Dynamic Degradation Quantification of Wind Turbine High Speed Shaft Bearing Based on Oscillation Based Sparsity Indices

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Abstract. Wind turbine (WT) high speed shaft (HSS) bearing fault is important due to its significant number of failures. However, due to its non-stationary operation under varying speed condition, it is a challenging issue to quantify the degradation of WT-HSS bearing by conventional bearing indices. Aiming at the aforementioned issue, in this paper, tunable Q factor wavelet transform (TQWT) preprocessed sparsity indices are proposed to achieve the dynamic degradation quantification of WT-HSS bearing. Firstly, based on the ability of TQWT in dynamic extraction of fault component of a bearing signal under varying speed condition, low oscillatory transient signal component is separated from a noisy commercial WT-HSS bearing signal by continuously adjustable tunable Q factor wavelet transform (TQWT). Then, considering the suitability of sparsity indices in quantifying extracted fault component based on its energy concentration, four representative sparsity indices namely kurtosis, gini index, negative entropy and reciprocal smoothness index are used to quantify the separated low oscillatory signal component as a measure of WT-HSS bearing health. The proposed indices show a better performance than original sparsity indices and an improved version of sparsity indices based on adaptive weighted signal preprocessing in dynamic degradation quantification of a commercial WT-HSS bearing.

1. Introduction

As a renewable source of energy, wind turbines (WT) are gaining more and more popularity worldwide [1]. Due to the growing demand of green energy, it is important that WT operate in a reliable manner. In most cases, WT are situated in a rural area where they are subjected to harsh operating conditions such as vibration and shock under varying rotating speed condition. As a result, operational and maintenance cost of WT become very high [2].

Among different parts in a WT set up, the maintenance cost of its gearbox is high due to high downtime per failure. According to the national renewable energy laboratory gearbox reliability dataset, bearings are primary source of faults in a WT gearbox. Among them high speed shaft bearing is one of the major sources of failure. Condition degradation of bearing is a dynamically progressing phenomenon. Hence, understanding the level of degradation is the most effective approach for designing a proper bearing maintenance strategy [3]. Besides, degradation quantification is highly associated with the fault progression tendency, which is an important measure for the researches related to the remaining useful life calculation of the bearing.
Vibration based condition monitoring is one of the most effective techniques for wind turbine gearbox bearings [4]. In recent years, extensive amount of research has been done regarding bearing health indices under constant rotating speed operating condition [5-7]. However, vibration signals collected from WT-HSS bearing operate under fluctuating rotating speed condition. In such case, signal becomes nonstationary and appearance of transient impulses in the faulty vibration signal is no longer periodic. Hence, under this condition, dynamic bearing health indices constructed based on the periodic appearance of transients become ineffective under time varying speed operating condition [8].

Another intuitive approach for dynamic rolling element bearing health index construction is based on the energy of the signals. With the degradation of a bearing condition, energy of the signal increases. Thus energy based indices such as root mean square (RMS), Peak, crest factor are extensively used for bearing health index construction [9]. However, amplitude of the vibration signal will be affected by varying speed condition. Hence, dynamic rolling element bearing health degradation quantification by direct application of energy based indices under varying speed condition is not reliable [9]. One of the conventional approaches for solving the problem of speed fluctuation in dynamic WT-HSS bearing health index construction is resampling the signal via order tracking method. In order tracking method, vibration signals are resampled at a fixed angular period and convert a non-stationary signal into a stationary one [10]. However, the application of order tracking method is limited by interpolation error [11]. In this context, Elforjani et al. proposed signal intensity estimator technique for condition monitoring of WT-HSS bearing [12]. One of the major drawbacks of signal intensity estimator technique is that it depends on the prior knowledge of rotational speed. However, calculating rotational speed with a tachometer is not cost effective and their adjustment is not convenient in all the cases [13].

Lately, sparsity indices are a hot topic among researchers from different arena such as face recognition, oceanic engineering, image processing [14] etc. Sparsity indices quantify the energy concentration of a signal independent of its periodicity [15]. If the whole energy of a signal is concentrated at one point, the value of sparsity indices will be maximized and vice versa. In this context, sparsity measures have an important application in machinery health monitoring application [14]. Theoretically, sparsity indices should be independent of speed fluctuation since they are independent of frequency variation [16].

Prior to the quantification of a WT-HSS bearing vibration signal by sparsity indices, it is necessary to preprocess the signal. Band pass based filtering methods are most commonly used method for this purpose [17, 18]. In this context, Saidi et al. used spectral kurtosis technique to select the pass band for extracting the transients and subsequently calculate the indices to quantify the WT-HSS bearing condition [19]. However, band pass filtering techniques are limited by in band noise problem [16]. Moreover, band pass filtering techniques are not very suitable under varying speed condition. In this context, tunable Q factor wavelet transform (TQWT) is a continuously adjustable parameter based method proposed by Selesnick which is suitable for preprocessing the bearing signal under time varying speed condition [16, 20]. TQWT decomposes a bearing signal into low oscillatory and high oscillatory components. The low oscillatory component extracted by TQWT can be considered as the train of transients caused by WT-HSS bearing fault [21].

Based on above discussion, in this paper, TQWT is used to extract optimal low oscillatory component from a WT-HSS bearing signal. Since, TQWT extracted low oscillatory component can be considered as the WT-HSS bearing signal component possessing the impulsive transients [16], four representative sparsity indices namely kurtosis, gini index, negative entropy and reciprocal smoothness index are used to quantify it as a measure of rolling element bearing condition. As, the proposed method consists of an extraction scheme of the impulse train from the WT-HSS bearing signal based on oscillatory behavior, derived indices are termed respectively as oscillation based kurtosis (OBK), oscillation based gini index (OBGI), oscillation based negative entropy (OBNE), oscillation based reciprocal smoothness index (OBRSI).

In view of all the above, rest of the paper is proceeded in the following way. In section 2, theoretical framework regarding the proposed indices has been explained. Section 3 shows the
resulting benefits of the proposed indices by a commercial WT-HSS case study. Lastly, conclusions are drawn at section 4.

2. Theoretical framework of the proposed indices

2.1. Low oscillatory bearing signal component extraction by TQWT

Tunable Q factor wavelet transform (TQWT) is a sparse signal decomposition technique, which can decompose a signal into high oscillatory and low oscillatory components based on the Q factor of the wavelet bases. Q factor of a wavelet base can be defined as:

\[ Q = \frac{F_c}{W} \]  

(1)

Where \( F_c \) is defined as the center frequency and \( W \) is defined as the bandwidth of the pulse.

A two channel filter bank can be used to implement TQWT with the help of low pass scaling (associated with parameter \( \alpha \)) and high pass scaling (associated with parameter \( \beta \)). Equation (2) shows the relationship between \( \alpha \) and \( \beta \) with Q factor and redundancy \( r \) as follows:

\[ \alpha = 1 - \frac{\beta}{r}, \beta = \frac{2}{Q + 1} \]  

(2)

Low pass filter \( H_0(\omega) \) and high pass filter \( H_1(\omega) \) can respectively be represented by Equation (3) and equation (4) as follows:

\[
H_0(\omega) = \begin{cases} 
1, & |\omega| \leq (1 - \beta)\pi \\
\theta(\frac{\alpha + (\beta - 1)\pi}{\alpha + \beta - 1}), & (1 - \beta)\pi \leq \omega \leq \alpha \pi \\
0, & \alpha \pi \leq |\omega| < \pi 
\end{cases}
\]  

(3)

\[
H_1(\omega) = \begin{cases} 
0, & |\omega| \leq (1 - \beta)\pi \\
\theta(\frac{\alpha \pi - \omega}{\alpha + \beta - 1}), & (1 - \beta)\pi \leq \omega < \alpha \pi \\
1, & \alpha \pi \leq |\omega| < \pi 
\end{cases}
\]  

(4)

Equation (2), equation (3) and equation (4) can be used to parametrize TQWT. Figure 1 shows the two channel filter bank based implementation of TQWT.
Equation 5 can be used to calculate the maximum allowable decomposition level, $L_{\text{max}}$ for a $N$ point signal as follows [22]

$$L_{\text{max}} = \left\lfloor \frac{\log(N / 4(Q + 1))}{\log((Q + 1) / ((Q + 1) - 2/r))} \right\rfloor$$

(5)

Where $\lfloor \cdot \rfloor$ represents a rounding operation. Finally, “$L+1$” sub bands are generated.

Given a WT-HSS bearing signal “$x_{\text{WT-HSS-bearing}}$” consisting of both high oscillatory component “$x_{h(\text{WT-HSS-bearing})}$” and low oscillatory component “$x_{l(\text{WT-HSS-bearing})}$” such as

$$x_{\text{WT-HSS-bearing}} = x_{h(\text{WT-HSS-bearing})} + x_{l(\text{WT-HSS-bearing})}$$

(6)

In this research, our aim is to decompose “$x_{\text{WT-HSS-bearing}}$” into “$x_{h(\text{WT-HSS-bearing})}$” and “$x_{l(\text{WT-HSS-bearing})}$” respectively with the help of morphological component analysis (MCA) [23].

Given that low Q factor ($Q_l$) and high Q factor ($Q_h$) are used for two separate TQWTs namely TQWT1 and TQWT2 respectively, equation 7 can be implemented for the targeted decomposition.

$$\arg\min_{w_1,w_2} \frac{\sum_{j=1}^{12} \lambda_j ||w_{1j}||^2 + \sum_{j=1}^{12} \lambda_{2j} ||w_{2j}||^2}{w_{1j} + w_{2j}}$$

$$x_{\text{WT-HSS-bearing}} = \text{TQWT1}^{-1}(w_1) + \text{TQWT2}^{-1}(w_2)$$

(7)

Where $\lambda_1$ and $\lambda_2$ are regularization parameter and $W_i$ represents the sub bands for $TQWT_i (i=1,2)$.

After obtaining the values of $w_1$ and $w_2$, we can find the $x_{h(\text{WT-HSS-bearing})}$ and $x_{l(\text{WT-HSS-bearing})}$ as follows:

$$x_{h(\text{WT-HSS-bearing})} = \text{TQWT1}(w_1), \ x_{l(\text{WT-HSS-bearing})} = \text{TQWT2}(w_2)$$

(8)

Noise is present in the collected WT-HSS bearing vibration signal. As a result, equation 8 can be expressed as

$$x_{\text{WT-HSS-bearing}} = x_{h(\text{WT-HSS-bearing})} + x_{l(\text{WT-HSS-bearing})} + \text{noise}$$

(9)

Finally, equation 10 can be implemented to obtain a solution.

$$\arg\min_{w_1,w_2} \frac{\sum_{j=1}^{12} \lambda_{1j} ||w_{1j}||^2 + \sum_{j=1}^{12} \lambda_{2j} ||w_{2j}||^2}{w_{1j} - w_{2j}}$$

$$x_{\text{WT-HSS-bearing}} = \phi_1 w_1 - \phi_2 w_2$$

(10)

Where $\phi_1$ and $\phi_2$ respectively infers the inverse TQWT. Values of $\lambda_1$ and $\lambda_2$ can be chosen according to signal power.

Value of number of decomposition level of TQWT algorithm can be calculated by equation 5 and the value of redundancy “$r$” is chosen as 3 [24]. Moreover, the value of low Q factor “$Q_l$” is chosen as...
1 and the value of high Q factor “$Q_h$” is selected by an iterative smoothness index guided approach as discussed in the research [21].

2.2. Oscillatory sparsity indices calculation for dynamic WT-HSS bearing degradation quantification

After extracting the low oscillatory component from a bearing vibration signal, in the proposed method, Kurtosis, gini index, negative entropy and reciprocal smoothness index have been used to quantify it to achieve continuous bearing health monitoring. Referring to the original theory of calculating kurtosis, gini index, negative entropy and reciprocal smoothness index [18], oscillation based kurtosis (OBK), oscillation based gini index (OBGI), oscillation based negative entropy (OBNE), oscillation based reciprocal smoothness index (OBRSI) can be calculated by following steps:

Step 1: At a time instant $R$, a WT-HSS bearing vibration signal $x_{WT-HSS\text{-bearing}}^R$ is collected. The value of $R$ is

$$R = R_0 + \Delta r$$  \hspace{1cm} (11)

where $R_0$ infers the starting time of data acquisition and $\Delta r$ infers the definite time interval between collection of each recording.

Step 2: Extract the low oscillatory component $x_{WT-HSS\text{-bearing}}^R$ from $x_{WT-HSS\text{-bearing}}^R$.

Step 3: Calculate oscillation based kurtosis $OBK_{WT-HSS\text{-bearing}}^R$, oscillation based gini index $OBGI_{WT-HSS\text{-bearing}}^R$, oscillation based negative entropy $OBNE_{WT-HSS\text{-bearing}}^R$ and oscillation based reciprocal of smoothness index $OBRSI_{WT-HSS\text{-bearing}}^R$ for the extracted $x_{WT-HSS\text{-bearing}}^R$ as follows:

$$OBK_{WT-HSS\text{-bearing}}^R[n] = \frac{1}{N} \sum_{n=1}^{N} \left( \frac{1}{N} \sum_{h=1}^{N} (x_{(WT-HSS\text{-bearing})}^R - \mu_{x_{(WT-HSS\text{-bearing})}^R})^2 \right)^{\frac{1}{2}}$$  \hspace{1cm} (12)

$$OBGI_{WT-HSS\text{-bearing}}^R[n] = 1 - 2 \sum_{n=1}^{N} \frac{SE_{order}^{x_{(WT-HSS\text{-bearing})}^R}[n]}{SE_{x_{(WT-HSS\text{-bearing})}^R}[n]} \left( \frac{N-n+1}{N} \right)$$  \hspace{1cm} (13)

$$OBNE_{WT-HSS\text{-bearing}}^R[n] = \frac{SE_{x_{(WT-HSS\text{-bearing})}^R}[n]}{\ln(\frac{SE_{x_{(WT-HSS\text{-bearing})}^R}[n]}{SE_{x_{(WT-HSS\text{-bearing})}^R}[n]})}$$  \hspace{1cm} (14)

$$OBRSI_{WT-HSS\text{-bearing}}^R[n] = \sqrt{\frac{\sum_{n=1}^{N} SE_{x_{(WT-HSS\text{-bearing})}^R}[n]}{N}}$$  \hspace{1cm} (15)

Where $N$ is the data length of the extracted $x_{(WT-HSS\text{-bearing})}^R$, $\mu_{x_{(WT-HSS\text{-bearing})}^R}$ is the mean of $x_{(WT-HSS\text{-bearing})}^R$, $SE_{x_{(WT-HSS\text{-bearing})}^R}$ represents the squared envelope of the extracted $x_{(WT-HSS\text{-bearing})}^R$ which can be calculated as

$$SE_{x_{(WT-HSS\text{-bearing})}^R}[n] = \left| x_{(WT-HSS\text{-bearing})}^R[n] \right|^2$$  \hspace{1cm} (16)

Where $x_{(WT-HSS\text{-bearing})}^R[n]$ represents the analytic signal version of $x_{(WT-HSS\text{-bearing})}^R$ and can be written as

$$x_{(WT-HSS\text{-bearing})}^R[n] = x_{(WT-HSS\text{-bearing})}^R[n] + j \times \text{hilbert}\{x_{(WT-HSS\text{-bearing})}^R[n]\}$$  \hspace{1cm} (17)
Moreover, $SE_{order}^n = [SE_{order_1}^n, SE_{order_2}^n, SE_{order_3}^n, ..., SE_{order_{N-1}}^n, SE_{order_N}^n]$ in which all elements are ranked from the smallest to the largest such as $SE_{order_1}^n \leq SE_{order_2}^n \leq SE_{order_3}^n \leq ... \leq SE_{order_{N-1}}^n \leq SE_{order_N}^n$. Additionally, $\{\}$ represents an averaging operator.

Figure 2 represents an illustration of the proposed method.

3. Experimental verification

In order to investigate the utility of OBK, OBGI, OBNE and OBRSI in dynamic degradation quantification of WT-HSS bearing, vibration data collected from a commercial 2.2 MW wind turbine [19] is used. Data is collected from a WT-HSS bearing for consecutive 50 days. At the end of data collection, inner race bearing fault is found after inspection. The sampling frequency of the data collection is 100KHz. Recording time for one day’s data collection is 6s. Type of bearing used is SKF 32222 J2 tapered roller bearing. Radial accelerometer is used to measure the vibration response. Wind turbine high speed bearing shaft rotating speed vary considerably due to several natural phenomena such as sudden change of weather, land features etc.. Figure 3 demonstrates the fluctuations of average rotating speed high speed wind turbine shaft over 50 days of measurement.

Figure 3. Variation in average shaft rate over 50 days
From figure 3, it can be seen that the average speed of bearing shaft varies over 50 days. Thus, the corresponding monitoring process can be termed as time varying speed bearing health monitoring process. Change of amplitude of vibration signal over the 50 days monitoring period is shown in figure 4 as follows.

From figure 4, it can be seen that there are three distinct phases of bearing vibration signal amplitude. Phase 1 is from day 1 to day 25. A rise in vibration amplitude is noticed at day 26 which is the starting point of phase 2. Phase 2 ends at day 47 and at day 48 another distinctive rise in vibration amplitude is noticed which denotes the start of phase 3. In order to narrow down the estimation of time to start point (TSP) of the fault a 1-D exhaustive searching method is utilized with the help of envelope spectrum analysis of each starting signal file for different phases. Based on the bearing specifications, fault characteristic co-efficient (FCC) for inner race fault is 9.46 [12]. Considering the effect of fluctuating shaft frequency, range of fault characteristic frequencies (FCF) are calculated for day 1, day 26 and day 48. It is to be noted that these FCFs are estimated based on the average shaft speed recorded by tachometer on the corresponding days. Table 1 presents the FCFs on day 1, day 26 and day 48.

| Bearing component | Fault characteristic frequency | Day 1 FCF(avg.) | Day 26 FCF(avg.) | Day 48 FCF(avg.) |
|-------------------|--------------------------------|----------------|----------------|----------------|
| Inner race        | Bearing inner race frequency (BPFI) | 284.2730 Hz. | 284.0838 Hz. | 284.4622 Hz. |

Frequencies calculated in table 1 are used to estimate the phase where the TSP point of inner race fault is present in the 1-D envelope spectrum analysis based search. The envelope spectrums of files corresponding to day 1, day 26 and day 48 have been presented in figure 5.
Figure 5. Envelope spectrum analysis of data file corresponding to: (a) day 1; (b) day 26; (c) day 48

From figure 5, it can be seen that in the envelope spectrum predominant spikes are present at the BPFIs and their harmonics (Calculated based on average shaft speed) from the beginning of data collection. So, it can be said that the inner race fault is present from the beginning of data collection. According to the theory of irreversible nature of the physical bearing degradation, with the development of the defect, parameters employed for quantification of WT-HSS bearing degradation should reveal the growth of bearing defect. In this context, performance of OBK, OBGI, OBNE and OBRSI have been compared with the original sparsity indices and adaptive weighted signal preprocessing technique (AWSPT) [25] based sparsity indices. For each of the data files corresponding to day 1, day 26 and day 48, 50 segments of 4096 data points length each are chosen to calculate the values of the indices. The mean values are used to represent the actual index value for the corresponding day. The experimental result is shown in figure 6.
Figure 6. Sparsity indices measure at various phases of wind turbine health deterioration: (a) comparison between original kurtosis (K), AWSPT based kurtosis ($K_{AWSPT}$), oscillatory kurtosis (OBK); (b) comparison between original gini index (GI), AWSPT based gini index ($G_{AWSPT}$), oscillatory gini index (OBGI); (c) comparison between original negative entropy (NE), AWSPT based negative entropy ($NE_{AWSPT}$), oscillatory negative entropy (OBNE); (d) comparison between original reciprocal smoothness index (RSI), AWSPT based reciprocal smoothness index ($RSI_{AWSPT}$), oscillatory smoothness index (OBRSI).

From figure 6, it can be seen that unlike original sparsity indices and AWSPT based sparsity indices, oscillatory sparsity indices show a consistent increasing trend with the deterioration of wind turbine bearing health. In addition, values of the oscillatory sparsity indices are highest in different stages of fault in compare to that of original sparsity indices and AWSPT based sparsity indices. Moreover, among the proposed oscillation based sparsity indices, the rate of increase of OBK, OBGI, OBNE and OBRSI are respectively 2.42%, 0.78%, 2.16% and 2.56% with the progression of the fault from day 1 to day 26. Similarly, the rate of increase of OBK, OBGI, OBNE and OBRSI are respectively 32.74%, 8.08%, 23.89% and 14.32% with the progression of the fault from day 26 to day 48. Hence, it can be said that among the proposed oscillation based sparsity indices, OBRSI is most efficient in WT-HSS bearing degradation quantification when the fault size is relatively small while OBK is most efficient in the severe stage of fault.

4. Conclusion

Application of oscillation based sparsity indices in WT-HSS bearing degradation quantification has been proposed in this research. Four oscillation based sparsity indices namely OBK, OBGI, OBNE and OBRSI have been used on a commercial WT-HSS bearing dataset and its effectiveness has been compared with original sparsity indices and AWSPT based sparsity indices. Following advantages of the proposed sparsity indices have been obtained:

1. Dynamic health degradation quantification for WT-HSS bearing has been obtained.
2. Proposed indices show better performance than original sparsity indices and AWSPT based sparsity indices in dynamic degradation quantification for WT-HSS bearing.

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