VTT Technical Research Centre of Finland

Journal bearing lubrication status identication with acoustic emission measurements and data clustering

Tervo, Jyrki; Junttila, Jukka; Ronkainen, Helena

Published in:
22nd TRIBO-PPRIME WORKSHOP, October 12 - 13, 2023. Chasseneuil du Poitou, France

Published: 10/10/2023

Document Version
Publisher's final version

Journal bearing status identification with acoustic emission measurements and data clustering

Identification de l'état des paliers à l'aide de mesures d'émissions acoustiques et de regroupement de données

Tervo J, Junttila J, Ronkainen H

VTT Technical Research Center of Finland Ltd, Kemistintie 3, FI-02044, VTT (Espoo), Finland.

Keywords: Journal bearing, lubrication regime, acoustic emission, machine learning, mean-shift clustering.
Mots clés: Palier lisse, régime de lubrification, d'émission acoustique, machine learning, mean-shift clustering.

The laboratory scale journal bearing lubrication regimes were analysed with wide band acoustic emission (AE) measurements. Data analysis was supported by data-based clustering of AE data. The approach can be effectively used to reveal fundamental lubrication modes, i.e., hydrodynamic (HL), mixed (ML) and boundary (BL) lubrication as a function of Hersey number. Besides AE the other parameters monitored were friction torque, bearing temperature, loading, sliding velocity and oil pressure. The materials used in the experiments were case-hardened 18CrNiMo7-6 steel and nitrided 42CrMo7 steel. The tests were lubricated with synthetic extreme-pressure gear oil (SGN 320) and the bearing temperature was kept constant during the tests. The bearing pressure and sliding velocity during tests were varied in the wide range resulting in different lubrication situations. The acoustic emission signals power and frequency content was analysed, and essential features were extracted for data clustering. For lubrication regime change identification the parameters such as signal RMS and coefficient of variation (CV) proved to be important, while signal kurtosis showed to be the most sensitive in discovering anomalies. The sensitivity requires data filtering to remove erroneous peaks. It is also interesting to notice the changes in AE frequency due to different lubrication situation. In literature different clustering and classification methods has been proposed and applied for journal bearing status identification. Here the selected unsupervised clustering method was the mean-shift clustering due to fact, that the lubrication regimes in the Stribeck curve form an inseparable continuum. The algorithm does not require specifying the number of clusters in advance, i.e., the clusters are determined by the algorithm with respect to the data.

Le fonctionnement d'un palier lisse en régime de lubrification hydrodynamique (HL) ou élastohydrodynamique (EHL) est une condition préalable à un fonctionnement fiable. Le basculement vers des régimes de lubrification mixte (ML) ou limite (BL) augmente le frottement et le risque de défaillance du palier. La détection du régime de lubrification est donc essentielle pour éviter les défaillances des paliers lisses. Les techniques de Machine Learning at de Data Analytics permettent une reconnaissance rapide, précise, demandant de ressources informatiques peu coûteuse en temps de calcul. Dans cette étude, c'est la méthode "unsupervised mean-shift clustering" qui a été appliqué. L'algorithme ne nécessite pas de spécifier le nombre de clusters à l'avance car celui-là est déterminé par l'algorithme en fonction des données. Les données utilisées pour l'extraction des caractéristiques ont été mesurées à l'aide d'un système d'émission acoustique (AE) à large bande. Les autres paramètres contrôlés ont été le frottement, les températures, la charge, la vitesse de glissement et la pression de l'huile. Les matériaux utilisés étaient de l'acier cémenté 18CrNiMo7-6 et de l'acier nitruré 42CrMo7. Le lubrifiant utilisé était de l'huile synthétique EP pour engrenages (SGN 320). La température du palier a été maintenue constante. La pression et la vitesse de glissement ont été variées pendant les tests, ce qui a permis d'obtenir des résultats pour une large gamme en termes de nombre de Hersey. La puissance et la fréquence des signaux d'émission acoustique ont été analysées et les caractéristiques essentielles ont été extraites pour le traitement des données. Le kurtosis, le RMS et le coefficient de variation des signaux AE ont été représentés en fonction du nombre de Hersey. Le kurtosis a montré la plus grande sensibilité pour la détection des anomalies. Une sensibilité élevée nécessite un filtrage des

données pour éliminer les pics erronés. Des observations ont également été faites sur le niveau de fréquence de l'AE en fonction des différents régimes de lubrification.

1 Introduction

In industrial systems it is not often possible to monitor all the vital components. The amount and quality of data may be restricted due to excessive cost or noisy environment, respectively. Virtual sensing and/or hybrid approaches has been suggested instead. Hybrid systems rely on modelling, while virtual sensing techniques aim to reduce the number of sensors by using data from available measurements to estimate additional unknown quantities of interest indirectly. Data-based clustering of AE data can be effectively used to reveal fundamental lubrication modes, i.e., hydrodynamic (HL), mixed (ML) and boundary (BL) lubrication. Acoustic emission (AE) means spontaneous elastic mechanical waves which result from abrupt strain changes within material body [1]. AE can be measured with a special surface mounted sensor if the energy of waves is high enough to cause surface motion with sufficient amplitude. The measured signal contains information about nature, location, and characteristics of the source [2, 3, 4]. Sources of AE in frictional contact include elastic interactions, as well as plastic deformation in wide respect, strain hardening (apparently including phase changes), fatigue, and different wear modes [5]. Abrasive wear increases AE signal amplitude significantly, e.g., 2 – 3 times. This is of course good news considering monitoring of lubrication mode and status. Lubrication regimes are usually presented in the form of a Stribeck curve [6, 7], i.e., friction as a function of dimensionless Hersey number (equation 1):

$$H = \frac{\eta\omega}{p}, \tag{1}$$

where H represents Hersey number, h is dynamic viscosity (Pas), ω is rotational velocity (m/s) and p is the load per line length (N/m). The Stribeck curve (presented in Fig 1) has been studied extensively in numerous papers and books, e.g., [6, 7, 8, 9, 10].

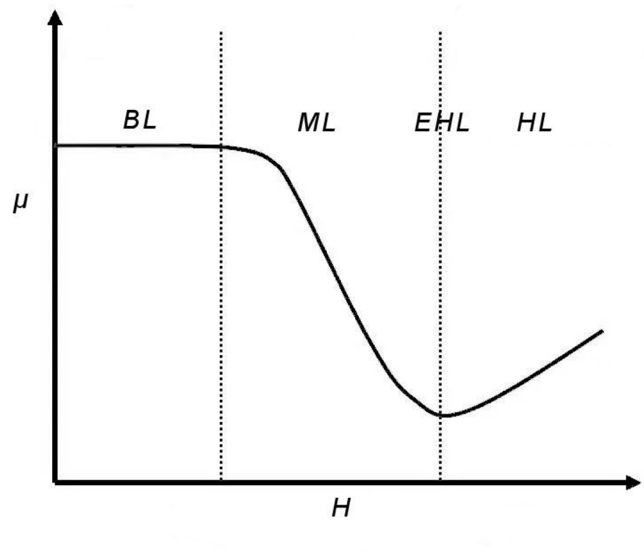

Fig 1 – Schematic presentation of the Stribeck curve.

The smallest Hersey numbers (H) represent the boundary lubrication regime (BL in Fig 1), usually representing a coefficient of friction of (very roughly) about 0.1 or higher. The lowest value of the friction coefficient usually marks the transition from mixed (ML in Fig 1) to elastohydrodynamic film lubrication (EHL in Fig 1), where the fluid film is just thick enough to avoid asperity collisions. Thus, the surface roughness affects the classification and is usually applied in terms of lambda (λ) value. A minor increase in friction coefficient in Stribeck curve with respect to further increased Hersey number takes place at hydrodynamic lubrication region (HL in Fig 1) due to increased viscous losses. For machine components operating in EHL regime the curve may look different with a coefficient of friction not increasing in the full film regime due to higher pressures and different thermal conditions [6]. Asperity contact is the essential source of AE signals, which is evident in RMS value. Both AE RMS and kurtosis have inverse correlation with oil film thickness [11]. In dry steady state wear the AE signal increases with increasing applied load and sliding speed. AE energy is influenced by the friction coefficient, and RMS value correlates with friction to some extent. AE RMS increases due to increase of maximum stress and asperity deformation as contact becomes more localized. As the oil film thickness increases the maximum stress decreases due to more uniform distribution of load. In journal bearings the friction states, i.e., lubrication regimes, can be separated by using AE [12]. The features derived from AE signals, were AE RMS, AE entropy, AE median frequency and AE kurtosis. The most significant features were kurtosis and median frequency, which could readily be applied for a feature space presentation. The sensitivity of extracted features was enhanced by applying continuous wavelet transform (CWT) and transforming signals to frequency-time domain. Support vector machine (SVM) was used to classify signals further into three different friction classes: mixed friction, mild mixed friction, and fluid friction. It was noticed that Stribeck curves having AE RMS as abscissa can be used for wear progress and remaining life estimation. Also, the effect of temperature induced viscosity changes, as well as speed and load variation on AE have been studied [13]. AE RMS was reported to show good correlation with the journal bearing wear volume [13]. It has also been discovered that that AE RMS and AE energy parameters can be used for detection of particle contamination in lubricating oil [14]. In comparison of AE-based condition monitoring system for roller bearings to vibration-based condition monitoring it has been discovered that the former gives earlier warning than the latter. Also, the AE sensitivity to detect condition of lubrication was reported [15]. Monitoring accuracy of AE signal kurtosis and RMS value can be enhanced by separating signals to frequency bands, since the highest intensities of certain incidents are reported to be found in certain frequency bands [16]. The method can be used to reveal several operating wear mechanisms with different characteristic frequency. Combined time–frequency analysis based on Morlet wavelet coefficient and fast kurtogram (MWC-has been proposed for gear fault detection [17]. Kurtogram is a fourth order spectral analysis tool and can be used to detect transient faults contained in signals [18]. Kurtogram has also been demonstrated jointly with deep learning [19]. AE features has been applied in developing data driven and machine learning methods for journal bearing wear regime distinction [20] as well as wear mode identification [21].

2 Measurement arrangements and results

Laboratory scale journal bearing tests were carried out with the journal bearing test rig (Fig 2). The journal bearing consisted of a shaft made of tempered gas nitrided 42CrMo7 steel, while the bearing was made of case hardened 18CrNiMo7-6 steel. The journal inner diameter was 30 mm, while the width of the bearing was 20 mm. The surface roughness of the shafts and the bearing prior to tests was Ra 0.2 - 0.3 µm. The friction force was measured during the tests with a force sensor positioned above the torque arm transferring the friction torque from the bearing case. The friction generated by the seals was determined experimentally prior to actual measurements and the effect was subtracted from the measured friction force values, thereby reaching the friction coefficient. The journal bearing tests were lubricated with the synthetic extreme pressure gear oil of ISO Viscosity Grade SGN 320. During testing the lubricant temperature was maintained at 65 ± 2 °C. The temperature was measured from the bearing near the contact surface. The kinematic viscosity of the lubricant is 109.2 mm^2/s at 65 °C. The specific gravity of the oil is 867.6 kg/m^3. A single test run consisted of operating the bearing test rig under a constant load and varying the rotation speed to reach different lubrication situations. Various test runs were performed under different loads ranging between 0.5 kN and 13 kN. At moderate loads the lubrication status remained in the HL range. Notable lubrication regime changes occurred only at loads of 10.0 kN, 11.0 kN, and 13.0 kN, which were then included in the data-based clustering. During the journal bearing tests AE signal was measured with a Kistler 8152C AE wide frequency spectra sensor (50 – 900 kHz). The sensor has channels for pure AE signal and the RMS of the AE. Due to its large size, the sensor was attached on top of the bearing housing. Before each test the sensor sensitivity was verified by pencil-lead breaking [22]. The feature values for the data-based clustering were extracted from the measured AE and friction signals over a window of 0.1 seconds without overlapping. The friction is presented as Stribeck curve relative to Hersey number in Fig 3. The calculated acoustic emission parameters (rms, coefficient of variation and kurtosis) are presented similarly as functions of Hersey number. When calculating the Hersey number values, the temperature, and thus, the dynamic viscosity of the lubricant was assumed constant. Therefore, the Hersey number values used were dependent on the load and the rotation speed only.

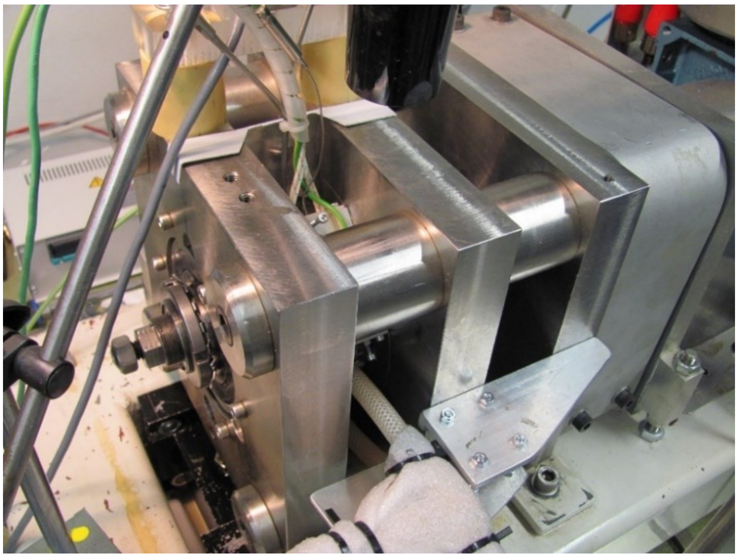

Fig 2 – Journal bearing test bench at VTT.

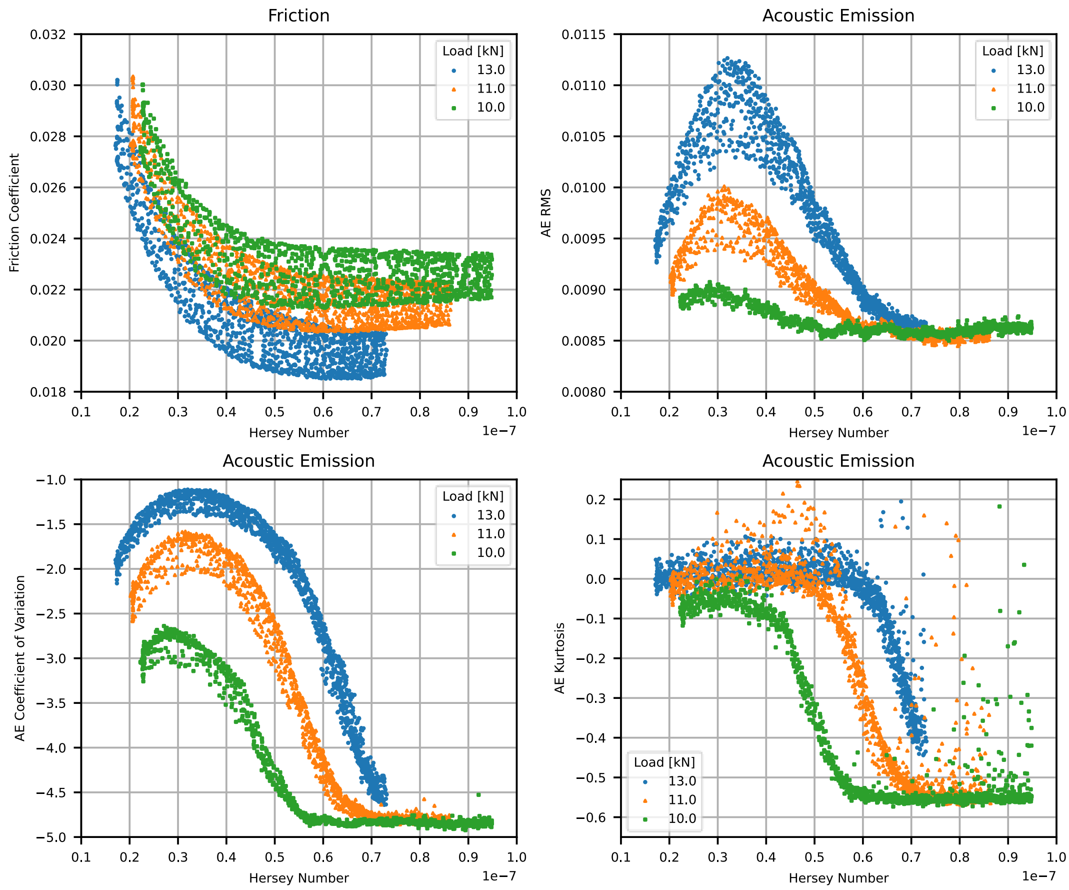

Fig 3 – Friction and extracted parameters (features) from AE signals.

Choosing only time-domain based features extraction methods ensures the high computational efficiency of the feature extraction process. Frequency content of the signals were not applied for clustering, although the change in lubrication regime is clearly visible in median normalized frequency of AE as well (Fig 4). In the present study the frequency content does not increase the information content, since only the lubrication regime change was of interest.

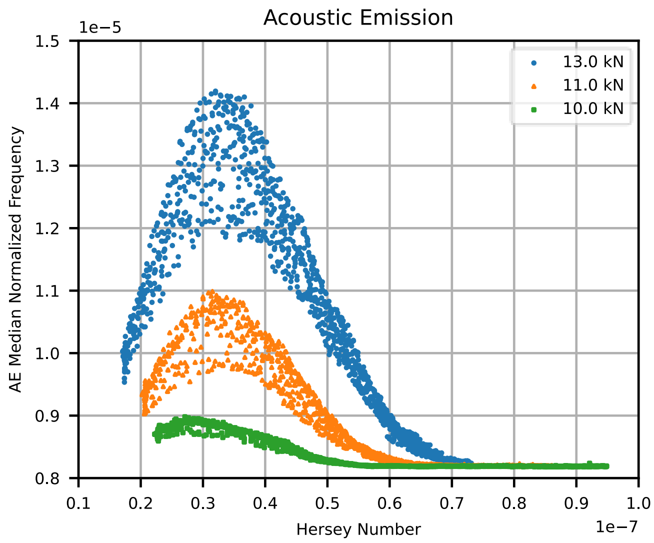

Fig 4 – Median normalized frequency response to lubrication regime change.

3 Data-based clustering

If the data samples were to comprise examples of the input data with their corresponding known fundamental lubrication modes and regimes, the unknown modes for new data samples could be found by using supervised learning methods. However, because there are no direct boundaries between the different lubrication regimes along the Stribeck curve (Fig 1), the input data does not contain corresponding labels for the lubrication regimes. Thus, unsupervised learning needs to be used first to discover the groups, i.e., clusters, of similar examples within the data. The objective of the clustering is to maximize the similarity within each cluster and minimize the similarity between other clusters.

Thus, in general, the objective of the data-based lubrication regime identification is to learn the underlying relations of the given feature vectors by means of unsupervised clustering. Ideally the clustering provides the boundaries of the lubrication regimes and the possible outliers. Therefore, the clustering algorithm's capability of finding the correct number of different possible lubrication regimes is important. Such an algorithm would enable the automatization of the clustering process of the lubrication regimes which could be thereafter utilized in the next phase, i.e., in the real-time identification of the lubrication status. The clustering method chosen for this study is called mean-shift clustering. The main concept of the mean-shift clustering can be stated as a set of iterative shifts of each input data point to the regional mean. In this study, the mean itself is based on the bandwidth of neighborhood of each data point, and the bandwidth is defined with the predefined quantile of all pairwise distances. Mathematically the mean shift procedure is obtained by successive computation of the mean shift vector $\mathbf{m}_h(\mathbf{x}^t)$ at iteration t and updating the candidate centroid $\mathbf{x}^t$ within the neighborhood as $\mathbf{x}^{t+1} = \mathbf{x}^t + \mathbf{m}_h(\mathbf{x}^t)$ until converged to a point where the gradient of the density function inside the mean shift vector is zero. The detailed procedure of the mean-shift clustering method is given e.g., in [23]. It was selected due to fact that the lubrication regimes in the Stribeck curve comprise a rather inseparable continuum of regimes. Thus, the mean-shift clustering is an effective tool to resolve the separation task with the minimum information given.

Mean-shift clustering was tested using various combinations of the following features: Friction coefficient, AE RMS, AE coefficient of variation, AE kurtosis, and Hersey number. The clustering results are presented in Fig 5 using all features, in Fig 6 using AE coefficient of variation and AE kurtosis with Hersey number, and in Fig 7 using only AE coefficient of variation and AE kurtosis. All clustering results presented in Fig 5 – Fig 7 include three clusters, but the desired clustering result can be seen only in Fig 6. The distribution of the three clusters in Fig 6 represent roughly the ML (Cluster 1 in Fig 6), EHL (Cluster 2 in Fig 6), and HL (Cluster 3 in Fig 6) regimes in the Stribeck curve.

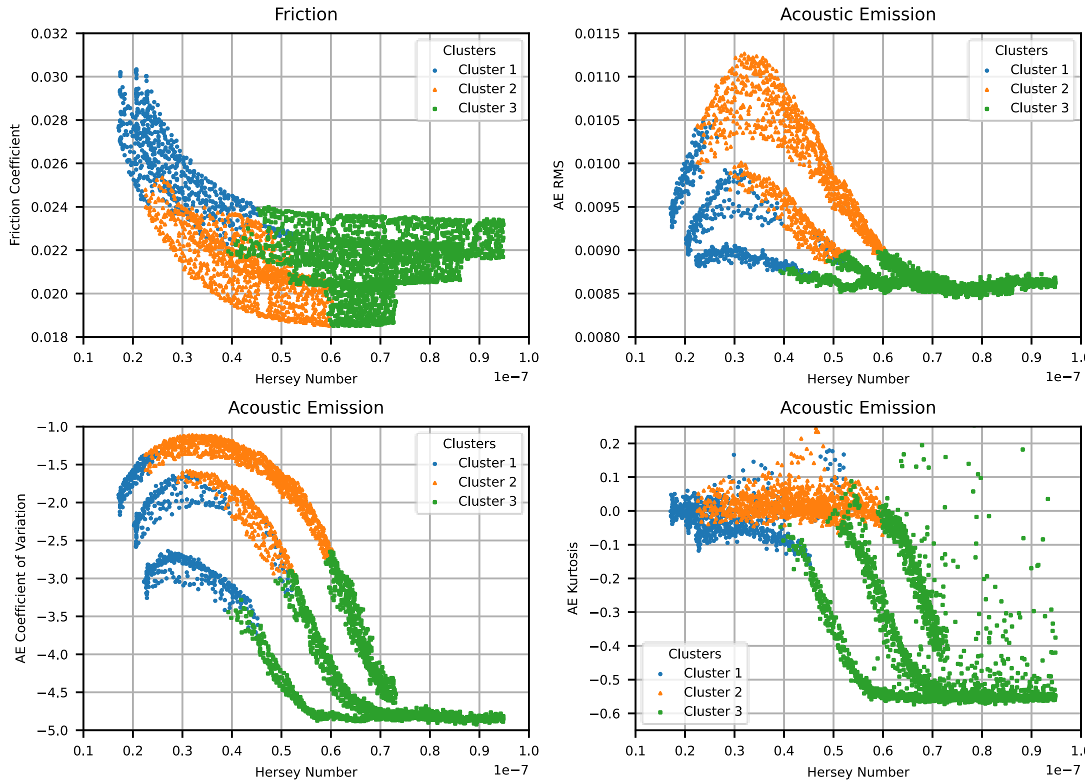

Fig 5 – Clustering results using all features.

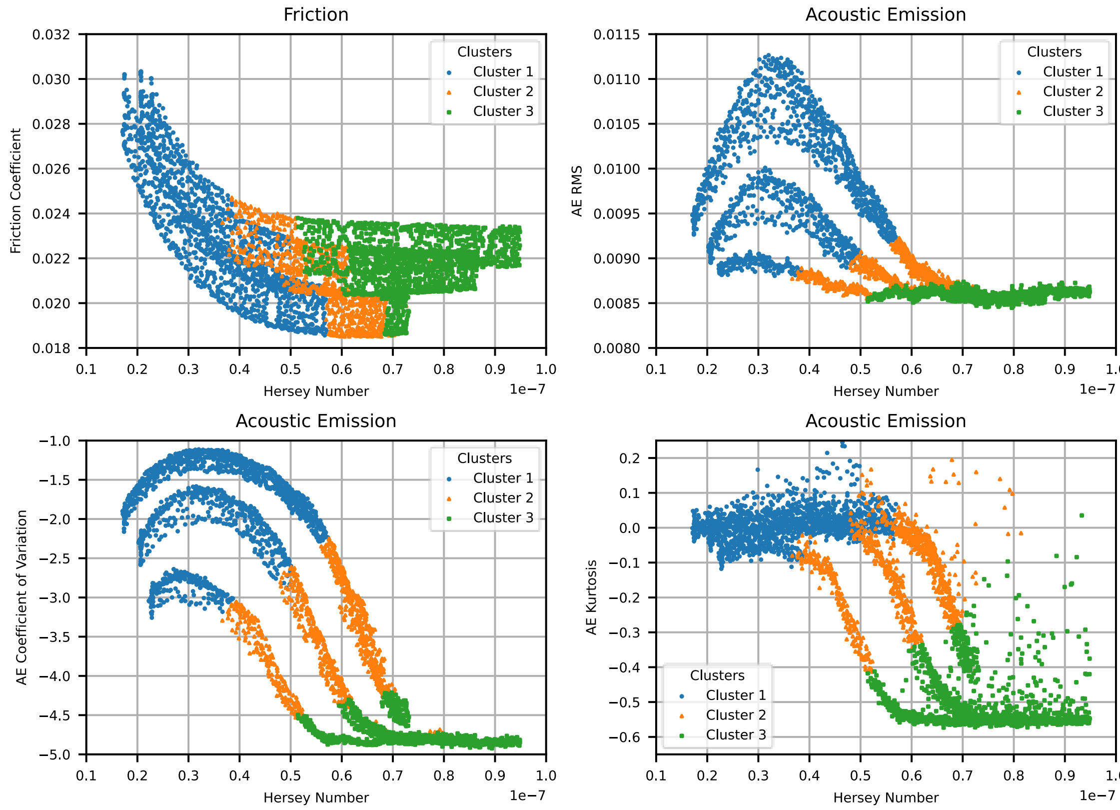

Fig 6 – Clustering results using AE coefficient of variation, AE kurtosis, and Hersey number as features.

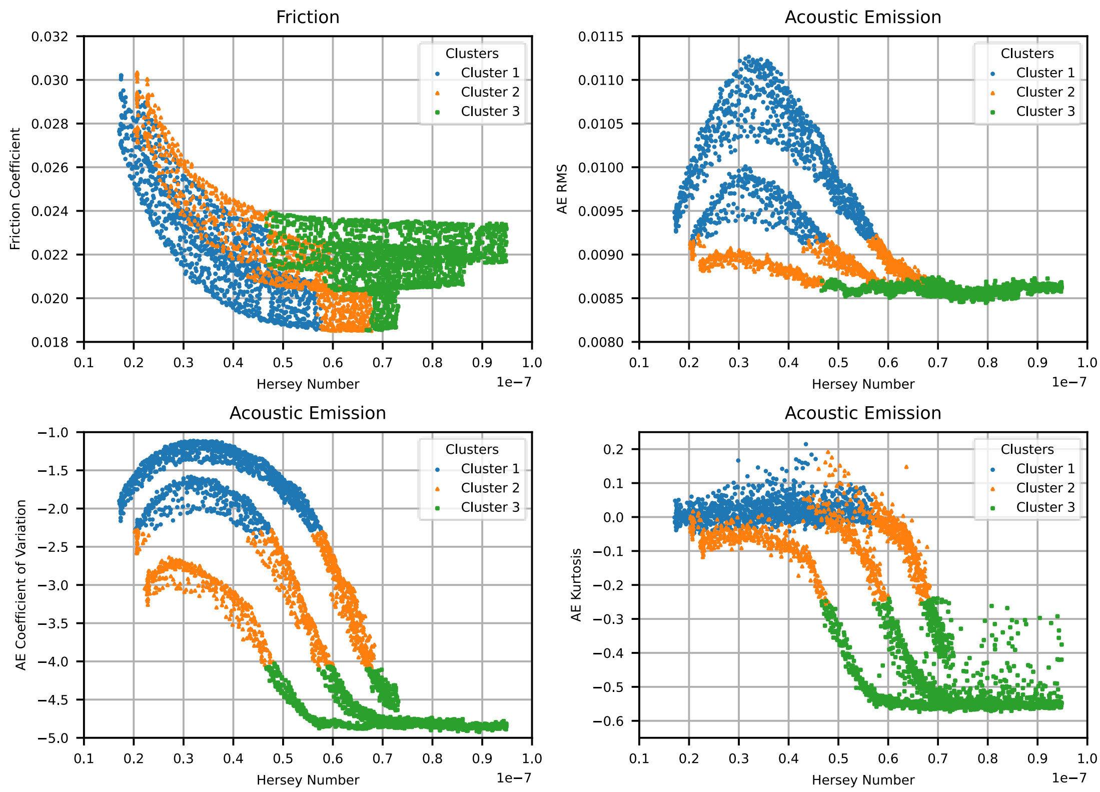

Fig 7 – Clustering results using AE coefficient of variation and AE kurtosis as features.

4 Summary

The goal of the study was to use machine learning as computationally light method to support near real-time monitoring of the journal bearing lubrication status. The shape of the Stribeck curve reveals that the regime identification problem is problematic and nonlinear. The minimum requirement for the creation of the data-based model is that there is measurement data available for each lubrication regime. Laboratory scale journal bearing tests were carried by measuring friction and wide band AE signals. Loading and sliding velocity were varied in a wide range during tests resulting in different lubrication situations, the most interesting changes appearing at loads 10 kN, 11 kN and 13 kN. Different combinations of feature vectors were studied for the model development and tested using the mean-shift clustering algorithm. The mean-shift algorithm does not require specifying the number of clusters in advance, i.e., the clusters are determined by the algorithm with respect to the data. The best clustering results, that is the results most comparable to the Stribeck curve, were achieved by using AE kurtosis, coefficient of variation, and Hersey number as features. Using more features, such as the friction coefficient, does not necessarily improve the result in the present configuration. Thus, it can be concluded that AE kurtosis is an important feature for lubrication status detection in journal bearings. Among the compared features the kurtosis appears to be the most sensitive parameter to signal changes. The sensitivity of kurtosis requires considerations of data filtering since random variations due to electromagnetic and mechanical interferences are emphasized due to the nature of kurtosis.

Acknowledgements

This research was conducted as a partial fulfilment of the project INNTERESTING (https://www.innterestingproject.eu/), which received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 851245. The support of Artur Korostavyi with journal bearing test set-up and Ville Lämsä with data clustering is acknowledged with gratitude.

5 References

[1] Eitzen, D., Wadley, H., Acoustic Emission: Establishing the Fundamentals. Journal of Research of the National Bureau of Standards, Vol. 89, No.1, January-February 1984, pp. 75 – 100.

[2] Ohtsu, M., Ono, K., A generalized theory of acoustic emission and Green's functions in half space. Journal of Acoustic Emission. Vol 3 (1984), No 1, pp. 27 – 40.

[3] Ohtsu, M., Ono, K., The generalized theory and source representations of acoustic emission. Journal of Acoustic Emission. Volume 5 (1986), No. 4, pp. 124 – 133.

[4] Baranov, V., Kudryavtsev, E., Sarychev, G., Modelling of the parameters of acoustic emission under sliding friction of solids. Wear, Vol. 202 (1997), pp. 125 – 133.

[5] Baranov, V., Kudryavtsev, E., Sarychev, G., Schavelin, V., Acoustic Emission in Friction (ed. B.J. Briscoe), Tribology and Interface Engineering Series, Elsevier, Oxford, 2007.

[6] Björling, M., Friction in Elastohydrodynamic Lubrication. Doctoral Thesis, 2014, Luleå University of Technology. 292 p.

[7] Stribeck, R., Die wesentlichen Eigenschaften der Gleit- und Rollenlager. Zeitschrift des Vereins Deutscher Ingenieure, Band 46 (1902), Nr. 36, 1341 - 1348.

[8] Woydt, M., Wäsche, R., The history of the Stribeck curve and ball bearing steels: The role of Adolf Martens. Wear, Vol 268 (2010), pp. 1542–1546.

[9] Bannister, K., Lubrication for Industry, Industrial Press, 1996.

[10] Moder, J.; Bergmann, P.; Grün, F. Lubrication Regime Classification of Hydrodynamic Journal Bearings by Machine Learning Using Torque Data. Lubricants 2018, 6, 108. https://doi.org/10.3390/lubricants6040108

[11] Hamel, M., Addali, A., Mba, D., Monitoring oil film regimes with acoustic emission. Proc IMechE Part J: J Engineering Tribology, 2014, Vol 228(2) 223–231

[12] Mokhtari, N., Gühmann, C., Classification of journal bearing friction states based on acoustic emission signals. Technisches Messen 2018, 85(6), pp. 434 – 442.

[13] Mokhtari, N., Pelham, J., Nowoisky, S., Bote-Garcia, J-L, Gühmann, C., Friction and Wear Monitoring Methods for Journal Bearings of Geared Turbofans Based on Acoustic Emission Signals and Machine Learning. Lubricants 2020, 8, 29; https://doi:10.3390/lubricants8030029.

[14] Poddar, S., Tandon, N., Detection of particle contamination in journal bearing using acoustic emission and vibration monitoring techniques. Tribology International. Vol 134 (2019, pp. 154 – 164.

[15] Cornel, D., Gutiérrez Guzmán, F., Jacobs, G., Neumann, S., Condition Monitoring of roller bearings using Acoustic Emission. Wind Energ. Sci., Vol 6 (2021), pp. 367–376.

[16] Renhart, P., Maier, M., Strablegg, C., Summer, F., Grün, F., Eder, A., Monitoring Tribological Events by Acoustic Emission Measurements for Bearing Contacts. Lubricants 2021, 9, pp. 109 – 1-14. https://doi.org/10.3390/lubricants9110109.

[17] Naima, G., Elias, H.A., Salah, S., An Improved Fast Kurtogram Based on an Optimal Wavelet Coefficient for Wind Turbine Gear Fault Detection. Journal of Electrical Engineering & Technology (2022) 17:1335–1346.

[18] Antoni, J., Fast computation of the kurtogram for the detection of transient faults. Mechanical Systems and Signal Processing 21 (2007), 108–124. https://doi:10.1016/j.ymssp.2005.12.002

[19] Udmale, S., Singh, S., Bhirud, S., A bearing data analysis based on kurtogram and deep learning sequence models. Measurement, Volume 145, October 2019, Pages 665-677. https://doi.org/10.1016/j.measurement.2019.05.039

[20] König(a), F., Marnheineke, J., Jacobs. G., Sous, C., Zuo, Ming, J., Tian, Z., Data-driven wear monitoring for sliding bearings using acoustic emission signals and long short-term memory neural networks. Wear, Vol 476 (2021), pp. 203616 – 1-7

[21] König(b), F., Sous, C., Ouald Chaib, A., & Jacobs, G. (2021). Machine learning based anomaly detection and classification of acoustic emission events for wear monitoring in sliding bearing systems. Tribology International, 155(October 2020). https://doi.org/10.1016/j.triboint.2020.106811

[22] Sause, M., Investigation of pencil-lead breaks as acoustic emission sources. J. Acoustic Emission, Vol 29 (2011), pp. 184 – 196.

[23] D. Comaniciu and P. Meer, "Mean shift: a robust approach toward feature space analysis," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, no. 5, pp. 603-619, May 2002, doi: 10.1109/34.1000236.