]. The amplitude and frequency of IMF can be time-varying, and they are called the instantaneous amplitude and instantaneous frequency, respectively. Unlike the WT which requires to preselect the base function, in the EMD process its base function comes directly from the signal itself, and different signals will produce different basis functions, making EMD potentially superior to the Fourier and wavelet transforms. EMD has been widely applied to nonlinear and non-stationary signal analysis. Its capability to analyze such data has been utilized in various applications. However, the mode mixing is one of the major shortcomings of EMD, and it not only leads to serious abasing in the time-frequency distribution but also makes the physical meaning of individual IMF ambiguous.

To eliminate the defects of EMD, the Ensemble Empirical Mode Decomposition (EEMD) is proposed, which is a noise-assisted data analysis method by adding white noise to the investigated signal [6]. However, in the EEMD process, how to choose suitable amplitude of the added noise and the ensemble number have remained a topic. Wu and Huang described the effect of the added white noise and determined these two parameters by experience [6]. Zhang introduced the principle of adding noise based on the energy ratio of the added white noise and the original signal，but his method considered only the signals composed of two components, and did not study the signal with multiple mode components [7]. Chen proposed an improved method of determining these two parameters in the EEMD process. Due to the influence of noise and modal aliasing, the first IMF cannot represent accurately the high frequency information of the investigated signal [8]. The signal-to-noise ratio (SNR) was introduced by Chang [9]. Yeh presented a novel noise-enhanced data analysis method to determine these two parameters [10]. Wang proposed the criterion of the energy standard difference for adding white noise into the EEMD [11]. However, the premise of proper use of the method is to know beforehand the information of each component contained in the processed signal. This limits the application of the method to actual signals. Lei uses coloured noise instead of Gauss white noise, which effectively improves the distribution of extreme points, but the research does not establish the criterion of adding noise [12]. Niazy [13] uses the relative root- mean-square error criterion to determine the performance of EEMD, but it does not give a method to select the appropriate noise amplitude. Kong used the distribution of signal extreme points as an evaluation index to determine the optimal amplitude of Gaussian white noise through an ergodic process. However, the noise interval selection in this method still requires to be artificially set, and the pre-treatment time is longer [14]. Therefore, if these two parameters, the amplitude of the added noise and the ensemble number in the EEMD process, can be obtained adaptively according to the actual signals, it will be of a great significance for improving the performance of EEMD.

The pressure pulsations measured on a turbocharger turbine can come from different sources. Detecting the weak useful signal under noise background may become difficult if signal processing error interferes. These authors had encountered such difficulty in their work when processing the strain gauge and sound signals of a turbocharger turbine. This prompted them to search for a possible explanation and a solution to the problem. This paper reports the results of the investigation.

The paper describes a signal processing problem in a small turbocharger turbine and gives an introduction to the theory and algorithms for data processing of pulsation signals from the turbine based on optimal EEMD and TEO. The results of sound and strain signals analysis of the turbine are presented in the following sections of this paper.

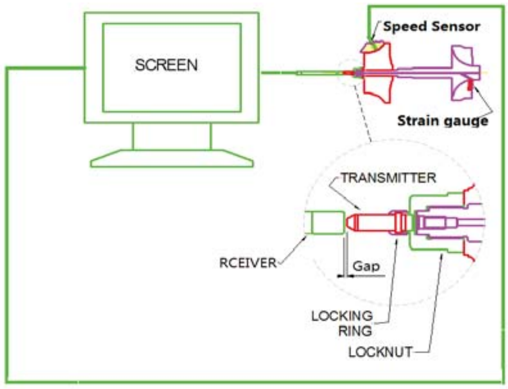
A SIGNAL PROCESSING PROBLEM

The involved turbine is a small turbocharger turbine of Cummins Turbo Technologies for small diesel engine application. In evaluating turbine's high cycle fatigue (HCF) life, some of the turbine blades were strain gauged to measure the blade deformation during turbine operation [15]. Cummins Turbo Technologies has multi-year experience in measuring vibratory blade strain by using strain gauge and has established a good correlation between measured strains and HCF life of their turbine wheels. Fig. 1(a) shows a strain gauged turbine wheel. Due to the small size of the turbine, only one blade was strain gauged. As currently before testing all the blades there is no simple way to determine which blade has the largest vibratory strain due to mistuning effect [16], multiple tests are necessary. But this type of test is time consuming and costly, therefore Cummins Turbo Technologies and Dalian Maritime University are working together to find solutions to reduce experiment time and cost, including a possible use of the sound signature of turbines in operation. For this reason, a microphone was placed a half meter away from turbine exhaust manifold. Fig.1(b) and (c) show such arrangement. The turbocharger was installed in a gas stand test cell. A burner which can generate inlet gas temperature up to 760°c to drive the turbine wheel, is connected to the turbine housing inlet by using long pipes. A valve controller on the burner is used to control fuel and air flow to achieve the required conditions of steady state turbine inlet pressure and temperature. A blade pass speed sensor is installed into the compressor cover to count impeller blade passing pulses to calculate turbocharger speed during operation.

The exducer flap mode of the turbine blades is the concern, and the natural frequency of this mode of the strain gauged blade was measured to be 12,670Hz at stationary and room temperature condition. The turbocharger was run on an engine, and its rotational speed was ramped up and down constantly so that this mode could be excited. Fig. 2(a), (b) and (c) give an example of recorded signals of turbine speed, blade strain and sound, respectively, and signals in Fig. 2(b) and (c) are normalized. These data were taken at a sampling rate of 102.4 KHz. The data in Fig. 2 were analysed, and the results are shown in Fig. 3 and 4 for the measured blade strain and sound, respectively. Fig. 3 gives the power spectrum of the blade strain, based on FFT analysis. The largest peak occurs at the frequency of 13,650Hz.

Turbine blade with strain gauge

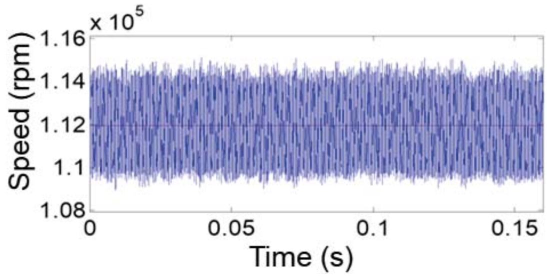
Photo of test rig



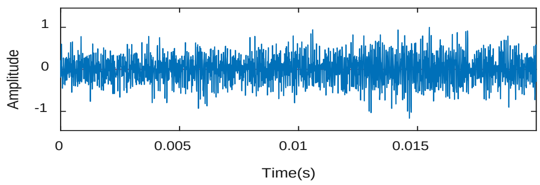
Strain gauge and microphone measuring system

Fig. 1. Strain gauge and microphone for blade strain and turbine sound measurements

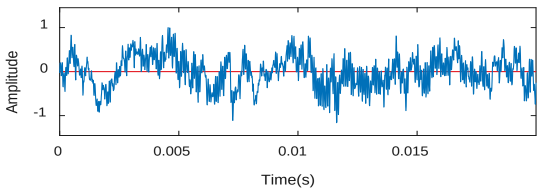
This is an unexpected result: the natural frequency of the first blade mode is 12,670Hz for the blade at room temperature and stationary condition, however one expects that the maximum strain should appear near or at this frequency, due to the combining effects of centrifugal stiffening and Young's modulus reduction of turbine blade material at the hot running condition. The engine frequency order in this case is seven, so the excitation force is relatively small, and small blade strain is expected. But the occurrence of the peak strain at 13,650Hz is puzzling and needs an explanation.



Turbine speed signal



Blade strain signal from the strain gauge



(c) Sound signal from the microphone

Fig. 2. Turbine speed, blade strain and sound signals measured on an engine

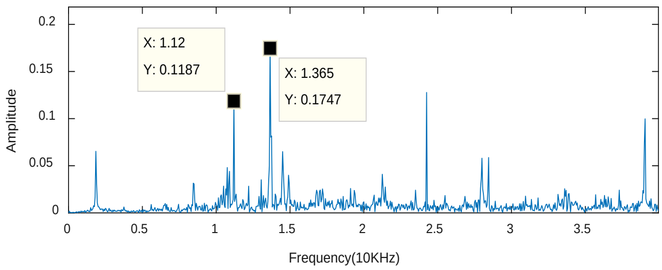


Fig. 3. Power spectrum of the blade strain based on the data in Fig. 2(b) processed by FFT analysis

Fig. 4 shows the power spectrum of the sound signal by using FFT. No frequency near 12,000Hz is found with the FFT results of the sound signal either. At this stage one may not blame the signal analysis for the lack because the blade vibratory signal may be too weak to be picked up by an external microphone. The largest peak of the sound power occurs at 13,050Hz, a frequency very close to compressor blade passing frequency (BPF) which, calculated from the speed signal in Fig. 2(a), is 13067Hz (~112,000rpm/60x7, as the compressor has 7 inducer blades).

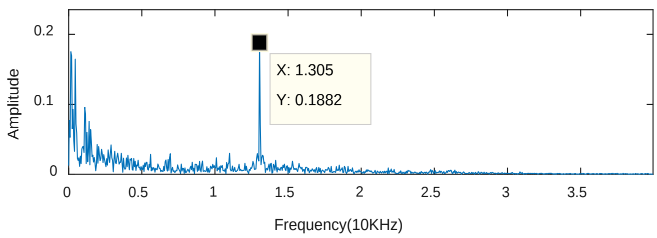


Fig. 4. Power spectrum of the sound signal based on the data in Fig. 2(c) processed by FFT analysis

NEW THEORY AND METHOD

OPTIMAL PARAMETERS OF EEMD
EMD AND EEMD

EMD is based on the local characteristic time scale of signal and can decompose a complicated signal $x(t)$ into a number of IMFs, $c_j(t)$

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

The IMFs, $c_j(t)$, represent the natural, oscillatory mode embedded in the signal and work as the basis functions which are determined by the signal itself, rather than pre-determined kernels. As a self-adaptive signal processing method, EMD has been widely applied to non-linear and non-stationary signal analysis. However, the decomposition results can suffer from mode mixing which is defined as a single IMF either consisting of signals of widely disparate scales, or a signal residing in different IMF components. It not only leads to serious abasing in the time-frequency distribution but also makes the physical meaning of individual IMF ambiguous. To overcome the problem of mode mixing, EEMD is developed, which is a noise-assisted data analysis method by adding white noise to the investigated signal [6]. The EEMD algorithm can be given as follows:

(1) Add a white noise series to the targeted data.

$$X(t) = x(t) + N(t) \quad (2)$$

(2) Decompose the data with added white noise into IMFs.

$$X(t) = \sum_{j=1}^{n} c_j(t) + r_n(t) \quad (3)$$

(3) Repeat step 1 and step 2 again and again, but with different white noise series each time, $i = 1 \sim m$,

$$X_i(t) = x(t) + N_i(t) \quad (4)$$

$$X_i(t) = \sum_{j=1}^{n} c_j(t) + r_n(t) \quad (5)$$

(4) Obtain the means of corresponding IMFs as the final result,

$$c_j(t) = \frac{1}{m}\sum_{i=1}^{m} c_j(t) \quad (6)$$

In the EEMD process, two critical parameters, the amplitude of the added noise and the ensemble number, are to be pre-set. The selection of these two parameters will directly affect the decomposition results of signal.

OPTIMIZATION OF PARAMETERS FOR EEMD

In the EEMD process of noise aided analysis method, there is no strict theoretical basis for the selection of the amplitude of the added noise and the ensemble number. If the selection of the two parameters is inappropriate, the decomposition error will increase, and the decomposition result may become meaningless. Much investigation carried out for determining these two parameters shows that when the amplitude of the added noise is too small it may not introduce enough changes in the local extremum of the decomposed signal and has little or no effect on the change in the local time span of the original signal; if, however, the amplitude of the added noise is too large, the decomposition error will increase and the original signal characteristics may be destroyed. Once the amplitude of the added noise is determined, a larger value of ensemble number, not considering the computational cost, will be helpful for reducing the remaining noise in each IMF. However, continuing increasing the ensemble number not only rises the computational effort, but also results in only a minor change in error. Wu and Huang suggested that the amplitude of the white noise a_N is defined by the amplitude standard deviation SD of the original signal multiplied by a magnitude factor k , k , $a_N = k \times SD$. The ensemble number m can be determined by setting the decomposition error. This method is empirical and non-adaptive. Therefore, it would be useful to adaptively determine these two parameters to improve the decomposition capability of EEMD for different signals. In engineering the measured signals are usually composed of background noise, main signal components and some minor signal components. A set of IMFs is obtained by using EEMD for the signal, wherein the main signal component is the IMF with the largest correlation coefficient with the original signal, which is denoted as $c_{\max}(t)$. In this way, the EEMD decomposition performance of signals under different amplitudes of white noise can be evaluated by evaluating $c_{\max}(t)$. The relative root-mean-square error ($RRMSE$) is introduced to analyze the difference between $c_{\max}(t)$ and original signal. It is expressed as follows:

$$RRMSE = \sqrt{\frac{\sum_{n=1}^{N}(x(t) - c_{\max}(t)^{2}}{\sum_{n=1}^{N}(x(t) - x_m)^2}} \quad (7)$$

where x_m is the mean of the original signal, N is the number of samples in the original signal. If $RRMSE$ is small or close to zero, it indicates that component $c_{\max}(t)$ is infinitely close to the original signal, which contains not only the main component of the original signal, but also some noise or some low correlation signal components. This shows that the difference between the component $c_{\max}(t)$ and the original signal is small, and the decomposition quality of EEMD is not good. In order to get good quality of EEMD, $RRMSE$ should reach the maximum value, so that the selected IMF, $c_{\max}(t)$, contains only the main component of the original signal. This is the desired decomposition result, and the corresponding noise amplitude is the optimal one.

In the proposed adaptive EEMD, the amplitude coefficient of added white noise k is determined as follows:

(1) First, a small value of ensemble number m is set, and a small value of k is chosen as the initial amplitude coefficient for the white noise.

(2) The white noise is added to the original signal for EEMD. The correlation coefficients of each IMF are calculated, and the $c_{\max}(t)$which has the largest correlation with the original signal, is selected.

(3) Then $RRMSE$ between the $c_{\max}(t)$ and the original signal is calculated.

(4) Gradually increase the amplitude coefficient k of white noise, keep the ensemble number value *m* unchanged, repeat steps (2), (3).

(5) Analyze the trends in $RRMSE$ with white noise amplitude coefficient k , when the value of $RRMSE$ is the maximum, the corresponding white noise is the best one that should be added into EEMD.

Once the amplitude of the added noise is determined, the appropriate value of the ensemble number m can be determined. In the EEMD process, too large value of m will lead to a higher computation cost. However, too small value of m will not be able to cancel out the noise remaining in each IMF. Based on the statistical characteristics of white noise using EMD, Wu found that the product of the energy density of the component IMF and its mean period is a constant [17]. Gao proposed a method to test whether the IMFs of a noisy signal contain useful information [18]. Here, the widely used measure, the signal-to-noise ratio (SNR), is introduced to determine the appropriate value of m . The procedure is as follows:

(1) Fix the optimal noise level as described earlier, a smaller value of m is initially chosen as the ensemble number in EEMD.

(2) EEMD is performed and the product of the energy density and the mean period is calculated respectively for the IMFs. The IMFs containing useful information were obtained and the original signal after de-noising is constructed and the SNR value is calculated.

(3) Gradually increase the value of m , repeat steps (2) until the change in the SNR value is relatively small, and the corresponding value is the reasonable ensemble number for EEMD.

TEAGER ENERGY OPERATOR (TEO)

The TEO of the time-varying signal is defined as follows, [19-20]:

$$J[x(t)] = [\dot{x}(t)]^2 + x(t)\ddot{x}(t) \quad (8)$$

where $\dot{x}(t)$ and $\ddot{x}(t)$ are the first and the second order derivatives of the signal x (t) relative to time t, respectively. The output of the TEO tracks the total energy required to produce the signal.

At any given moment, the mechanical energy of the vibration system is the sum of the kinetic energy in the spring and the kinetic energy of the mass block,

$$E = \frac{1}{2}k[x(t)]^2 + \frac{1}{2}m[\dot{x}(t)]^2 = \frac{1}{2}mA^2\omega^2 \quad (9)$$

Applying the TEO defined by Eq. (8) to the harmonic vibration x(t) described by Eq. (9), one obtains:

$$J[x(t)] = J[A\cos(\omega t + \varphi)] = A^2\omega^2 \quad (10)$$

Comparing Eq. (9) with Eq. (10), one can see that the output of the TEO and the instantaneous total energy of the harmonic vibration differ only by a constant m/2, so TEO tracks the total energy required to generate the harmonic vibration.

Traditionally, the signal energy is defined as the square of the amplitude of the signal, representing only kinetic energy or potential energy. Although it may also highlight the transient characteristics of impact type of signals if an impact amplitude is small, the impact component may however be hidden by other components. Because of the high vibration frequency of the transient impact, the TEO method can effectively highlight the transient characteristics of the impact.

The TEO in Eq. (8) is defined for the continuous time signal $x(t)$. For the discrete time signal $x(n)$, the TEO is transformed into a discrete time signal:

$$J[x(n)] = [x(n)]^2 - x(n-1)x(n+1) \quad (11)$$

For the discrete time signal, TEO requires only three sample data at any time to calculate signal energy. Therefore, it has a good time resolution for the instantaneous changes of signals and can detect transient components in a signal. TEO is only suitable for narrowband signals, and complex multi-component signals, the EEMD of optimal parameters can be employed first to decompose the signals into IMFs. Through screening the sensitive components, the selected component can then be analyzed by using the TEO.

CORRELATION KURTOSIS

The Correlation Kurtosis (CK) not only retains the characteristics of kurtosis, but also has the characteristics of correlation functions. It is a parameter that reflects the intensity of periodic pulse signals in faulty signals [21]. When applied to the signal of turbine blades, if there is a disturbance in the pressure distributions introduced by the rotating blade, which is similar to an impact signal with a distinct cycle, the kurtosis is large, while the CK of other impact signals will be very small. Moreover, the larger CK the greater the proportion of the blades' disturbance signal in the pressure pulsation signal. Therefore, CK can be used to extract disturbance signals more effectively, and as the screening index of the sensitive components. The first m IMFs with the maximum correlation kurtosis value are selected as sensitive components. CK is computed as:

$$CK_M(T) = \frac{\sum_{n=1}^{N}\left(\prod_{m=0}^{M} x_{n-mT}\right)^2}{\left(\sum_{n=1}^{N} x_n^2\right)^{M+1}} \quad (12)$$

where x_n is the signal sequence, N is the number of samples in the original signal, T is the cycle of the pulse signal of interest, M is the number of cycles of shift.

Based on the above theories and methods, the procedures of the proposed method are as follows:

(1) The turbine blade signals are decomposed by using EEMD of optimal parameters, the IMFs containing the critical feature information are obtained,

(2) CK is used to screen the sensitive feature components.

(3) TEO is applied to the selected sensitive IMFs and the characteristic frequencies of the measured signal are identified.

APPLICATIONS OF THE PROPOSED METHOD AND RESULTS

SOUND SIGNAL ANALYSIS

The sound signal in Fig. 2(c) was decomposed by using the EEMD, and the first four IMFs of decomposition results are shown in Fig. 5.

The first IMF, $c_1(t)$, contains the impulse characteristic signal, and the marginal spectrum of $c_1(t)$ is shown in Fig. 6. Both the blade vibration and the blade passing disturbances are captured. Despite this success, the peak of the blade vibration mode in Fig. 6 is not distinct as noise interferes.

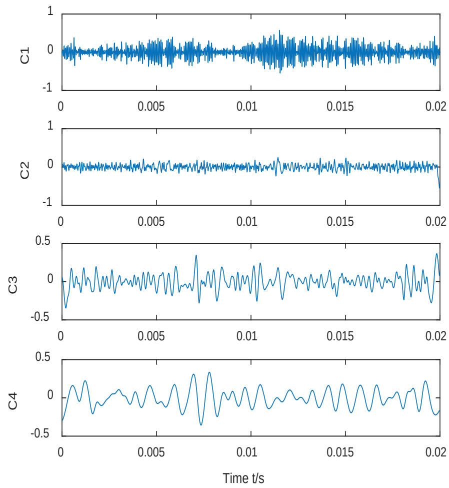


Fig. 5. The first four IMFs of sound signal obtained by using EEMD

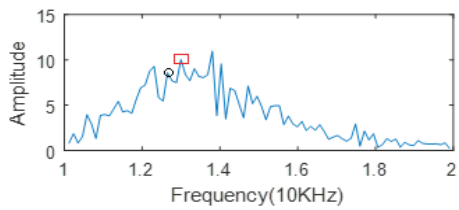


Fig. 6. The marginal spectrum of IMF1 in Fig. 5. The circle mark corresponds to 12,600Hz, and the rectangle mark to 13,000Hz.

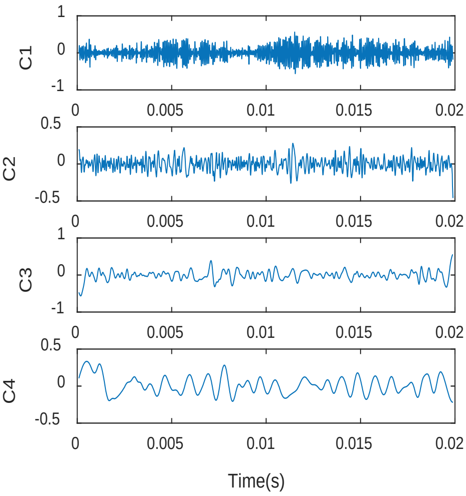


Fig. 7. The first four IMFs of sound signal obtained by using EEMD of optimal parameters

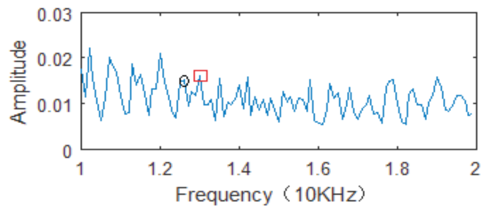


Fig. 8. Teager envelope spectrum of IMF2 in Fig. 7. The circle mark corresponds to 12,600Hz, and the rectangle mark to 13,000Hz.

The same sound signal was again investigated by the proposed new method. Firstly, the EEMD of optimal parameters is applied to the sound signal in Fig. 2(c), and the first four IMFs of the decomposition results are shown in Fig. 7.

As the pressure pulsations can come from different disturbance sources, the disturbance sources information contained in the original signal is decomposed into each component. CK was used as the screening index of the sensitive components to extract the disturbance source feature. The CK values of each IMF component were calculated by using the period of detected components T (=1/12670). In accordance with the criterion of maximum CK, the second IMF $c_2(t)$ was selected as the sensitive component. TEO analysis was then applied to $c_2(t)$ and the Teager envelope spectrum is shown in Fig. 8. Compared with the results in Fig. 6, the peaks around 12,000Hz ~ 13,000Hz are more distinct and narrower banded. Both the known blade vibration and the compressor blade passing signals are well captured.

STRAIN SIGNAL ANALYSIS

For the blade strain signal in Fig. 2(b), the strain signal near the natural frequency of the measured turbine blade is very weak form the power spectrum of the blade strain obtained from FFT analysis in Fig.3. The strain signal was next decomposed by using the traditional EEMD, and the first four IMFs of decomposition results are shown in Fig. 9.

The second IMF, $c_2(t)$, contains the impulse characteristic signal, and the marginal spectrum of $c_2(t)$ is shown in Fig. 10. A peak of 12,650Hz is just identifiable. This is likely the pursued vibration mode of the blade. A stronger peak with a higher frequency of 13,070Hz is also present, but the reason of its occurrence is not clear. The FFT result in Fig. 3 has also a large peak at 13,650Hz. So, compared with the FFT, the traditional EEMD was more efficient in identifying the blade mode, but this identification is still weak.

Therefore, the proposed new method was employed for the strain signal. Firstly, the EEMD of optimal parameters was applied to the strain signal in Fig. 2(b), and the first four IMFs of the decomposition results are shown in Fig. 11.

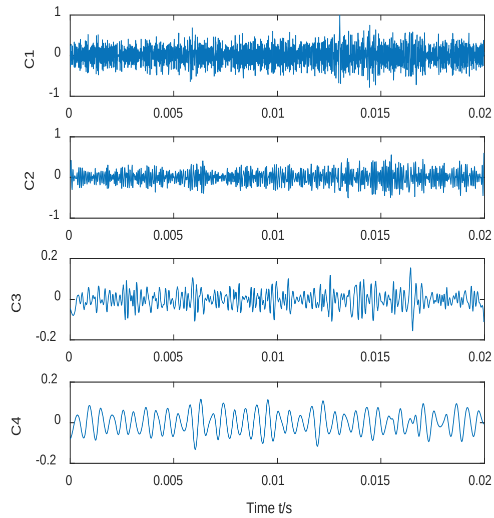


Fig. 9. The first four IMFs of blade strain signal obtained by using traditional EEMD

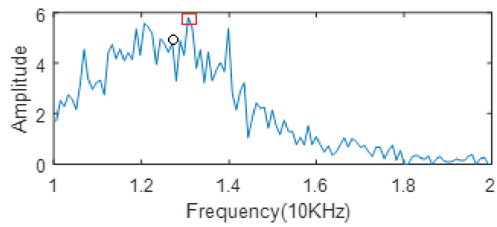


Fig. 10. The marginal spectrum of IMF2 in Fig. 9. The circle mark corresponds to 12,650Hz, and the rectangle mark to 13,070Hz.

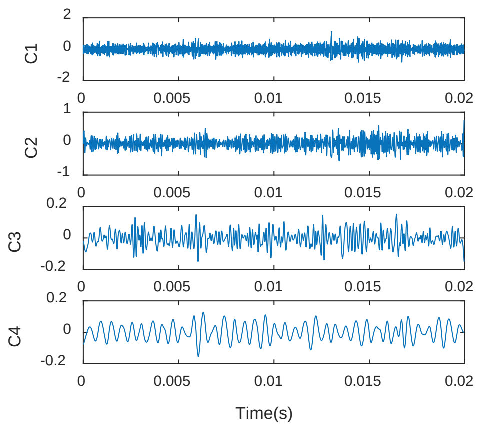


Fig. 11. The first four IMFs of blade strain signal obtained by using EEMD of optimal parameters

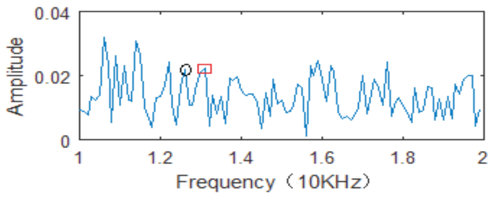


Fig. 12. Teager envelope spectrum of IMF1 in Fig. 11. The circle mark corresponds to 12,650Hz, and the rectangle mark to 13,070Hz

The CK values of each IMF component were calculated by using the period of detected components $T = 1/12670$. In accordance with the criterion of maximum CK, the first IMF , $c_1(t)$, was selected in this case as the sensitive component. TEO analysis was then applied to $c_1(t)$ and the Teager envelope spectrum is shown in Fig. 12. In the figure one can clearly observe a distinct peak at 12,650Hz. This result, compared with the result of the traditional EEMD (Fig. 10) and that of FFT (Fig. 3), again demonstrates the value of the new method.

CONCLUSIONS

In this research, sound signals and strain gauge signal were used for the identification of the first vibratory mode of turbocharger turbine blades. An optimization method was developed for adaptive determining appropriate EEMD parameters for the measured signals, so that the significant feature components could be extracted from the original vibration signal and separated from background noise and some irrelevant components. By using CK, the sensitive feature component is screened out, which can effectively eliminate interfering components and capture the feature information. TEO enhances the detection of weak impact characteristic frequencies.

Experiments on a turbine wheel were carried out to verify the effectiveness of this method against both FFT and traditional EEMD method. The results show that it can identify the first blade vibratory mode from both the weak sound signal and the strain gauge signal, which was difficult in this case for conventional FFT technique and to a lesser degree for the traditional EEMD method.

This investigation suggests that it might be possible to identify the characteristics of the first blade vibratory mode of turbocharger turbine rotors by using feature extraction of sound signal. It is of a great importance to determine which blade has the largest vibratory strain due to mistuning effect, and to reduce in this simple way experiment time and cost of strain gauging or tip timing measurement. The current study also shows that there is still some way to go before this aim can be achieved.

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