Diagnostics of bearings in presence of strong operating conditions non-stationarity—A procedure of load-dependent features processing with application to wind turbine bearings

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ABSTRACT

Condition monitoring of bearings used in Wind Turbines (WT) is an important issue. In general, bearings diagnostics is a well recognized field of research; however, it is not the case for machines operating under non-stationary load. In the case of varying load/speed, vibration signal generated by rolling element bearings is affected by operation factors, and makes the diagnosis relatively difficult. These difficulties come from the variation of vibration-based diagnostic features caused mostly by load/speed variation (operation factors), low energy of sought-after features, and low signal-to-noise levels. Analysis of the signal from the main bearing is even more difficult due to a very low rotational speed of the main shaft. In the paper, a novel diagnostic approach is proposed for bearings used in wind turbines. As an input data we use parameters obtained from commercial diagnostic system (peak-to-peak and root mean square (RMS) of vibration acceleration, and generator power that is related to the operating conditions). The received data cover the period of several months.

The method presented in the paper was triggered by two case studies, which will be presented here: first when the bearing has been replaced due to its failure and the new one has been installed, second when bearing in good condition has significantly changed its condition. Due to serious variability of the mentioned data, a decision making process on the condition of bearings is difficult. Application of classical statistical pattern recognition techniques for “bad condition” and “good condition” data is not sufficient because the probability distribution/density functions (pdf) of features overlap each other (for example probability distribution/density function of peak-to-peak feature for bad and good conditions). It was found that these data are strongly dependent on operating condition (generator power) variation, and there is a need to remove such dependency by suitable data presentation. To achieve it, load susceptibility characteristics (LSCh) presenting as feature – operating condition space has been used. Presented approach is based on an idea proposed earlier for planetary gearboxes, i.e. to analyse data for bad/good conditions in two dimensional space, feature – load/rotation speed. Here it has been proven experimentally for the first time that there are two types of susceptibility characteristics related to the type of a fault.

The novelty of the paper also comes from an extension of previous study that is statistical processing of data (linear regression analysis) in moving window in the long time

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of a turbine operation is used for feature extraction. It is proposed here to use novel features for long term monitoring. It will be shown that parameters of regression analysis can be used as unvarying, and fault sensitive features for decision making.

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1. Introduction

Vibration based condition monitoring is nowadays widely used in many branches of the industry. Rapidly growing field of potential applications of condition monitoring systems results in development of more advanced data processing methods suitable for more complex machinery frequently operating under conditions of relatively significant variability. Good example of such machinery might be wind turbines. They become widely used for the electric power generation and they are also frequently considered as an interesting object from condition monitoring perspective [1–7].

Most of diagnostics efforts are focused on rolling element bearings [8–14] and gearboxes [15–21] damage detection. In general, gears and bearings diagnostics is well recognized field; however, it is not the case for machines working under non-stationary load. In the case of varying operational conditions, a vibration signal is often relatively difficult to analyse due to influence of speed/load variation on vibration signal [19,32]. Estimation of operational conditions and their influence on raw vibration signals has been a subject of number of studies [22–25]. Majority of difficulties in vibration-based condition monitoring come from the variation of diagnostic features caused mostly by load/speed changes, low energy of sought – after features and high noise levels [26–37]. Time varying operating conditions, in the case of wind turbines, are related to non-stationary wind behavior (wind power) [5,22–24] that plays an important role and might be understood as the time varying excitation of the system.

In this paper a novel diagnostic approach is proposed for bearings used in the machinery operating under non-stationary operational conditions. The paper extends previous study done for planetary gearbox diagnosis [30]. In Ref. [30] it has been shown that the load susceptibility characteristics (LSCh) of monitored machinery can be approximated by linear regression model. Research results introduced in this paper show that linear regression parameters calculated for subsequent short-time data segments can be presented as long term time series. It is shown that such parameters (results of regression analysis for data segment) are relatively unvarying; however, fault sensitive, which makes them very efficient as fault indicators. The novelty presented in this paper is the concept of replacing traditional vibration-based features (peak-to-peak, RMS, etc.) with regression parameters for practical long-term condition monitoring. It is the authors’ belief that proposed approach will simplify decision making process by presenting fault indicators in simple and comprehensible way.

The idea of novel approach is provided by analysis of two case studies presented in the paper. First one discusses rolling element bearing degradation process development. Second one examines data obtained during operation of damaged bearing and after its replacement.

In order to provide diagnostic decision, two kinds of information (measurements) have been acquired: namely peak-to-peak and RMS of vibration acceleration and generator power that is related to the operating conditions. The received data cover the period of several months. These data come from a commercial diagnostic system. (It should be underlined here, that our intent was to use the available data from existing monitoring systems. We were not able to process raw vibration to obtain other, maybe more sensitive features).

Due to serious variability of the mentioned data, a decision making regarding the condition of bearings is difficult. Application of classical statistical pattern recognition techniques for “bad condition” and “good condition” data is not sufficient because the probability distribution/density functions (pdfs) of features overlap each other (for example, pdfs of peak-to-peak feature for bad and good conditions).

It was found that these data are strongly dependent on the operating condition (generator power) variation and there is a need to remove such dependency by a suitable data presentation. To achieve it, the load susceptibility characteristics (LSCh) presenting as feature – operating condition space has been used.

2. Bearings diagnostics – a brief review

It should be clarified that, in general, one may easily find several interesting papers regarding bearing diagnostics using envelope analysis [8], wavelets [9], adaptive filters [10,11], exploiting cyclostationary of vibration [12,13], and many others [14].

Wind turbine is an example of machinery operating under varying operational conditions and – as it was shown – the damage detection of bearings in such condition is relatively challenging [3–5]. Some of state of the art works try to discuss/compare/evaluate existing algorithms [2,4]. Several examples of successful applications of vibration-based condition monitoring are discussed in Refs. [5–7], where techniques based on advanced signal processing (spectral kurtosis, wavelet), data compression and analysis using SVD, etc., were used. As it was mentioned, external, environmental issues are also important, because they affect operation of wind turbine [1,3,5]. However, idea presented in the paper was to use diagnostic data provided by the online monitoring system, not raw vibration signals. In order to use raw vibration signals one needs to build advanced feature extracting module in online version that would be rather expensive. For offline processing, it is not
so problematic, and as it was mentioned, some techniques for multidimensional features extraction and further processing using, for example, SVD might be used. Some recent works developed for similar problems show ability of multidimensional data processing using Principal Component Analysis, data projection techniques, outliers analysis etc. [20,21,31,33,38]. However, it should be noted that in practical situation validation of data seems to be serious problem [1] so increasing of system complexity should be done very carefully.

3. Aim of this paper – problem definition

In a typical situation, the online condition monitoring system measures several physical variables and compares them to predetermined threshold levels. Obviously, threshold values are difficult to establish. In practice, they are set based on the experience of maintenance staff and monitoring system provider. When the value of diagnostic parameter/feature is higher than alarm level, some action to validate the warning is done. Unfortunately, such approach often does not fulfill expectations in real life, especially when machine (i.e. wind turbine) is working under time varying operational conditions. Due to non-stationary operating conditions, values of diagnostic parameters manifest substantial variability (Fig. 1). In practice, it leads to misleading messages from system. More advanced approaches are difficult to implement online and usually increase the cost of monitoring systems. The purpose of this paper is to use the same data, (i.e. no extra acquisition channels or advanced expert systems are required) but with novel data processing technique used for decision making. Taking into account the expected simplicity of our novel procedure, we can say that it is very easy to implement and interpret. Therefore, we hope that it can actually be validated in an online system.

Simple statistical analysis (when ignoring load variation) are very difficult to interpret. Based on probability density function of feature (Fig. 2), it is extremely difficult (or even impossible) to establish threshold value to separate (classify) good and bad condition data. In Fig. 2 one might see results for data corresponding to good and bad technical condition for two different objects (left: peak to peak values related to main bearing, right: RMS values related to generator bearing).

From Fig. 2 one might conclude that pdfs of features are non-Gaussian, and they cover partially the same range of features values for good and bad condition machine. Additionally, distribution of data presented in the Fig. 2 appears to be bimodal. From Fig. 1 one can see that the power generated by a wind turbine varies from 5–90% of maximum value of 1500 kW. As one can see from Fig. 1 that generated power occurs frequently around 5% what is seen in data measured distribution Fig. 2, which is equivalent to first mode of data distribution. Second mode of a distribution is connected with rational/efficient power generation. This due to the fact that majority of wind turbines should generate power at average wind speed.

4. A proposal of new algorithm for statistical data processing

In this section a novel algorithm for mentioned data processing is introduced. It is proposed to use a long term time series of chosen vibration-based feature and power variation as an input data. After processing, one may obtain novel, load-independent features with highly reduced spread. It is the authors’ belief that such representation is relatively easy to interpret and makes automatic decision making process possible.

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**Fig. 1.** Example of long-term data acquired from peak-to-peak of vibration for bearing and power variation.
Methodology. The idea of processing is to divide long term trends into several segments for the selected vibration based feature (peak to peak, RMS etc.) and chosen reference data (e.g. power). Data portions length $N$ depends on the data variability and should be chosen experimentally. The length of data segment should be long enough to provide successful regression analysis. Additionally, data in each segment should cover, if possible, whole range of chosen reference data values. For cases presented in this paper, segments based on $N=1000$ samples was used based on visual examination of power data variability.

At this point it should be stated that for majority of industrial wind turbines condition-monitoring systems new vibration-based features should be stored in database every 10 min [1]; therefore, segment of $N=1000$ samples covers around 7 days of data. As mentioned earlier in this section, each data segment should cover whole range of reference data variability. Therefore, it appears to be reasonable to use segments of varying length as a function of reference data variability. However, due to high variability of power generated by the turbine and for simplicity of presented method, constant segment length was chosen. Fig. 3 presents the concept of proposed procedure.

Process each segment using feature-load space concept, i.e. analyze data as function of power, estimate regression parameters: “$a$” and “$b$” from linear regression (feature = $a \times$ power + $b$). Fig. 4 shows example of such analysis. It can be seen that data is distributed from about 75–1500 kW (whole power range of turbine under study). At this point, it has to be stated that in order to apply proposed approach, feature-load dependency has to be assumed linear. More exhaustive description of feature-load space concept can be found in Ref. [30].

5. Analyze variability of parameters $a$ and $b$ from regression equation

When the previous step is finished (i.e. all segments of data have been analyzed in a feature-power space), one may get a new plot describing how parameters of regression were changing during machine lifetime. According to Bartelmus and Zimroz [30], change of condition should change load susceptibility characteristics of machine, i.e. distribution of data clouds and character of feature-power dependency should change as well. Fig. 5 shows the idea of decision making using regression parameters. In fact it is exactly the same rule as commonly used for available condition monitoring systems; however, as it will be seen in case study section, novel features (parameters $a$ and $b$) are better suited for such diagnostics than classical (peak to peak or RMS) features.
It should be highlighted that behavior of regression (values of parameter a and b) results may depend on damage type.

First type is described for gears in Ref. [30] where two machines were considered: one in good and one in bad condition. LSCh plots (presenting vibration-based feature vs. operating conditions) for good and bad condition were very different. In case of good condition machine, vibration-operating condition dependency was week (absolute value of parameter “a” from regression was small). For second machine (bad condition) vibration-operating condition dependency was strong (absolute value of parameter “a” from regression was higher).

The second type of LSCh is presented and experimentally examined in this paper for the first time. It is presented clearly in Figs. 9 and 13, these results will be discussed later.

In paper Bartelmus and Zimroz [29] it has been found that diagnostic features are load-dependent. Some more complete investigation has been presented in paper [30,28] where one type of a gear fault using LSCh has been identified. The characteristics of susceptibility to load are interpreted as follows. The case for a good condition of gearbox shows that planetary gearbox behaves as a linear system under graduated increasing load. It means with increasing load the system is characterized by linear regression line with some small parameter “a”. In the case of bad condition, as a result of frictional wear of bearings, gearbox operates under the condition of misalignment of the internal shafts, which gives a linear increase of the gear transmission error under increasing load. It means that with increase of external load and linear increase of inter teeth force, which cause linear increase of a vibration acceleration signal as it is presented by linear regression line with increased “a” parameter in comparing with the case when the system is in good condition.

It also has been found that LSCh-based approach can separate good-bad condition data efficiently, better than when the data are presented using probability distribution functions with serious overlapping.

Results presented in this paper shows that LSCh approach can be used also to diagnose rolling element bearings. In such case characteristics are different; faults which occur in rolling element bearings will mainly cause an increase of “b” parameter and some minor change of “a” parameter.

In a paper Xiaoan et al. [39] there are given results of investigations, which show that different diagnostic features are in most cases constant when the bearing is in a good condition. One may see three different periods of bearing condition...
namely: good condition period, change of condition period and bad condition period. The period of condition change is very short and diagnostic features are unstable with some tendency to increase and decrease. The bad condition period is characterized by higher approximately stabilized diagnostic features. The results obtained in Ref. [39] are similar to results obtained in presented in this paper.

6. Experiment description

In order to test the efficiency of proposed approach two cases of rolling element bearing faults in wind turbine drive train were selected. The first one presents the development of a generator bearing fault. The second one contains the data from the case when the damaged main bearing was replaced with a new one.

A typical layout of a wind turbine is presented in Fig. 6. The main rotor with three blades is supported by the main bearing and transmits the torque to the planetary gear. The second bearing supporting the rotor is incorporated into the gearbox. The planetary gear has three planets, which are driven by the planet carrier. The planets transmit the torque to the sun gear, at the same time increasing the rotational speed. The sun shaft is the output of the planetary gear and drives the two-stage parallel gearbox. The parallel gearbox has three shafts: the slow shaft connected to the sun shaft, the intermediate shaft and the high speed shaft, which drives the generator. The generator produces AC current of a varying frequency. This current is converted first into DC power and then into AC current of frequency equal to the grid frequency. Electric transformations are performed by the converter at the base of the tower. The gearbox set-up changes the rotational speed from about 25 rpm on the main rotor to about 1500 rpm at the generator.

Fig. 6 also shows location of sensors used for data acquisition performed by a commercial online monitoring system. Input data delivered from the online monitoring system includes time series that means acceleration of peak to peak (P–P), and RMS of vibration, instantaneous power of generator, wind speed, rotational velocity, kurtosis of vibration etc. Examples of long term data that can be obtained from the system are presented in Fig. 1. In this work two types of data will be used: acceleration signals and its features, peak-to-peak value of vibration and RMS of vibration and power of generator as an indicator of operating conditions.

Fig. 6. Layout of a typical wind turbine and location of sensors.

Fig. 7. Input data for generator bearing: RMS long term time series with significant change of condition around $T=1.5e^{-4}$. 
7. A case study

As mentioned earlier two case studies will be discussed as examples of the application of proposed procedure. The first one is related to RMS data captured from a generator rolling element bearing, the second one is associated with a main rolling element bearing with peak to peak value of measured vibrations used as a feature. For both cases additional variable, i.e. power of generator is analyzed in parallel.

7.1. Example 1

In this example the application of a novel procedure to feature data related to signals measured on generator bearing is presented. For this case RMS of vibration signal acquired from online monitoring system is used. The task defined here is to obtain more reliable feature in order to detect the bearing condition change. Input data is shown in Fig. 7. As it is marked by circle, around $T=1.5 \times 10^4$ [samples] a significant change of condition has appeared. (please note that T is expressed in samples, and covers period of several months, compared with Fig. 1).

According to the procedure described in previous section, long term RMS trend has been segmented (Fig. 7); for each segment of data regression analysis were performed in the $\text{RMS-power space}$. Fig. 8 shows two examples for segment 2 (good condition) and segment 16 (bad condition).

Results of processing are shown in Fig. 9 (left) when regression parameters "a" and "b" are shown for the whole scope of data as function of time. It is clearly seen that both parameters “a” and “b” have changed significantly giving the evidence of the bearing condition change. Especially variation of b is very useful from the diagnostic point of view because it is a measure of LSCh shift. When looking again at Fig. 8, one may notice that indeed, distribution of bad condition data has been shifted up in comparison to good condition. It gives the evidence of the second type of susceptibility characteristics. Using the procedure proposed in Section 4 one may obtain limited number of points on final picture (one point for one segment).

To improve resolution in time domain, segmentation with overlapping might be used. Fig. 9b shows time series of new features for segment length $N=500$ and overlapping 490 samples. It can be noticed that variation of parameters is the same; however, results became smoother.

![Fig. 8. Example of regression analysis: (a) for bearing in good condition (data segment no 2) and (b) for bearing in bad condition (data segment no. 16).](image)

![Fig. 9. Final data output: variability of linear regression coefficients (a – coefficient “a”, b – coefficient “b”), without overlapping (left), with overlapping (right). Comment: clear change for $T=1.5 \times 10^4$, both a and b have increased.](image)
Fig. 10 shows deeper regression analysis of data for segments before and after change of the condition (lifetime \( T = 1.5 \times 10^{-4} \)) with reference to segment 2 (definitely good).

Fig. 11. Detailed estimation of data regressions load/power susceptibility characteristics: Comparison of data regression of segment 2 (bearing in definitely good condition and segments from 13 and 14 (bearing in probably still good condition), 15 (bearing in bad), 16, 17 and 27, 28 (bearing in bad condition).

Fig. 11. Input data for main bearing: top – peak to peak long term time series with significant change of condition around \( T = 5500 \) 10 min samples, bottom – power variation.
7.2. Case study – example 2

In this example the authors analyze the results of application of the novel procedure to the main bearing condition assessment given by peak-to-peak of vibration acceleration signals acquired from a commercial online monitoring system. The task defined here is similar as in example 1: to obtain more suitable data presentation in order to find change of condition. However, in contrast to previous case, due to information provided by the turbine operator, observation period has started when bearing under study was damaged. After certain monitoring period, faulty bearing was replaced in scheduled maintenance routine preceded by endoscopic examination of the bearing (bad condition bearing has been replaced around $T=5500$, see Fig. 11, time $t$ in samples, time between samples is 10 min). The resulting behavior of the monitored vibration-features (peak to peak) was examined by application of proposed approach.

![Fig. 12. Example of regression analysis: left – for bad condition data (segment no. 15) and right – good condition data (segment no. 37).](image)

![Fig. 13. Final data output: – variability of coefficients a and b from regression analysis. left – without overlapping, right with overlapping. Comment: clear change (jump) for $T=5500$ 10 min samples, both a and b have changed but change of "b" is "global", while "a" is local.](image)

![Fig. 14. Detailed analysis of long term b variation with selected segments marked by arrow to highlight the change of condition.](image)
By analogy to previous section, Fig. 12 shows example of regression analysis for segments 15 and 37, that correspond to a bearing in bad condition and good condition (after bearing replacement), respectively. The results of processing are shown in Fig. 13 where regression parameters \(a\) and \(b\) are shown for whole data. In this case parameter \(b\) has decreased significantly after replacement. Parameter \(a\) has increased rapidly just before the damage occurrence which might indicate that it is much more sensitive to damage and unstable as it is shown in Ref. [39] for some features used in Ref. [39], however, after replacement mean value of a parameter is similar. It is related to different nature of degradation process.

Fig. 13 right presents detection ability related to parameters \(a\) and \(b\). Differences between bad and good condition data are significant and establishing a threshold is possible. By analogy, Fig. 13(right) shows results of segmentation with overlapping.

Comment: clear change (jump) for \(T=5500\) 10 min samples, both a and b have changed but change of \(b\) is “global”, while. “a” is local

To prove (validate) that significant changes in the variation of the “\(b\)” parameter might be used for diagnostic purposes, Figs. 14 and 15 are discussed. Fig. 14 shows detailed analysis of long term “\(b\)” variation with selected segments marked by arrow to highlight the change of condition: For selected segments regressions (load susceptibility characteristics) are plotted in Fig. 15. It is clear evidence that three segments (5,15,22), which represent the bearing in bad condition (before replacement) and several segments (34–38) related to the bearing in good condition (after replacement) manifest quite different feature–power relationship. The difference is mainly related to the change of “\(b\)” parameter.

Fig. 15 also shows that in bad bearing condition its mechanical properties have changed and are not stable (wider spread of data, varying parameters for regression lines), in contrast to the case when a diagnosed bearing is in good condition.

8. Conclusions

It has been proposed that for machines operating under non-stationary load/speed condition, the representation of data as load susceptibility characteristics (which means presenting the data in feature-operating condition space) can be useful way to perform robust diagnosis of machinery operating in harsh and varying operational conditions. However, it has been
also noticed that feature-power dependency might change in a different way, depending on the damage/fault occurred in the machine. The attempt of generalization of such feature dependency is presented in Fig. 16. The conclusion is that when the condition is changing, the “a” (it can be interpreted as angle “alpha”) and “b” parameters will change, but depending on the damage/fault type, it can be a simultaneous change of both a, b parameters, or just one of them.

Understanding of the damage process and root cause analysis results is crucial issue for diagnostics. When the system is in bad condition and “b” parameter has been increased, as is given here for rolling element bearings (can be interpreted as shifting up of feature load relation). If “a” parameter of the regression line shows its change (it can be interpreted as increasing load susceptibility, i.e. machine is more sensitive to load) that is the case for gearboxes with bearings with over-limit backlash [30].

It is the authors’ intention to propose a new approach to feature-based condition monitoring. Presenting linear regression parameters as a long-time trend can be efficient alternative to traditional pure vibration-based features (RMS, peak-to-peak etc.). Proposed novel diagnostic parameters are load independent, which is a fundamental difference in comparison with vibration-based features delivered by the diagnostic system in presence of time varying load conditions. It appears that the proposed approach might significantly improve the functionality of industrial condition monitoring systems. Due to the independence of operational conditions both: automatic alarm threshold level estimation and technical condition decision making procedures might be more efficient.

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