Identification of Rolling Bearing Condition by Means of a Classification Tree

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Abstract

The paper deals with the problem of evaluation of technical condition of rolling bearings on the basis of synchronously measured vibroacoustic symptoms and temperature. Rolling bearings were subjected to accelerated wear under controlled conditions. The values recorded in the study were sound pressure in a broad band including ultrasound (band up to 40 kHz), vibration acceleration in a radial direction, ultrasound in a band up to 100 kHz (processed into audible band), and bearing housing temperature. The identification of the condition was carried out with the help of a supervised learning system. Two conditions were distinguished: fit - examples were obtained in the initial phase of bearing operation in temperature stability conditions, and pre-failure - examples were obtained from fragments of recording just before the occurrence of bearing failure. The CART (Classification and Regression Tree) binary tree method was used to determine the technical condition and significance of particular diagnostic symptoms.

Keywords: vibroacoustic diagnostics, rolling bearings, classification tree

1. Introduction

It can be assumed that up to 80% of machines have rolling bearings in their design and therefore they are very important elements in the context of machine maintenance. Rolling bearings are the cause of a significant number of failures in industry. They occur before the nominal life of the bearings is reached and result from incorrect installation or operating conditions (poor lubrication conditions, grease contamination, excessive loads [1]). Of course, there are many methods of diagnosing bearings based on such symptoms as: increase in temperature, increase in resistance to motion, grease or oil pollution, increase in emitted noise (in audible and ultrasound bands) and/or vibrations, phenomena of acoustic emission. In the case of vibrations, the SMP (Shock Pulse Method) method is commonly used in industry [2]. Bearing damage can also be detected by measurement of kurtosis, observation of crest factor changes in a broad frequency band, envelope analysis, wavelet analysis, synchronous averaging and many others [3-7]. In order to clearly determine the technical condition of a rolling bearing, especially in automatic systems, synchronous observation of many diagnostic symptoms and the use of classification methods give good results [8]. In order to build the classifier it is necessary to have a rich collection of training examples. However, in the case of a large number of data concerning the same or similar objects, the construction of such a system is feasible.

Classifiers are used in a wide range of fields, for example in the processing of large data resources [9-15]. There are many publications on the use of machine learning, including deep learning, in diagnostics, for example: [16-22]. The classification process can be carried out using many methods with specific properties and capabilities [22-26]: neural networks, distance classifiers, statistical classifiers, approximation classifiers, fuzzy classifiers, etc. One of the widely used methods are CART classification and regression trees developed by Breiman in 1984 [23, 25, 26]. The advantage of the tree structure is the way the knowledge can be represented after the learning process. It is easy to generate a set of human-readable rules on the basis of such a structure, which is very important at the stage of preparing diagnostic procedures to be used by maintenance services. This is one of the main reasons why the classification tree method has been proposed here. In addition, the tree enables to identify those diagnostic symptoms that are relevant to the process of classification of state. This is another important reason for proposing this method for classification in this work. The CART method does not require the user to discretize the values of input variables, which undoubtedly facilitates its use. Details of the operation of the tree structure algorithm can be found, for example, in [23].

2. Description of tests

Diagnostic data on rolling bearing vibrations in various phases of their life were obtained during accelerated bearing wear tests carried out on a test stand specially designed for this purpose. Figure 1 shows a photograph of the stand, including the measuring head, in which the bearing was mounted. The effect of accelerated wear was achieved by improper lubrication conditions and excessive axial loads on the bearing.

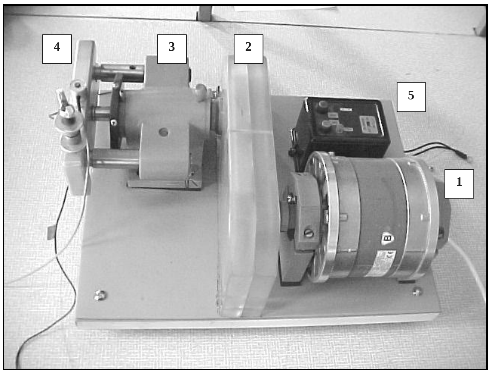

Figure 1. General view of the test stand (1 – motor, 2 – belt transmission, 3 – support, 4 – measuring head, 5 – motor control and protection system) – photo by R. Barczewski

The bearings were monitored during continuous operation. The temperature of the casing, acceleration of absolute vibrations in the band up to 1000 Hz and up to 12800 Hz, sound pressure levels in the band up to 40 kHz, and ultrasound signal in the band up to 100 kHz processed into the audible band (in the range from 50 Hz to 3 kHz) were recorded. Based on the signals, a number of measures were determined (34 different components of the observation vector). Teaching examples were obtained by selecting a few initial observations after stabilization of thermal conditions and a few observations immediately preceding the failure. A total of 16 bearings were tested. The vectors of observation were described with the label – "fit" and "pre-failure". As a result of the experiment, 160 examples were collected, with almost half (77 examples) referring to a fit condition and the second part to a pre-failure condition. The uneven distribution was due to the omission of a few unusual observations (outliers) probably resulting from the fact of getting into the bearing contamination in the form of solid substance. To measure vibration acceleration in both bands and the ultrasonic signal in the band from 20 kHz to 100 kHz recorded with the Ultraprobe 2000 instrument, the following measures were used: rms value, peak (upper and lower peak), mean, absolute peak, interpeak, kurtosis, crest factor, clearance and shape. The maximum, minimum and average sound pressure levels were used to measure the sound pressure in the band from 16 Hz to 40 kHz. All measurements were obtained from 30 second recording buffers acquired every 10 minutes.

Figure 2 shows a block diagram of the measuring chain.

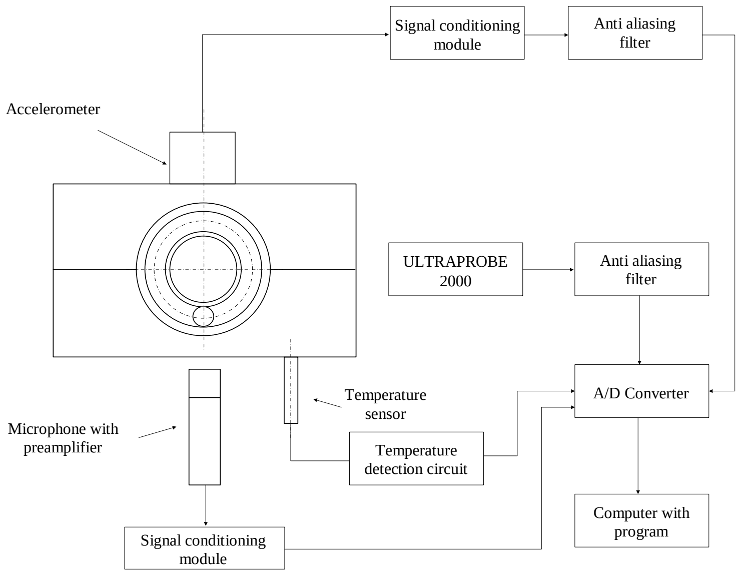

Figure 2. Block diagram of the measuring chain

Figure 3 shows examples of symptom life curves for one of the bearings. In order to present them in a clear way on one drawing and simultaneously show the dynamics of changes during the experiment, the measured values were normalized to the mean of several initial values.

As the figure shows, an unambiguous assessment of the technical condition of the bearing is not simple in the case at hand. There are rapid increases in the values of some symptoms and then decreases in their values before failure. In addition, there is a problem of determining limit values for individual symptoms. Taking into account the whole set of bearings it seems that the application of diagnostics based on many symptoms and the application of machine learning should facilitate such diagnosis, especially because the proposed method can provide clear rules to determine the technical condition of the bearing.

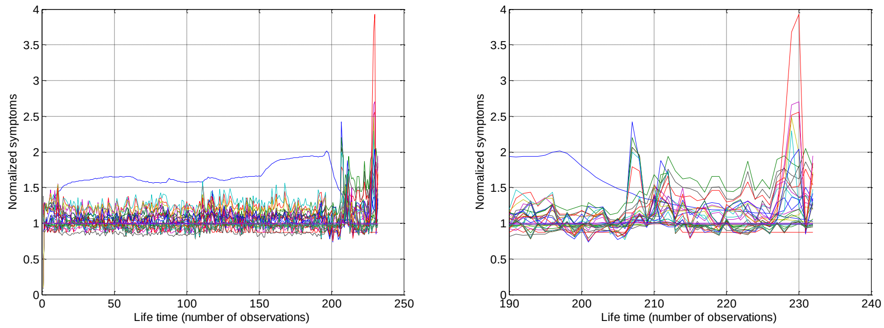

Figure 3. Normalized values for vibroacoustic symptoms and temperatures obtained during the experiment. Drawing on the left - all life curves, drawing on the right - the final fragment just before the failure

Figure 4 presents the data obtained in the space of features created by selected features.

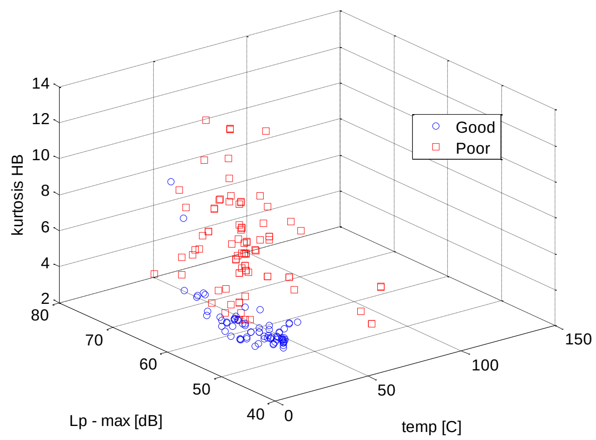

Figure 4. Measurements obtained in the sample space of features formed by temperature, maximum sound pressure level and vibration acceleration kurtosis in the HB band (up to 12.8 kHz)

3. Application of the CART method to data

In order to develop the methodology of two-state classification of rolling bearing condition, a CART type tree was used. The Gini index [26] was used as a measure of node contamination. The main advantage of classification trees here is generation of clear rules, which will allow to develop a simple algorithm for detecting the pre-failure condition of a bearing. Such understandable diagnostic rules may be used by maintenance services to identify the technical condition of an object. Another important advantage is that there is no need to select diagnostic features. This selection is performed by the algorithm during the tree construction.

The first step in building a tree was to optimize it. For this purpose, a leave-one-out cross validation test was used for different values of the minimum leaf size. The choice of this test was based on a small number of available data. The analysis shows that the optimal tree is a tree in which the hyperparameter associated with the minimum number of observations in a leaf is 1 or 2. In the next step the most important input features of the classifier were selected. This is done by examining the change in the mean square error (MSE) at each breakdown for each predictor. Table 1 shows the three best rated measures of recorded signals.

Table 1. The best symptoms obtained on the basis of the classification tree

Pos.	Symptom
1	Rms value of vibration acceleration in the HB band (up to 12.8 kHz)
2	Bearing temperature
3	Peak value of vibration accelerations in the LB band (up to 1 kHz)

As can be seen from the table above, the most important parameter in determining the condition of the bearing in the conducted experimental studies was the rms value of vibration accelerations in a wide frequency band, which confirms the validity of the measurement of this value. The second parameter turned out to be the temperature. This is due to the fact that the bearing was brought to failure and thus also reached the thermal phase of wear. The last parameter affecting the determination of the technical condition of the tested bearings was the peak value of vibration accelerations. However, it appears that it should be determined in a narrower frequency range than the rms value. Of course it is not possible to generalize this conclusion for all bearings, but it may turn out that measures such as the crest factor may not be effective in diagnosis, because both values on which it depends should be determined in different bands.

After determining the most important predictors, the tree was re-constructed on their base. On the basis of the leave-one-out test, results were obtained, which are presented in Table 2.

Table 2. Results obtained for the optimally selected classifier's hyper-parameter and a limited number of the best predictors

Total classification error	True Positive Rate TPP	True Negative Rate TNR	Positive Predictive Value PPV	Negative Predictive Value NPV
0.019	0.998	1.000	1.000	0.987

A small classification error of 1.9% shows the possibilities of the method in the case of an optimally selected hyperparameter as well as input quantities. The probability of detecting an impending bearing failure when it is actually in this state is close to 1.0

(0.998 to be precise). The TNR indicator indicates the probability that a fit condition will be detected if the bearing is in that condition. On the other hand, PPV determines to what extent it is possible to be sure that the result is true if a pre-failure condition is detected. Similarly, the NPV indicator for the fit condition can be defined. All values indicate very good properties of the classifier.

An important reason for using the classification tree was to generate knowledge that could be useful for maintenance services. For example, the following rules can be generated from the finally built classifier:

R1: IF RMS (in the HB band) >=4,8 m/s^2 AND TEMP >= 34,7 C THEN PRE-FAILURE CONDITION

R2: IF RMS (in the HB band) >=4,8 m/s^2 AND TEMP < 34,7 C THEN FIT CONDITION

R3: IF RMS (in the HB band) < 4,8 m/s^2 AND PEAK (in the LB band) >= 16,7 m/s^2 THEN PRE-FAILURE CONDITION

R4: IF RMS (in the HB band) < 4,8 m/s^2 AND PEAK (in the LB band) < 16,7 m/s^2 THEN FIT CONDITION

where: RMS – rms value of absolute vibration accelerations, PEAK – peak value of absolute vibration accelerations, TEMP – bearing housing temperature, HB – measurement in the band up to 12.8 kHz, LB – measurement in the band up to 1 kHz.

The simple rules generated can enable you to make the right diagnostic decisions. Of course, in the case of bearings and operating conditions other than the tested ones, it may turn out that the given rules do not work. The presented methodology, however, can be easily applied in other cases (e.g. by bearing manufacturers), as soon as a suitable database is available.

4. Conclusions

Vibroacoustic diagnostics of rolling bearings is a very important element of the machine maintenance strategy depending on the technical condition. By using classification methods it is possible to assess the technical condition of bearings on the basis of many symptoms measured synchronously. Such an approach may be necessary in many cases, as it may turn out that the measurements of one measure of the diagnostic signal are insufficient to determine the technical condition of the bearing. This creates the problem of defining limit values for various measures that can be used in the diagnosis process. In addition, it may turn out that one combination of measures will work in a given case and not in another one. The use of machine learning methods makes it easy to develop a statistical approach to the problem and to eliminate these disadvantages. The only serious problem is the need to teach the system using examples that also include bearing damage. It may turn out, however, that with proper separation of vibroacoustic phenomena, it is sufficient to test the bearings themselves under more sterile conditions and extrapolate the results to complex objects. Furthermore, with a sufficiently large set of the same machines (pumps, fans, electric motors), obtaining a minimum number of training examples may be realistic. It is also important that thanks to the tree method, a clear knowledge base can be obtained in the form of a set of simple rules allowing its easy direct application in machine monitoring. In addition, information on the significance of the measured parameters is obtained, which may allow to reduce the redundancy of the diagnostic system over time.

The proposed methodology was applied to small-size bearings 608, but it can also be applied in other cases. In the example described above, a total classification error of 1.9% was achieved, which is a very good result. The entire diagnostic inference was reduced to just four simple rules.

It is also important to note that useful signal measures can be determined in different frequency bands, which means that the use of relative measures (e.g. crest factor, etc.) for bearing diagnostics may not be appropriate.

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References

1. S. Szymaniec, *Diagnostics of motor rolling bearings in conditions their industrial operating* (in Polish), Maszyny Elektryczne, **74** (2006).
2. N. Tandon, G. S. Yadava, K. M. Ramakrishna, *A comparison of some condition monitoring techniques for the detection of defect in induction motor ball bearings*, Mechanical Systems and Signal Processing, **21**(1) (2007) 244 – 256.
3. N. Tandon, A. Choudhury, *A review of vibration and acoustic measurement methods for detection of defects in rolling elements bearings*, Tribology International, **32**(8) (1999) 469 – 480.
4. Y. Yang, D. Yu. J. Cheng, *A fault diagnosis approach for roller bearings based on IMF envelope spectrum and SVM, Measurement*, **40**(9) (2007) 943 – 950.
5. Q. Sun, Y. Tang, *Singularity analysis using continues wavelet transform for bearing fault diagnosis*, Mechanical Systems and Signal Processing, **16**(6) (2002) 1025 – 1041.
6. P. McFadden, M. Toozhy, *Application of synchronous averaging to vibration monitoring of rolling element bearings*, Systems and Signal Processing, **14**(6) (2000) 891 – 906.
7. J. Wodecki, R. Zdunek, A. Wyłomańska, R. Zimroz, *Local fault detectionof rolling element bearing components by spectrogram clustering with Semi-Binary NMF*, Diagnostyka, **18**(1) (2017) 3 – 8.
8. M. Tabaszewski, *Forecasting in multi-symptom condition monitoring of machines* (in Polish), Wydawnictwo Politechniki Poznańskiej, 2010, pp. 153.
9. Y. Lei, Z. He, Y. Zi, *Application of an intelligent classification method to mechanical fault diagnosis*, Expert Systems with Applications, **36**(6) (August 2009) 9941 – 9948.
10. F. Sunar Erbek, C. Özkan, M. Taberner, *Comparison of maximum likelihood classification method with supervised artificial neural network algorithms for land use activities*, International Journal of Remote Sensing, **25**(9) (2004) 1733 – 1748.

11. H. Zhang, J. Li, Y. Huang, L. Zhang, *A Nonlocal Weighted Joint Sparse Representation Classification Method for Hyperspectral Imagery*, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, **7**(6) (2014) 2056 – 2065.
12. Abeer Badr El Din Ahmed, Ibrahim Sayed Elaraby, *Data Mining: A prediction for Student's Performance Using Classification Method*, World Journal of Computer Application and Technology, **2** (2014) 43 – 47.
13. C. Gorges, K. Oztruk, R. Liebich, *Impact detection using a machine learning approach and experimental road roughness classification*, Mechanical Systems and Signal Processing, **117** (2019) 738 – 756.
14. V. Leemans, H. Magein, M.-F. Destain, *Defect segmentation on 'Jonagold' apples using colour vision and a Bayesian classification method*, Computers and Electronics in Agriculture, **23**(1) (1999) 43 – 53.
15. T. Nguyen, G. Armitage, *A survey of techniques for internet traffic classification using machine learning*, IEEE Communications Surveys & Tutorials, **10**(4) (2008) 56 – 76.
16. C. Sobie, C. Freitas, M. Nicolai, *Simulation – driven machine learning: Bearing fault classification*, Mechanical Systems and Signal Processing, **99** (2018) 403 – 419.
17. A. Lahrache, M. Cocconcelli, R. Rubini, *Anomaly detection in a cutting tool by K-Means clustering and Support Vector Machines*, Diagnostyka, **18**(3) (2017) 21 – 29.
18. P. Potocnik, E. Govecar, *Semi-supervised vibration - based classification and condition monitoring of compressors*, Mechanical Systems and Signal Processing, **93** (2017) 51 – 65.
19. M. Ruiz, L. E. Mujica, S. Alférez, L. Acho, Ch. Tutivén, Y. Vidal, J. Rodellar, F. Pozo, *Wind turbine fault detection and classification by means of image texture analysis*, Mechanical Systems and Signal Processing, **107** (2018) 149 – 167.
20. F. Jia, Y. Lei, N. Lu, S. Xing, *Deep normalized convolutional neural network for imbalanced fault classification of machinery and its understanding via visualization*, Mechanical Systems and Signal Processing, **110** (2018) 349 – 367.
21. C. Mechefske, J. Mathew, *Fault detection and diagnosis in low speed rolling element bearings Part II: The use of nearest neighbour classification*, Mech. Syst. Sign. Process., **6**(4) (1992) 309 – 316.
22. J. Korbicz, J. M. Kościelny, Z. Kowalczuk, W. Cholewa (ed.), *Fault Diagnosis: Models, Artificial Intelligence, Applications*, Springer Science & Business Media, (2012) pp. 922.
23. D. T. Larose, *Discovering Knowledge in Data. An Introduction to DATA MINING*, John Wiley & Sons, Inc., (2005) pp. 227.
24. D. T. Larose, *Data Mining Methods and Models*, John Wiley & Sons, Inc., 2006.
25. O. Maimon, L. Rokach (ed.), *Data Mining and Knowledge Discovery Handbook*, Springer New York Dordrecht Heidelberg London, (2010) pp. 1285.
26. A. Géron, *Hands-On Machine Learning with Scikit-Learn and Tensor Flow*, O'Reilly Media, (2017) pp. 574.