Article citation info:
ZHANG X, KANG J, BECHHOEFER E, ZHAO J. A new feature extraction method for gear fault diagnosis and prognosis. Eksploatacja i Niezawodnosc – Maintenance and Reliability 2014; 16 (2): 295–300.

Xinghui ZHANG
Jianshe KANG
Eric BECHHOEFER
Jianmin ZHAO

A NEW FEATURE EXTRACTION METHOD FOR GEAR FAULT DIAGNOSIS AND PROGNOSIS

NOWA METODA DIAGNOZOWANIA I PROGNOZOWANIA USZKODZEŃ PRZEKŁADNI Z WYKORZYSTANIEM EKSTRAKCJI CECH

Robust features are very critical to track the degradation process of a gear. They are key factors for implementing fault diagnosis and prognosis. This has driven the need in research for extracting good features. This paper used a new method, Narrowband Interference Cancellation, to suppress the narrow band component and enhance the impulsive component enabling the gear fault detection easier. This method can improve the signal to noise ratio of impulse train associated with the gear fault frequency. A run-to-failure test is used to demonstrate the method's effectiveness. Based on the time synchronous signal of high speed shaft, Sideband Index is extracted from the signals processed by Narrowband Interference Cancellation. This feature has good degradation trend than traditional Sideband Index extracted from the time synchronous average signal directly. Comparison of features based on different extraction process proves the effectiveness of developed method.

***Keywords**: Narrowband Interference Cancellation, degradation, fault diagnosis, fault prognosis, sideband index.*

Cechy odporne (robustfeatures) mają krytyczne znaczenie w trakcie śledzenia procesu degradacji przekładni. Stanowią one kluczowy czynnik w procesie diagnozowania i prognozowania uszkodzeń. Fakt ten stwarza w badaniach naukowych potrzebę ekstrakcji pożądanych cech. W niniejszej pracy wykorzystano nową metodę, tzw. metodę eliminacji zakłóceń wąskopasmowych (NarrowbandInterferenceCancellation), za pomocą której można wytłumić składową wąskopasmową, a wzmocnić składową impulsową, co ułatwia wykrywanie uszkodzeń przekładni. Metoda ta pozwala poprawić stosunek sygnału do szumu w szeregu impulsów związanym z częstotliwością charakteryzującą uszkodzenie przekładni. Skuteczność przedstawionej metody można wykazać za pomocą badań typu „pracuj do awarii" (run-to-failure) . Na podstawie synchronicznego sygnału wału wysokoobrotowego, z sygnałów przetwarzanych za pomocą metody eliminacji zakłóceń wąskopasmowych ekstrahuje się wskaźnik wstęgi bocznej (Sideband Index). Cecha ta ma lepszy trend degradacji niż tradycyjny wskaźnik wstęgi bocznej ekstrahowany bezpośrednio z sygnału uśrednionego synchronicznie w czasie. Porównanie cech wyodrębnionych w różnych procesach ekstrakcji dowodzi skuteczności opracowanej metody.

***Słowa kluczowe**: Eliminacja zakłóceń wąskopasmowych, degradacja, diagnoza uszkodzeń, prognozowanie uszkodzeń, wskaźnik wstęgi bocznej.*

1. Introduction

Gears are critical elements in complex machinery, such as helicopter, wind turbine etc. Gear faults misdetection will increase the overall cost of customer or even lead to disaster. Condition based maintenance (CBM) [7] and Prognostics and Health Management (PHM) [5] are developed for supplement the traditional maintenance methods of capital equipment. Most operations and maintenance (O&M) organization are using fault diagnosis and prognosis to improve logistics support of high value equipment. As we know, extracting good features are key steps for effective fault diagnosis and prognosis. For vibration signals based gear fault diagnosis, there are time domain analysis, frequency domain analysis and time-frequency domain analysis. Some statistical features extracted from time domain signals can detect abnormal of gear effectively [10]. However, these techniques are limited in their ability to provide actionable information as to the location of the fault in the gearbox. Frequency domain analysis is difficult for gear faults involving soft/broken teeth as the FFT is not sensitive to impact events.

For many industries (wind farms for example), the investment in the infrastructure to support on-line analysis has not been made and the hardware is unavailable to record vibration signals of every inspection. That is, the cost benefic ratio of on-line equipment is not great enough to convince O&M organization to invest. The goal of this study is to develop robust analysis techniques such that the business case for implementing on-line analysis is made.

As noted, frequency analysis alone has limited effectiveness for some types of faults that occur on gears. Therefore, other time frequency analysis techniques are needed to allow development of condition indicators sensitive to impact/soft tooth/broken tooth faults. For the normal case, statistics of these condition indicators are calculated. Then if condition indicators exceed the predefined thresholds, this denotes the system abnormal. Additional frequency spectrum analysis can be implemented to the raw vibration signal recorded provide more actionable information: e.g. the fault locations in the gearbox. When the operating conditions are un-stationary, time-frequency analysis can be used to fix the fault location and severity.

For the whole degradation process of gear, we expect to detect fault as early as possible and extract effective features that have good deterioration trend. In real world condition, a fault signature is small relative to the vibration signals. The impulsive signals produced by incipient faults are immersed in quasi-stationary signal with far greater energy (e.g. gear mesh, shaft rates) which are noise in the fault detection process. Additionally, because acceleration is the second derivative of displacement, the problem is especially difficult on low speed shaft encountered on wind turbines (main shaft rate of 0.15 to 0.25 Hz for large machines).

In practice, for statistical features extracted from time domain signals or frequency domain analysis, it is very difficult to detect incipient fault of gears of low speed shaft. Wang and Wong [11] developed an autoregressive (AR) model based filtering technique to enhance the gear fault diagnosis. Then, Endo and Randall [6] proposed the use of the minimum entropy deconvolution (MED) technique to enhance the ability of the existing AR model based filtering technique to detect gear faults. AR model can filter the gear meshing waveforms out and only retain the impulsive signal produced by faults, allowing earlier fault detection. The MED searches for an optimum set of filter coefficients that recover the output signal with the maximum value of kurtosis. Therefore, it can enhance the gear fault impulses enabling the fault detection easily (assuming that there are no other impulsive sources, such as a bearing fault).

A limitation of the AR-MED method is the preference of the MED algorithm to deconvolve only a single impulse or a selection of impulses, as opposed to the desired periodic impulses repeating at the period of the fault. Inspired by the MED deconvolution technique, McDonald et al. [9] proposed an improved novel deconvolution norm, Correlated Kurtosis, which takes advantage of the periodicity of the faults and requires no AR model stage prior to deconvolution. Zhang et al. [12] developed a new condition indicator tracking the gear degradation under un-stationary condition based on the AR filtering. In the signals of gear faults, there is a number of narrow band tones and broad noise which mask the desired impulsive signal produced by gear faults. If one can find an effective method that can remove the narrow band tones out, the impulsive signal will be easily detected. Recently, Bechhoefer [2] developed a new method called Narrowband Interference Cancellation (NIC) to enhance the gear fault detection. This method can filter the narrow band signals out. So, the impulsive signals are enhanced.

Based on the work of Bechhoefer, this paper proposes a new feature, which can track the gear degradation effectively. Time synchronous (TS) technology is used to compensate the varying rotation speed. Then, NIC is implemented to filter the narrow band signal out. Finally, sideband index mentioned in [1] is extracted from post-NIC signals. The results demonstrate that this condition indicator is more robust than others.

2. Narrowband Interference Cancellation

We can categorize gears faults in two basic categories: wear (scuffing, micro-pitting) or breakage (soft tooth/broken tooth/crack tooth, etc). The second fault mode is of great interest because it can cause catastrophic fault of a gearbox. These types of faults are characterized by generated an impulse signals with the relative characteristic frequencies. The vibration signals collected from machines contain gear mesh, shaft rotation, bearing vibration and random noise, along with the impulsive signal of interest. The quasi-stationary signals produced by gear and shaft are narrowband, while the impulse signals generated by gear faults are in a wideband. Usually, the gear fault signals are very weak compared to the gear mesh tones and shaft rotation. Therefore, if we can cancel these narrowband signals, the gear faults will be detected easily. This phenomenology can be modeled as:

$$x(n) = s(n)+y(n)+v(n) \tag{1}$$

where

$s(n)$ is the signal of interest,

$y(n)$ is the signal associated with gear mesh, shafts rotation, e.g. interference,

$v(n)$ is random noise.

The interference signal is usually large compared to the signal of interest. It is necessary to remove the interfering signal $y(n)$ from $x(n)$ while preserving the signal of interest $s(n)$. Since the measured signal $x(n)$ and the interference signal $y(n)$ are correlated, one can estimate the interference using an optimal linear estimator:

$$\hat{y}(n) = \mathbf{c}_0^H \mathbf{x}\left(n-D\right) \tag{2}$$

$$\mathbf{R}\mathbf{c}_0 = \mathbf{d} \tag{3}$$

$$\mathbf{R} = E\{\mathbf{x}(n\text{-}D)\mathbf{x}^H(n\text{-}D)\} \tag{4}$$

$$\mathbf{d} = E\{\mathbf{x}(n\text{-}D)y^*(n)\} \tag{5}$$

where D is an integer delay operator. If D=1, then Eq. (2) is the LS forward linear predictor. If $\hat{y}(n) = y(n)$, the output of the filter is $x(n)$- $\hat{y}(n)$ = $s(n)+v(n)$. This means we can completely remove the interference and only the desired signal and noise remains. In practice, signal $y(n)$ is not available. To overcome this obstacle, we can use a minimum means square error D-step forward linear predictor, such that:

$$e^f(n) = x(n)+\mathbf{a}^H\mathbf{x}(n\text{-}D) \tag{6}$$

$$\mathbf{R}\mathbf{a} = \text{-}\mathbf{r}^f \tag{7}$$

where:

$$\mathbf{r}^f = E\{\mathbf{x}(n\text{-}D)x^*(n)\} \tag{8}$$

For this modeling, the components of the observed signal have the following properties:

- The signal of interest $s(n)$, the interference signal $y(n)$, and the noise signal $v(n)$ are mutually uncorrelated.
- The noise signal $v(n)$ is white.
- The signal of interest $s(n)$ is wideband and has a short correlation length (e.g. its impulsive).
- The interference signal $y(n)$ has a long correlation length: its autocorrelation length takes significant values over the range $0 \le |l| \le M$, for $M>D$.

In practice, the second and third properties mean that the desired signal and the noise are approximately uncorrelated after a certain small lag. These are precisely the properties exploited by the canceller to separate the narrowband interference from the desired signal and the background noise.

According to the first assumption, we have:

$$E\{x(n\text{-}k)y^*(n)\}=E\{y(n\text{-}k)y^*(n)\}=r_y(k) \tag{9}$$

$$r_x(l) = r_s(l) + r_y(l) + r_v(l) \tag{10}$$

If the second and third modeling assumptions hold true, we have:

$$r_x(l) = r_y(l) \text{ for } l \neq 0, 1, \ldots, D\text{-}1 \tag{11}$$

The exclusion of the lags for $l \neq 0, 1, \dots, D\text{-}1$ in **r** and **d** is critical, and we have arranged for that by forcing the filter and the predictor to form their estimates using the *delayed* data vector $\mathbf{x}(n\text{-}D)$. From (5), (8), and (11), we conclude that $\mathbf{d} = \mathbf{r}^f$ and therefore $\mathbf{c}_0 = \mathbf{a}_0$. Thus, the optimum NBI estimator $\mathbf{c}_0$ is equal to the D-step linear predictor $\mathbf{a}_0$, which can be determined exclusively from the input signal $x(n)$. Then, the signal with interference removed is:

$$x(\mathrm{n}) - \hat{y}(n) = x(n) - \mathrm{a}_0^H \mathbf{x}(n-D) = \mathrm{e}^{\mathrm{f}}(n) \qquad (12)$$

which is identical to the D-step forward prediction error. This leads to the linear prediction NIC shown in Figure 1. For a full description of the analysis, we can see (Manolakis et al. 2000) [9].

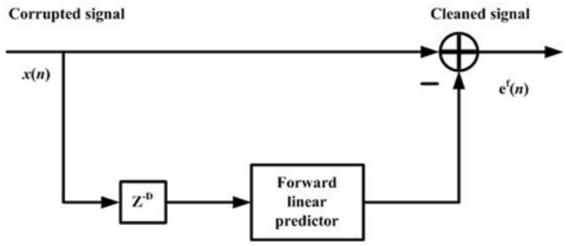

Fig. 1. Block diagram of linear prediction NBI canceller

3. Experiment

Figure 2 shows the experimental system used in this paper to verify the performance of the proposed method. The system includes a gearbox, a 4 kW three phase asynchronous motor for driving the gearbox, and a magnetic powder brake for loading. The motor rotating speed is controlled by an electromagnetic speed-adjustable motor, which allows the tested gear to operate under various speeds. The load is provided by the magnetic powder brake connected to the output shaft and the torque can be adjusted by a brake controller.

The data acquisition system is composed of acceleration transducers, PXI-1031 mainframe, PXI-4472B data acquisition cards, and LabVIEW software. The type of transducers is 3056B4 of Dytran Company. There are four transducers which are mounted in different places on gearbox. In order to acquire the speed and torque information, a speed and torque transducer is installed in the input shaft as illustrated in Figure 2. For this transducer, one revolution of input shaft will produce 60 impulses.

As shown in Figure 3, the gearbox has three shafts, which are mounted to the gearbox housing by rolling element bearings. Gear 1 on low speed (LS) shaft has 81 teeth and meshes with gear 3 with 18

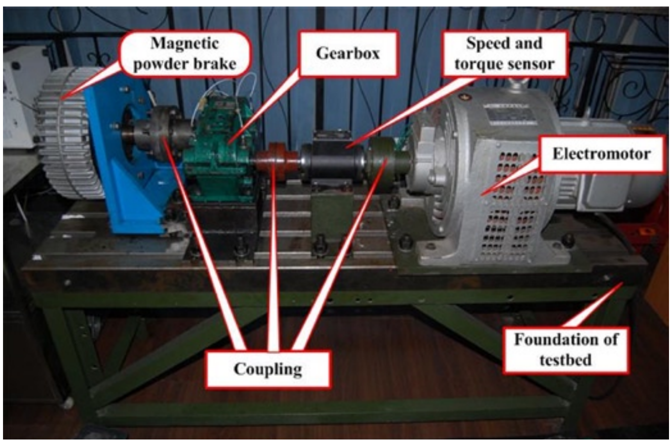

Fig. 2. Test-rig of gearbox

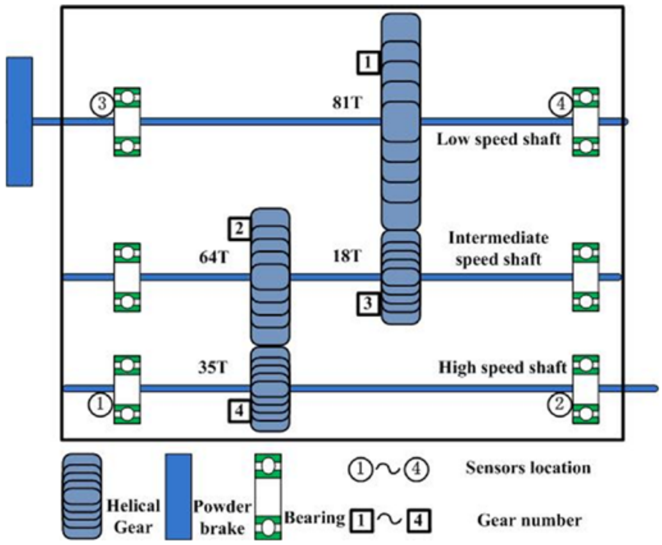

Fig. 3. Structure of gearbox and the transducers location

teeth. Gear 2 on Intermediate speed (IS) shaft has 64 teeth and meshes with gear 4, which is on the high speed (HS) shaft and has 35 teeth.

This experiment is a run-to-failure (RTF) test. It operated from normal to failure. When the vibration amplitude exceeds the 60 m/s^2, we define the gearbox failure. The whole process took 548 hours under approximate speed 1200 rpm and load 15 N•m. In this test, the sampling frequency was 20 KHz for 12 second. The sampling interval between two consecutive inspections is ten minutes. During the test, the gearbox was periodically inspected. It was found that the main fault mode was wear. Gear 2, 3, and 4 had slight wear. Gear 1 has serious wear and some teeth were broken. Then, the whole degradation process can be depicted as follows. When a normal gear operates some time, some pitting fault will appear on the gear face. With the time elapse, these pitting faults will extend to the spalling and lead to broken tooth finally. The degradation process of gear 1 can be depicted as Figure 4.

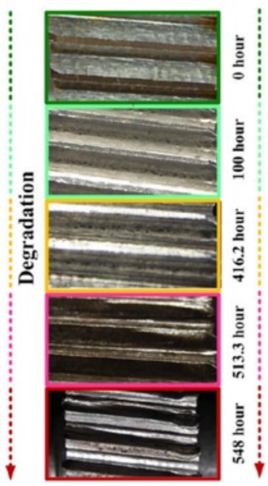

Fig. 4. Fault propagation over time

4. Data analysis and discussion

4.1. Degradation feature extraction

Because the rotating speed during the signal acquisition has small fluctuations, TS technology [3] must be used to mitigate the influence of varying speed. This was done by resampling the vibration data relative to a key-phasor [9]. Then, NIC is used to remove the narrowband signals out. Finally, sideband index (SI) is extracted from the NIC signals. SI is the average of the first order sidebands of the fundamental gear meshing frequency. It can be represented as Equation 13:

$$SI = (R_{I,-1}(x) + R_{I,+1}(x))/2 \tag{13}$$

In this analysis, the HS shaft is the synchronous shaft. In this paper, the parameters D and M of NIC are selected as 1 and 32 for all the data processing. For the RTF test described in Section 3, there are 3,288 inspection points in the gearbox life. From Figure 4, we can see that the gear had some incipient pitting fault in the face when it operated until 100 hours. In order to demonstrate the effectiveness of NIC technology, data collected at inspection point 601 (the first inspection point after 100 hours) was selected as the processing object. After time synchronous and NIC processing, results of time domain and frequency domain can be seen in Figure 6 and Figure 8.

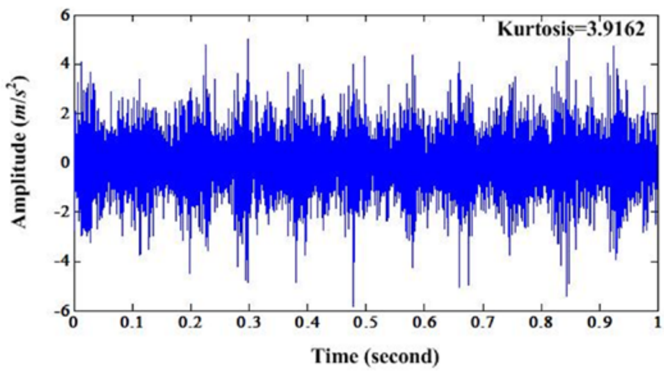

Fig. 5. Time domain signal of inspection point 601 without NIC processing

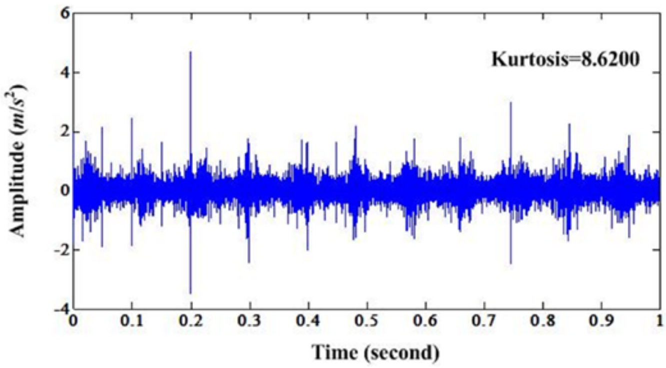

Fig. 6. Time domain signal of inspection point 601 after NIC processing

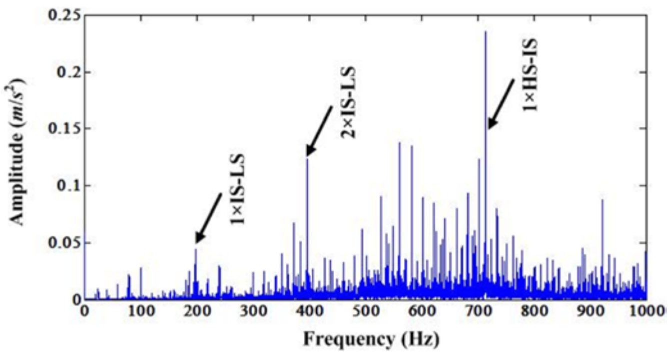

Fig. 7. Frequency domain information of inspection point 601 without NIC processing

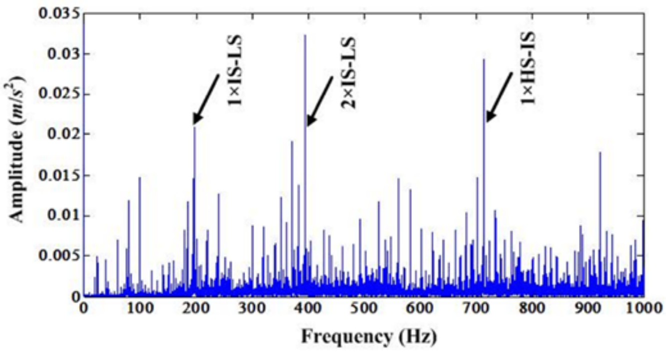

Fig. 8. Frequency domain information of inspection point 601 after NIC processing

Figure 5 is the time domain signal of inspection point 601 without NIC processing. Compared to the Figure 6, its kurtosis value is smaller. This denotes that NIC processing isolated the fault, which is impulsive in nature (e.g. higher kurotosis). From the view of frequency analysis, it is seen that the mesh tones of HS-IS (702.5764 Hz) are dominant in the frequency spectrum without NIC processing, as depicted in Figure 7. The main fault is found on gear 1. Mesh frequency of IS-LS (197.5996 Hz) and its harmonics should be dominant in the spectrum. Compared to Figure 7, Figure 8 shows that spectral energy of HS-IS (narrowband signal) is suppressed after NIC processing. This enabled the fault detection of gear 1 be more easily detected. Finally, the robust degradation feature SI can be extracted from the RTF data sets as illustrated in Figure 9.

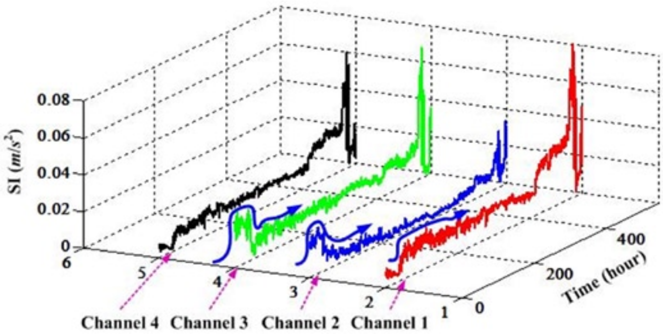

Fig. 9. Degradation feature SI extracted from NIC signal of four channels

From the Figure 9, we can see that degradation feature SI of channel four has the best performance. Its degradation trend is better than the features of other three channels. Degradation feature of channel 1increase after the gearbox operating a short time and it decrease gradually at the initial stage of gearbox's life. This is wear in, could possible affect the effectiveness of prognostic algorithms. Similarly, degradation features of channel 2 and channel 3 have high values at beginning and then enter into a relatively stationary process. These kinds of features will lead to ineffectiveness of the prognostic algorithms. In Figure 9, curves with arrow are used to denote the abnormal feature fluctuation.

4.2. Discussion

(1) In reference [9], degradation feature SI was extracted from time synchronous average (TSA) signals. We compared the SI extracted from TSA signals with the SI extracted from the NIC-TS signals. Here, the synchronous shaft is the LS shaft. SI extracted from TSA signals of four channels are depicted in Figure 10. Similar to Figure 9, degradation feature SI of channel four is the best. Figure 11 is the comparison of feature SI extracted from NIC-TS signals (showed in Figure 9) and TSA signals (showed in Figure 10) of channel four. It is showed

that SI extracted from NIC-TS signal is smoother than the SI extracted from TSA signals. SI extracted from TSA signals has large fluctuations at the early stage of gearbox's life.

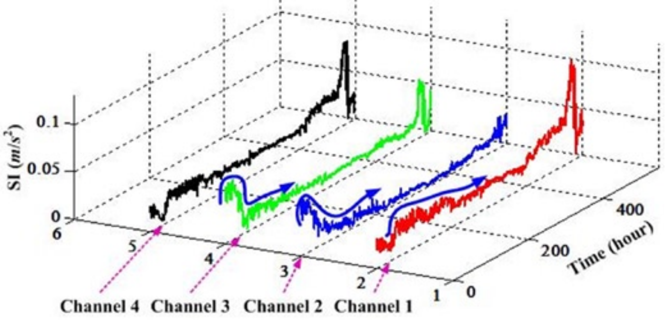

Fig. 10. Degradation feature SI extracted from TSA signal of four channels

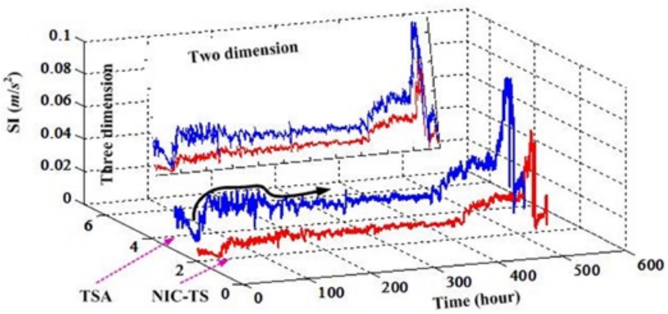

Fig. 11. Comparison of SI extracted from TSA and NIC-TS signals of channel four

(2) In section 4.1, the NIC was used to process the TS signal in which the HS shaft is the synchronous shaft. If the LS shaft is the synchronous shaft, the SIs based on the NIC-TSA processing and NIC-TS processing should be investigated. Figure 12 is the feature SI extracted from the NIC-TSA signals. It shows that all features SI of four channels have large fluctuations in the whole degradation process.

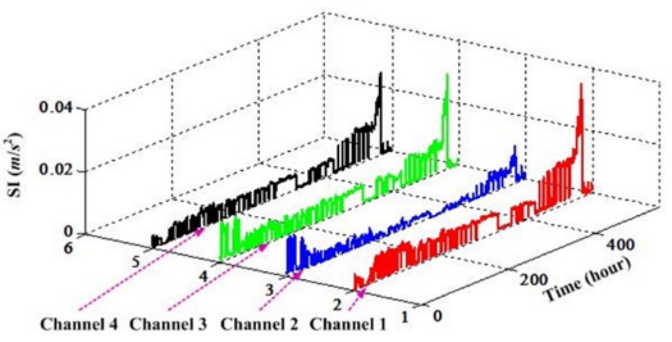

Fig. 12. SI extracted from NIC-TSA signals of four channels

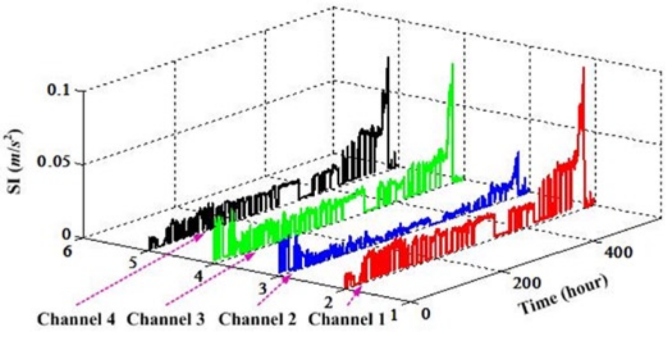

Fig. 13. SI extracted from NIC-TS signals of four channels

Figure 13 is the features SI extracted from the NIC-TS signals. It is very similar to Figure 12. Therefore, the degradation feature SI directly extracted from NIC-TS signal of HS shaft has the best performance.

From Figure 12 and Figure 13, it can be seen that all the features of four channels have large fluctuation when the gearbox degraded. Using LS shaft as the synchronous shaft, the TSA signal will have a very long length for one revolution. Really, there is nothing up there but noise which is due to the interpolation. So, this leads to the feature fluctuation.

(3) In this paper, the parameters D and M of NIC are selected by experience. The optimization of these two parameters can be investigated in future to enhance the NIC ability. Another problem is that the rotation speed and load are varying with time as depicted in Figure 14 and Figure 15. Even if the varying range is small, this will have certain influence to the trend of degradation feature. In real, taking wind turbine for example, its rotation speed and load are varying with wind speed. So, robust features which are not sensitive to speed and load varying need to be investigated in the future work.

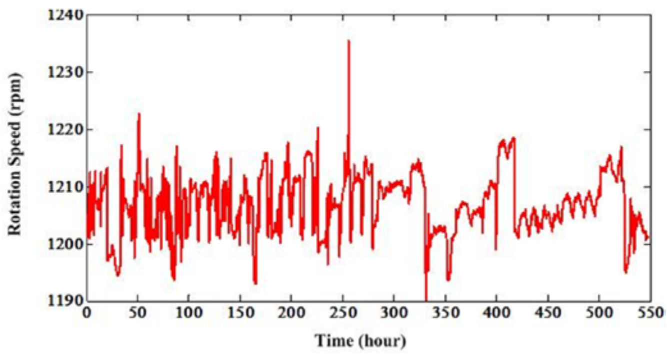

Fig. 14. Rotation speed of gearbox RTF data

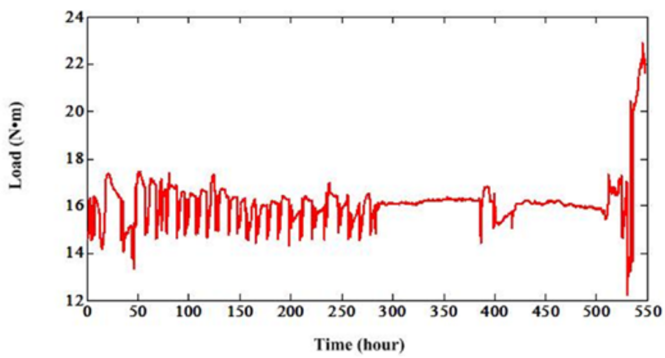

Fig. 15. Load of gearbox RTF data

5. Conclusion

This paper uses a new method NIC that can enhance the impulse signals produced by gear faults. NIC technology can suppress the interference of narrow band signal. Based on the TS signal of HS shaft, robust degradation feature can be extracted after NIC processing. Various results comparison from different view demonstrated the effectiveness of the proposed method.

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Xinghui ZHANG
Jianshe KANG
Jianmin ZHAO
Mechanical Engineering College
Shijiazhuang, 050003, China
E-mails: dynamicbnt@gmail.com, jskang201206@126.com, Jm_zhao@hotmail.com

Eric BECHHOEFER
GPMS LLC
Cornwall, VT, USA
E-mail: eric@gpms-vt.com