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Trends in condition monitoring for pitch bearings

D. Sandoval[1,2], U. Leturiondo[1], F. Pozo[2], Y. Vidal[2], O. Salgado[1] 1

Control and Monitoring Area, Ikerlan Technology Research Center
Pº. J. Mª. Arizmendiarrieta, 2. 20500 Arrasate-Mondragon, Spain´
Telephone: +34 943 712 400
dasandoval@ikerlan.es

2 Control, Modeling, Identification and Applications (CoDAlab)
Department of Mathematics, Escola d'Enginyeria de Barcelona Est (EEBE)
Universitat Politecnica de Catalunya (UPC), Campus Diagonal-Bes` os (CDB)`
Eduard Maristany, 16, 08019 Barcelona, Spain

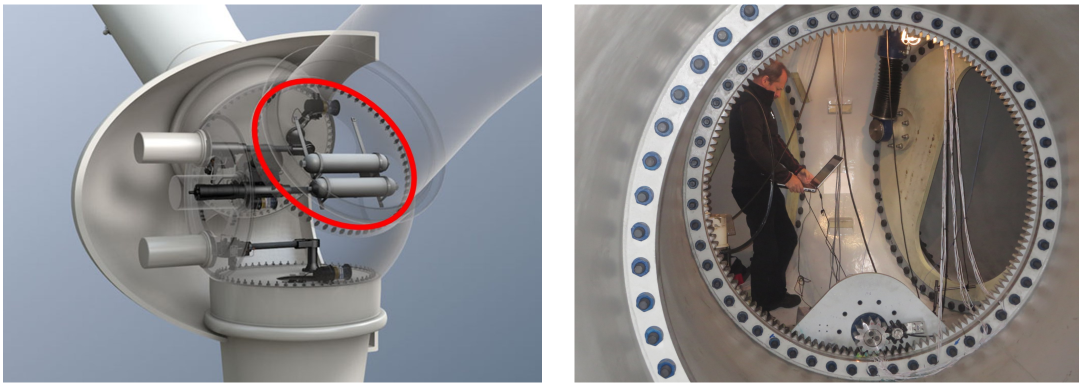
Abstract

The value of wind power generation for energy sustainability in the future is undeniable. Since operation and maintenance activities take a sizeable portion of the cost associated with offshore wind turbines operation, strategies are needed to decrease this cost. One strategy, condition monitoring (CM) of wind turbines, allows the extension of useful life for several parts, which has generated great interest in the industry. One critical part are the pitch bearings, by virtue of the time and logistics involved in their maintenance tasks. As the complex working conditions of pitch bearings entail the need for diverse and innovative monitoring techniques, the classical bearing analysis techniques are not suitable. This paper provides a literature review of several condition monitoring techniques, organized as follows: first, arranged according to the nature of the signal such as vibration, acoustic emission and others; second, arranged by relevant authors in compliance with signal nature. While little research has been found, an outline is significant for further contributions to the literature.

1. Introduction

Currently, wind energy is considered the most important source of clean energy for the Europe Union (EU) to replace fossil energy by 2050[(1)]. With EUR 26.7 billion of investments in 2018 (20 % more than 2017[(2)]), the economic factor of the budget for wind energy project has an important and decisive point for the realization. One of the key components of the budget is the operation and maintenance (O&M), which aims to achieve the greatest production without undue risk. The risk can be stated as health, safety and environmental, technical, commercial and financial risk considered equally[(3)]. Therefore, O&M is a fundamental part of a wind turbine project because it ensures the proper operation of wind turbines during the lifetime. For each megawatt produced in a wind farm, between 20 - 30 % of the price covers O&M expenses. Manufacturers attempt to lower these costs significantly by using a type of preventive maintenance called condition based maintenance (CBM). CBM is based on performance and/or parameter monitoring that may be scheduled, on request or continuous(4). From all the schemes of maintenance used nowadays in industry, CBM has the optimal point of maintenance and repair cost by virtue of the data adquisition(5).

O&M for wind turbines requires several characteristics to be taken into consideration. One of them is the variety of components present in a wind turbine. As components have an individual maintenance timing, the maintenance schedules can be complex and costly. To manage this situation, a wind turbine can be divided into subassemblies: electrical system, electronic control, sensors, hydraulic system, yaw system, rotor hub, mechanical brake, rotor blades, gearbox, generator, support & housing, and drive train(6). Given that several subassemblies require rolling element bearings, such as drive train, pitch system and yaw system, it is important to understand how bearings work in order to manage an efficient O&M.



(a) (b)

Figure 1. Place and dimension of pitch bearings: (a) pitch bearing placement on rotor hub(7) and (b) photograph of regular pitch bearing for dimension comparison(8).

Rolling elements bearings reduce the friction between moving parts and constrain the motion of other elements. Considering the variety of applications, there are many types of bearings. A classification for bearings can be set according to the rotational speed. Regardless the fact that there is no official regulation, the current consensus in Academia is 600 revolutions per minute (rpm)(9). Rotational speed under this value is categorized as low rotating speed and above it, high speed. A particular bearing subgroup works in the slow speed, named slewing bearing (SB). As these type of bearing usually holds heavy and slow oscillating load, its design differs from general-purpose bearings(10). In wind turbines, several types of bearings are involved in the electricity generation chain, including SBs. SBs are used for blade pitch (also known as pitch bearing), giving the feasibility to change the angle of incidence of the wind to the blade. The position of this type of bearing on rotor hub can be seen in Fig. 1.

For the health condition analysis of the SB, the loads and the rotational speed conditions have a strong influence. The operating conditions for pitch bearings depend on the power production, which is influenced by the fluctuation of the wind and the power generation control system. The pitch control reacts continuously to the fluctuation of the wind throughout the day. The random nature of the wind forces the movement of the SB in both directions around a setting point (clockwise and counter-clockwise), where no full turn is a normal situation(11). Due to the dimension of the bearing and the magnitude of the forces involved, the turning speed is relatively slow (up to 5 rpm).

The analysis of a bearing under low speed is particularly challenging, since the ratio between noise and signal is especially high under regular pitch bearings conditions(12). The impact from a defect spot and an element from the pitch bearing at low rotation has low energy emission, hence it can be hard to distinguish from the present noise. The damage can grow to a severe stage and it may be detected when it is too late. Both conditions (loads and rotational speed) have as a result that the methods and features, normally used for typical rolling element bearing, are less useful for identification of abnormal condition for slow rotational speed, and especially for the situation of SB(13).

The aim of this work is to present a review of the signal types and methods which are currently used in Academia to obtain condition monitoring information of the SB. This paper is organized as follows: Section 2 describes the methods arranged according to the nature of the signal. Section 3 highlights relevant authors who work particularly on SBs; and finally, conclusions are presented in Section 4.

2. Signal clasiffication

In order to understand the condition of a SB, several signal types and data sources can be used. Some of them are vibration signal (VB), acoustic emission (AE) or temperature. There is also the possibility to use oil analysis results as a data source, and some other sources such as parameters from motor actuator(14). Among these sources, the VB is the most used and studied in the literature. For this reason, it is the first signal to be reviewed.

2.1.Vibration signal

The analysis of VB can be done in particular domains, but there are common among domains: statistical features(15). One well known feature is the root mean square (RMS). The variance and some more precise features as kurtosis and skewness can be calculated, which are related to the probability density function (PDF)(16). The relationship of PDF and the state of the bearing is the reason to have kurtosis and skewness as features. Some other features can be easily calculated: shape and crest factor, upper and lower limit, impulse and margin factor. In time domain it is especially usual to calculate these features, and some of them have their counterpart in the frequency domain.

Besides the calculation of feature extraction, there are models applied in time domain that are found in the reviewed literature such as the autoregressive (AR) model. An AR model describes certain time-varying random process based on past behavior. The model has AR parameters[(17)], which applied to SB can vary according to the state of the bearing. Other types of AR models are autoregressive moving average (ARMA) models, n level AR model (AR(n)), autoregressive integrated moving average (ARIMA) model and threshold AR model.

The frequency domain is another approach to analyze the condition of SBs with VB signals. An statistical analysis can be performed as explained for the time domain with the spectral skewness, spectral kurtosis, spectral entropy and Shannon entropy[(18)]. The concept of spectral statistic is adopted in addition to the concept of the classical power spectral density (PSD)[(19)]. When the signal has stationary Gaussian noise in certain frequencies, PSD gives zeros values. During the occurrence of transients, it gives high positive values. The transient signals are hard to notice under the background noise, hence the fault is hard to detect. The skewness value can solve this problem by analyzing the frequency band and select the sensitive frequency band that corresponds to the bearing condition[(20)].

There are also several techniques where the information from the frequency and time domain are given at the same time, named time-frequency analysis. Short time Fourier transform is one of these techniques, where the analysis of the frequency domain is done at several time windows[(21)]. For each time window, the Fourier transform is applied to obtain the frequency information. The oddities on time can be perceived using the frequency information. An important parameter of this method is the size time interval. Another point of view for signal processing is the generalization of the concept behind the Fourier transform. The Fourier transform decomposes a signal into sine waves at several frequencies. This wave could be other class of wave, or generally speaking wavelets. Wavelet transform and decomposition are tools for information extraction and noise filtering[(22)]. Another concept is the empirical mode decomposition (EMD)[(23)], formulated as the decomposition of a data set into a number of intrinsic mode functions (IMFs). The IMFs generate instantaneous frequencies as functions of time by means of the Hilbert transform[(24)]. The information of the IMF can be better interpreted by a representation of the energy-frequency-time distribution called the Hilbert spectrum.

Additionally to the analysis of time and frequency domain, methods based on chaos theory and fractal dimension are also found on the reviewed literature. Qiao *et al.*[(25)] review the literature related to stochastic resonance (SR) applied to bearings fault detection. The review surveys the applications of SR with several methods based on classical bistable models, improved SR models, and processing methods. The largest Lyapunov exponent (LLE) algorithm is an established method which calculates the degree of the chaos of vibration signal at a certain time(26). The degree of chaos corresponds to any local instability in the vibration signal due to the dynamic contact between elements of bearing and defect spots during the SB operation. The approximate entropy quantifies the degree of regularity in the vibration signal; this value is larger when the behaviour of the signal is irregular(27) and smaller for regular behaviour. Yan *et al.*(28) related the deterioration of the bearing condition and the increase in the number of frequency components. As a consequence, the approximate entropy value will increase according to the deterioration of the bearing. The instantaneous angular speed based fault diagnosis is given by Moustafa *et al.*(29), in order to compensate for the shortcoming of conventional monitoring techniques for low-speed bearings. The Teager energy operator is used to strengthen the signal after wavelet noise reduction and combined with the complementary ensemble empirical mode decomposition (CEEMD) to extract bearing fault through IMF decomposition(30).

2.2.Acoustic emission

As the collection of waves (or signals) is the fundamental of AE, there are several parameters which are useful for evaluation: the number of events, peak amplitude, ring-down count and duration of the signal. These parameters are in the time domain, and they are used to discriminate the situation of the material(31). For the case of bearings, these parameters are not enough to recognize among faults. Consequently, further analysis is needed to comply with CM. Because the signal of an AE is different from VB, it is not possible to calculate the same parameters. The most frequent parameters calculated are average energy (AErms), average signal level (ASL) and kurtosis for single wave detection(32). Van Hecke *et al.*(33) use several condition indicators such as Shannon entropy, crest factor and histogram upper and lower bounds.

In order to follow a classification of CM and fault diagnosis methods for AE, the methods can be categorized as signal processing and feature extraction. If the assumption of the hidden periodicity of the energy flow of a signal is given, the concept of cyclostationary can be applied to AE signals(34). The analysis in frequency and the time domain is possible to state for AE signals with the use of wavelet concept(35), and spectral kurtosis(36). The AE signals have a multi-modal, multi-mode and multi-frequency spectrum, and the Wigner–Ville distribution can be implemented(37). For feature extraction methods, the use of AR coefficients(38) and approximate entropy(39) is stated in the reviewed literature. Elforjani *et al.*(40) demonstrates the use of AE measurements to monitor natural defect initiation and propagation. In further publications, Elforjani estimates the remaining useful life (RUL), and showed that techniques such as kurtosis and crest factor cannot be employed for observing high transient events(41).

2.3.Other signals

2.3.1.Shock Pulse

The shock pulse method (SPM) is a non-destructive method which is based on the detection of VB with a transducer tuned at 32 kHz resonance frequency. Because the frequency of the signals is distant from the regular vibration analysis range, the described waves are produced by the impact between the damaged surface and an element inside the bearing. From the beginning, SPM was used to slow speed bearing (2 rpm)(42). SPM is today mixed with several methods(43) and it is considered as a special case of vibration analysis. Yao *et al.*(44) proposed an improvement to the method, which may cause erroneous diagnosis in the presence of strong background noise or other shock sources. This is the reason to propose a pulse adaptive time-frequency transform method to extract the fault features of the damaged rolling element bearing. In the work of Mukane *et al.*(45) the use of HilbertHuang and wavelet transform along with SVM and the neuronal network is proposed to identify damage in bearings. Although in their origins it was proved the use of the method under low-speed operating conditions, today there is no further research in this aspect.

2.3.2.Oil analysis

The oil state from lubricated bearings, such as pitch bearing, can be analyzed to obtain information from the bearing state. Although it is not a signal as VB and AE, ferrography and spectrometric analysis can identify an abnormal condition of bearings efficiently from the contamination of the oil(46). One of the main goals for oil analysis is the development of automatic devices which allow the automatic analysis of the oil and consequently be used into CBM systems.

3. Current status

The CM of SBs is a restricted field of study. Although several methods and features calculation have been commented, some authors have relevant research works to be mentioned. Caesarendra started with a combined approach for bearing degradation prognostics, where he proposes the use of relevance vector machine, logistic regression (LR) and ARMA models to assess failure degradation(47). Later the author used EMD and ensemble EMD (EEMD) for fault recognition at 4.5 rpm, where the data from the fast Fourier transform (FFT) was not sufficient to identify the fault(48). A feature extraction with four types of nonlinear methods to a set of real data of 138 days slewing bearing test-rig at 1 rpm was done(49). The use of several indicators combined in a multivariate state estimation technique (MSET) estimate the RUL on VB data from laboratory(50). Another paper focused the work on the application of LLE on a SB dataset of 139 days with a contrast of FFT and time domain statistics(51). The same data was used for the calculation of several parameters(20), including Hjorth parameters (activity, mobility, complexity)(20). Prognosis was also proposed with an advanced predictive analytic called PANFIS, which is compared to some established methods such as ANFIS, eTS, and Simp eTS(52). Caesarendra *et al.* proposed a novel application for a circular domain feature calculation based for CM method[53] . In this publication they applied the method from Pewsey and Fisher for CM in SB vibration data[54]. Several publications continued the study of circular domain applied to SBs[55,56]. Finally, Caesarendra made a review and applied the CM methods to a 15 months data set from SB based on the acoustic emission signal data, with early defect evidence stated at the end of the data set[57].

Feng proposed an EEMD with a principle component analysis (PCA) based method as performance degradation model for SB using VB and it was applied to experimental data[58]. In another paper the same author proposed the least squares support vector machine (LSSVM) to estimate the trend of SB degradation with small sample data, using PCA to fuse multi-feature health state vectors of SB (root mean square, kurtosis, wavelet energy entropy, and IMF energy)[59]. The degradation trend was predicted using the LSSVM model. Feng also studied the feasibility of RUL prediction based on modified Weibull distribution, building a relationship with failure rate[60]. Zvokelj works on AEˇ signals applied to SB CBM. An application of EEMD-based multiscale PCA (EEMDMSPCA) is presented as performance degradation model for SB, with the use of AE[61]. A subsequent work used a kernel principal component analysis for a model called EEMDMSKPCA, whose validation is done with simulated and real VB and AE signals[62]. A final attempt proposed the integration of the independent component analysis[63].

4. Conclusion

Regardless that in the last 15 years a constant growth in the research of SB condition monitoring has been detected, its number of publications, in comparison to other bearings, is still low. The main focus of SB publications is not about CM, therefore the difficulty to find studies related to this field. Moreover, the CM of SBs is challenging and it can be noticed with the results of the reviewed publication. Additionally, the odd operating conditions stated for pitch bearings can give an additional layer of complexity. This is the main reason for the constrained feasibility of several methods used in bearings application. Nevertheless, the present work shows the principal trends on CM according to the signal nature and calculation domain.

The use of vibration signals is predominant in the reviewed literature, as seen in the number of papers. The methods used in the literature come from several knowledge fields, such as statistics, signal processing, and even neuroscience. AE signals are also a promising source of data for SB. Although the studies are not as vast as for VB signals, there are enough studies demonstrating its feasibility. One reason for this situation could be the complexity of the equipment required to meet the AE laboratory experiments and higher complexity methods, and thus a computationally more time-consuming monitoring approach.

There is enough space for improvement in the field of SBs. While there are limited studies about automated diagnosis for low-speed bearings using VB, the lack of this type of studies for AE is possible to notice in the literature . As seen in the reviewed literature, there is no one for all solution for CM of SBs, and future lines of research in this field can improve current results in the literature. Finally, a last interesting research area is the fusion of several signals from the SB, in order to establish their current and future state.

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