

# Gearbox Fault Diagnosis under Different Operating Conditions Based on Time Synchronous Average and Ensemble Empirical Mode Decomposition

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**Abstract:** In this paper, a new method is proposed by combining ensemble empirical mode decomposition (EEMD) with order tracking techniques to analyse the vibration signals from a two stage helical gearbox. The method improves EEMD results in that it overcomes the potential deficiencies and achieves better order spectrum representation for fault diagnosis. Based on the analysis, a diagnostic feature is designed based on the order spectra of extracted IFMs for detection and separation of gearbox faults. Experimental results show this feature is sensitive to different fault severities and robust to the influences from operating conditions and remote sensor locations.

**Keywords:** Empirical mode decomposition, Gearbox fault diagnosis, Time synchronous average

## 1. INTRODUCTION

Gearbox is used widely as one of critical mechanical components in industry. Its condition monitoring and fault diagnosis are essential for achieving maximum service availability. In recent years, a great deal of amount of work has been carried out to develop accurate diagnosis methods based on vibration measurement. The main direction in this field is to research more effective signal processing techniques including time domain statistical parameters (kurtosis, crest factor etc.), frequency domain analysis methods (Fourier spectrum, cepstrum, wavelet, etc.), joint-time frequency representation and so on [1-3] to obtain reliable and sensitive features for incipient fault diagnosis.

The challenge in processing vibration signal from gear box is that the signal to noise ratio is low. Many factors such as operating conditions, background noise and interferences from driving motor or other equipment are all included in the measured signal. In addition, vibration sensors have to be installed remotely in many cases because of access limitation. The signals recorded far away from gear box have more interferences due to long vibration transmission path. Therefore, more advanced methods are required to process the signals to obtain a feature which is robust to different noise and independent of operating conditions.

In this paper, an ensemble empirical model decomposition (EEMD) based method is proposed by combining EEMD with order tracking technique to extract the diagnostic feature from vibration signal adaptively. Time synchronous average (TSA) in order tracking method can help to obtain a definite periodic signal and reduce the influences from noise and the uncertainty during the adaptive process of EEMD. This method is then evaluated using the vibration data of a two stage helical gearbox diagnosis with different severity of gear damages under different operating conditions from different sensor locations.

## 2. ENSEMBLE EMD

Empirical mode decomposition (EMD) algorithm first proposed by Huang [4] is to decompose a signal into a sum of functions named intrinsic mode functions (IMFs) which have the same number of zero crossings and extrema and are symmetric with respect to the local mean. EMD algorithm has been proven to be quite versatile in many applications for extracting signals from nonlinear and non-stationary processes [5-7].

The basic EMD algorithm can be summarized as follows [4]:

Supposing the original signal is  $x(t)$ , the residue is  $r(t)$ , the  $i$ th IMF is  $imf_i(t)$

- (1) Initialize residue:  $r_0(t) = x(t)$ ,  $i = 1$
- (2) Initialize IMF  $h_0(t) = r_0(t)$ ,  $j = 1$
- (3) Identify all the local maxima and minima. Form the upper and lower envelopes,  $e_u(t)$  and  $e_l(t)$  by cubic spline interpolation.
- (4) Calculate the local mean:

$$m(t) = \frac{e_u(t) + e_l(t)}{2}$$

- (5)  $h_j(t) = h_{j-1}(t) - m(t)$
- (6) If stopping criterion is satisfied,  $imf_i(t) = h_j(t)$ , else go to (3) with  $j = j + 1$
- (7)  $r_i(t) = r_{i-1}(t) - imf_i(t)$
- (8) If  $r_i(t)$  has more than 2 extrema, go to (2) with  $i = i + 1$ , else EMD finishes and  $r_i(t)$  is the residue

However, the major drawback of EMD is mode mixing which means that a single IMF either consisting of signals of disparate scales, or a signal of a similar scale residing in different IMF components.

To resolve this problem, EEMD algorithm was proposed in [8]. This new noise-assisted data analysis method defines IMF as the mean of an ensemble of trials, each consisting of the signal plus white noise. The basic idea of this method is that the added white noise will provide a uniform reference scale distribution to facilitate EMD and enhance it to avoid mode mixing[8].

Based on the original EMD algorithm introduced above, EEMD can be described briefly as follows [8]:

- (1) Add white noise to original data
- (2) Decompose the new data into IMFs by classic EMD algorithm
- (3) Repeat step(1) and (2) with independent white noise series for hundreds epochs
- (4) Calculate the mean of corresponding IMFs as the final output pattern

In this work, EEMD method is adopted as an adaptive signal extractor to obtain vibration components which are relevant to gearbox dynamics.

### 3. GEARBOX VIBRATION SIGNAL ANALYSIS BY EEMD AND ORDER TRACKING

Order tracking has been applied to rotating machinery vibration signal processing extensively. It removes the interference of rotating speed and additive random noise so that it can obtain reliable order spectrum. However, it is difficult to eliminate the noise mixed with original signal, especially multiplicative noise. Fig. 1 shows the order spectrum of the vibration signals from healthy and faulty gearboxes under two different loads. Fault 1 has 50% damage in one tooth in tooth width direction whereas Fault 2 has 50% damage in two teeth. So Fault 2 is more serious than Fault 1 due to more damaged teeth. However, from these figures, the amplitudes of the tooth meshing frequency (order 34 which is the tooth number of the pinion of the 1<sup>st</sup> gear pair) and its sidebands cannot provide a trend consistent with the severity of the damage. Although the figure shows some increase feature by amplitudes, it is hard to decide the severity of the faults based on it.

To extract a reliable feature from gearbox vibration signal, time synchronous average for order tracking technique is used to process the raw signal firstly. It is not only to remove random noise including short time transient interference, but also generate the definite periodical signal to release over-decomposition or mode mixing in EEMD and select special IMFs for the following analysis.

Secondly, The TSA signal is decomposed into IMFs by EEMD method. Since TSA signal retains the periodic feature of gear vibration to maximum. According to IMF's periodicity feature, only several IMFs are identified and selected for fault diagnosis.

Additionally, to avoid the problem with mode mixing more, three improvements are also applied to the analysis process:

(1) Terminate EEMD when the frequency range of IMF is lower than shaft frequency. Because characteristic frequencies are usually higher than shaft frequency in gearbox vibration signal processing.

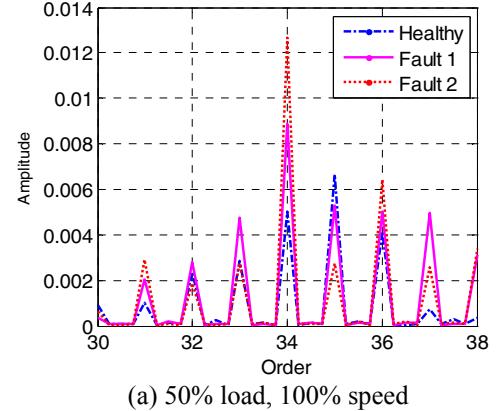
(2) Select the IMFs which exhibit more periodic characteristics. In theory, the vibration signal of gearbox should be periodic. IMFs obtained from TSA signal thus should be periodic. In contrast, the non-periodic IMFs may result from the noise or the other origins in the

EMD process and could be ignored.

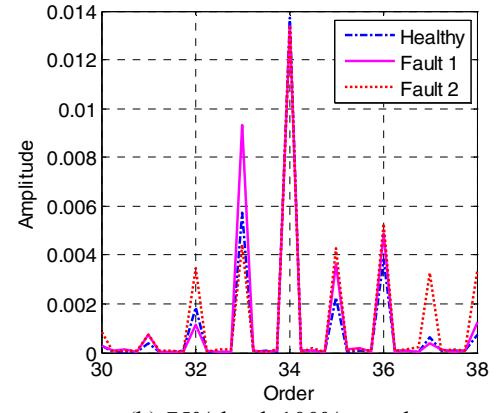
(3) Combine the selected IMFs into one IMF as gearbox feature signal for subsequent processing if more than one IMF is selected. This avoids the over-decomposition problem.

Then the order spectrum of the combined IMF is calculated.

Finally, based on the order spectrum of IMF, feature for gearbox fault diagnosis is extracted to achieve robust performance under different operating conditions from remote locations.



(a) 50% load, 100% speed



(b) 75% load, 100% speed

Fig. 1 Order spectrum of vibration signals from different gearboxes

## 4. EXPERIMENTAL STUDY

The test rig consists of a reduction gearbox with two stages of helical gears as shown in Fig. 2. The gear faults were simulated by 50% of one tooth ("Fault 1" or "F1") and 50% of two teeth ("Fault 2" or "F2") of the pinion gear. Table 1 presents the details of the two sets of gears.

In the experiment, speed signal is measured with rotary encoder attached to the motor shaft. The vibration signals were recorded with 50 kHz sampling rate by 2 accelerometers mounted at two locations: gearbox casing and motor casing respectively. The signals from location 2 have more influences from other vibration origins such as driving motor. The modified EEMD method described above was applied to the vibration

signals, and then order spectrum was calculated based on the combined IMF, in comparison with the traditional order spectrum achieved by computing order tracking method.

Table 1 Gearbox specification

Parameters	1st Stage	2nd Stage
number of teeth	34/70	29/52
full speed of shaft	24.33Hz	6.59Hz
tooth meshing frequency	827.73Hz	342.7Hz
contact ratio	1.359	1.479
overlap ratio	2.89	1.478

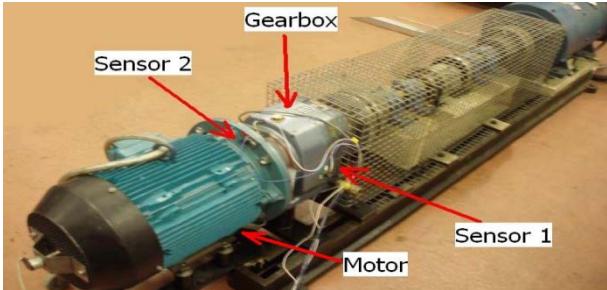
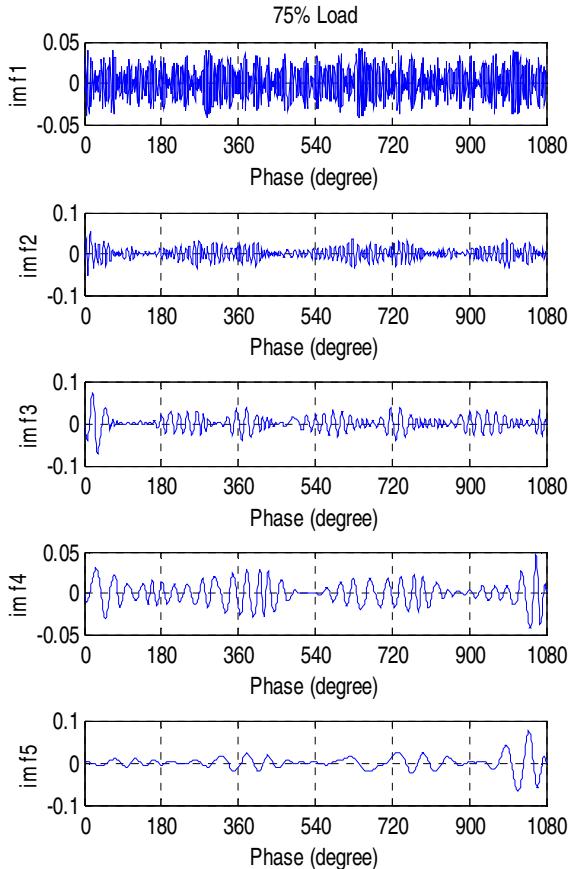


Fig. 2 Gearbox test rig



(a) The first 5 IMFs obtained by EMD

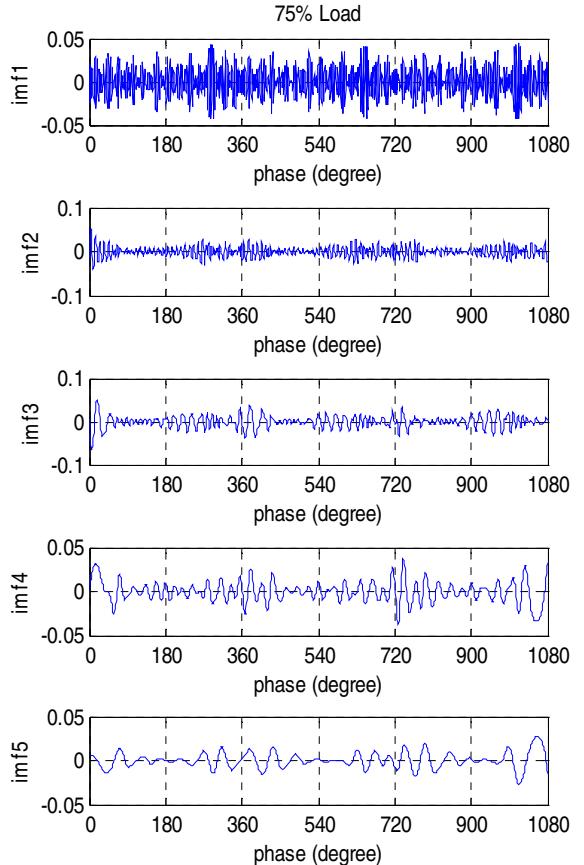
Fig. 3 IMFs obtained by EMD and EEMD respectively from the identical vibration signal

#### 4.1 IMFs obtained by modified EEMD

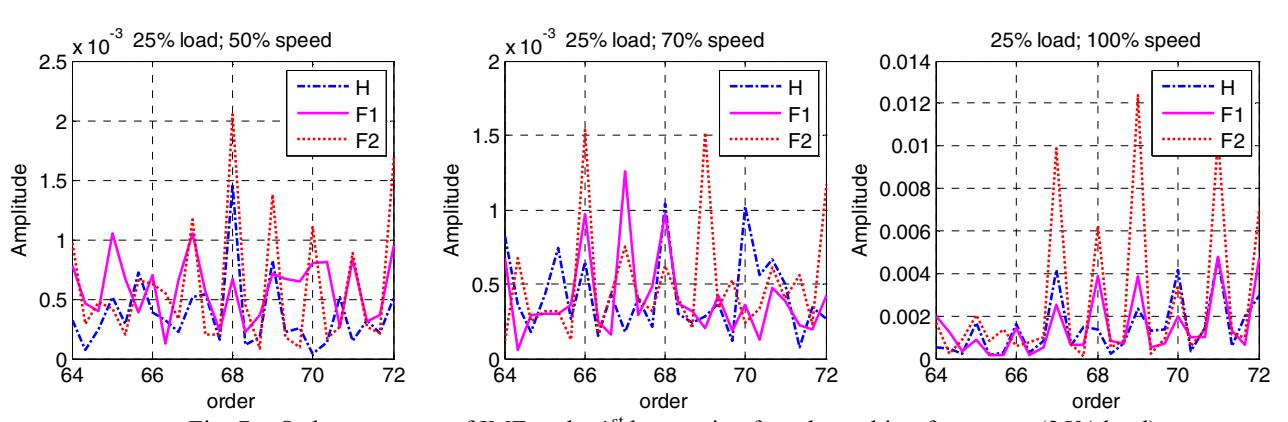
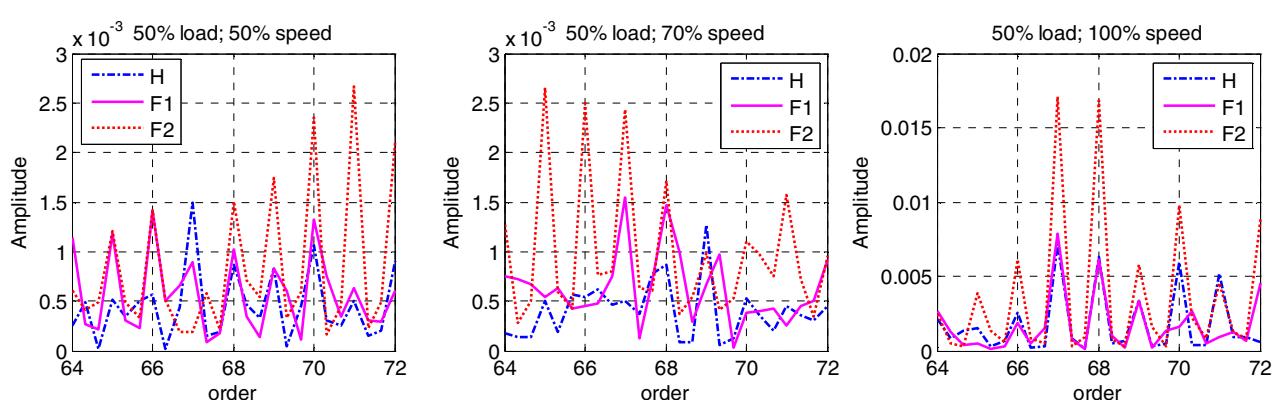
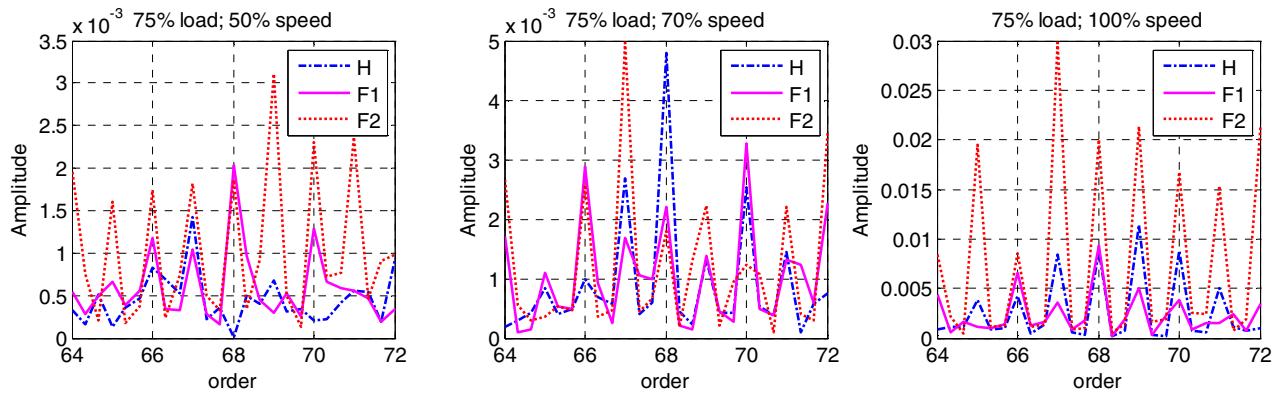
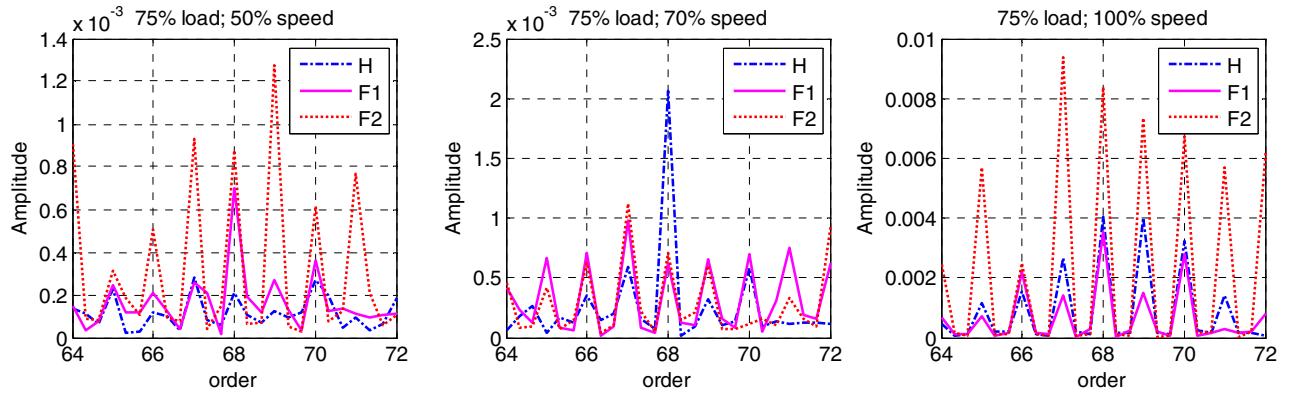
Fig. 3 (a) and (b) show the first five IMFs obtained by EEMD and EMD respectively from the same vibration signal with 75% load and 100% speed.

Comparing the time domain waveforms, the IMFs obtained by EEMD are less influenced by boundary effect which can results in distorted peaks at the beginning and end of data frames, as shown in the 5<sup>th</sup> IMF of Fig. 3 (a).

Moreover, it can be seen that the 2<sup>nd</sup> and 3<sup>rd</sup> IMF have more element of periodicity over time for different operating conditions. In the conventional frequency domain, the 2<sup>nd</sup> IMF contains several higher order harmonics of tooth meshing frequency. Especially, the amplitude of the 1<sup>st</sup> harmonic varies significantly with the severity of the fault evolution. On the other hand, the 3<sup>rd</sup> IMF contains only the fundamental tooth meshing frequency and its sidebands. They also vary with fault severity. These characteristics mean that IMFs can be the potential signal components for fault diagnosis.



(b) The first 5 IMFs obtained by EEMD



## 4.2 Order spectrum of selected IMFs under different operating conditions

Fig. 4 and Fig. 5 are the order spectra for traditional order tracking method and the proposed method respectively. The order spectra are calculated at shaft order 68 (the tooth number multiplied by 2 for the 1<sup>st</sup> harmonic component) based on the same datasets recorded under 75% of load at 50%, 70% 100% of full speed respectively. In comparison with traditional order spectrum, the order spectrum of the selected IMFs shows that the amplitude of the sidebands around tooth meshing frequencies increase with the severity of the faults, providing more consistent results with the fault severity. Especially, the order spectrum of IMFs for the condition of 75% load and 70% speed shown by the middle graph in Fig. 5, show much higher amplitude for the Fault 2, compared with that of the traditional method.

To examine the performance of IMF's order spectrum under different operating conditions, the order spectra is obtained from the 2<sup>nd</sup> and 3<sup>rd</sup> IMFs which are selected based on the periodicity feature. Fig. 5- Fig. 7 show the order spectra of IMFs around the 1<sup>st</sup> harmonic of tooth meshing frequency respective to different speed and load. In general, the amplitude is the lowest for the healthy gear and the highest for the Fault 2. The spectral amplitudes show an increase trend consistent with the

fault severity for all the operating conditions.

## 4.3 Diagnostic feature from order spectrum

From the order spectrum of selected IMF under multiple operating conditions, it has been observed that the amplitudes of sidebands around tooth meshing frequency and its harmonics increase with the fault severity. Thus the values of these can be used to measure the fault directly. For an overall measure, a diagnostic feature is obtained by averaging the amplitudes over 4 pairs of sidebands at the tooth meshing frequency and its first 4 harmonics. Fig. 8 shows the performance of this diagnostic feature. Obviously, the value of the feature increases with the fault severity and varies with the operation condition consistently.

To evaluate the effectiveness and robustness of the EEMD based method to changes of sensor locations, the signal recorded by the sensor located on the motor casing (shown in Fig. 2) is also processed with this method to extract the feature under the same operating conditions. The results in Fig. 9 show that the feature values extracted from the signal recorded by sensor 2 also has a gradual increase trend with fault severity under all operating conditions, demonstrating that the method can produce correct results even if the signal have more noise.

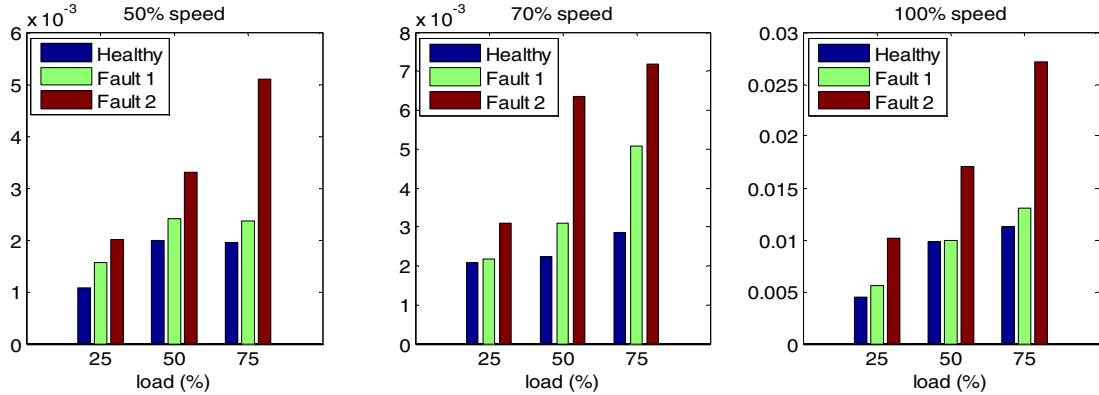


Fig. 8 Average amplitude of the sidebands around tooth meshing frequency and its harmonics  
(Sensor is fixed on the gearbox casing)

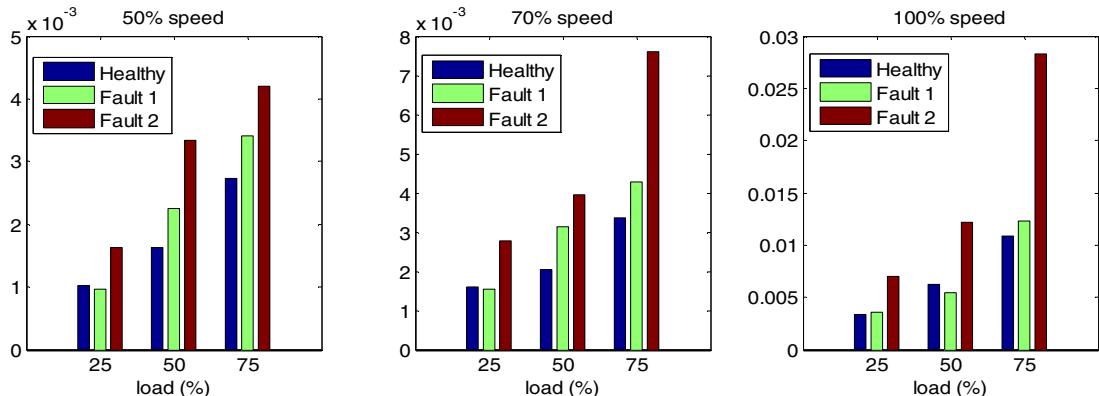


Fig. 9 Average amplitude of the sidebands around tooth meshing frequency and its harmonics  
(Sensor is fixed on the motor casing)

## 5. CONCLUSIONS

In this paper, a combination of the modified EEMD and order tracking is proposed as feature extraction method for gearbox fault diagnosis. It reduces influences of noise contamination and mode mixing problem in EMD methods significantly and allows meaningful IMFs of the TSA signal to be selected based on their frequency range and periodicity for feature extraction. The order spectrum of the selected IMFs produces more effective representation of the gear vibration for diagnostic feature development.

Experimental results show that this method produces a measure consistent with gear fault severity over different operating conditions and robust to the relative remote sensor locations. Future work will focus on developing multi-dimensional features with more advanced AI techniques based on the proposed analysis method.

## ACKNOWLEDGEMENTS

The authors are grateful for the financial support provided by the National Natural Science Foundation of China under Contact No.50675232.

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