

Oil condition monitoring, an AI application study using the Classification Learner Technics

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Abstract. The present study uses an estimation and prediction method and characteristic techniques to predict the life of the lubricating oil based on data collected directly from the mechanical or hydraulic system. The collected data is part of a complex data set with 19 lubricating oil status parameters resulting from online measurements on an experiment stand built and operated under conditions similar to those in a mechanical machining company. The data set was collected during six months, continuously validating the data in several 258646 instances for 19 operating parameters. To predict the values of the next steps of a sequence, the Classification Learner Technics has been approached by support vector machines (SVM) models. The answers obtained characterize and equate the training sequences with values changed by a step of the time, and this means that at each stage of the input sequence, the data structure learns to predict the output value at the next time step. To prevent divergence of the forecast, it was necessary to standardize the training data so that it will achieve a zero mean and unit variance. Also, the test data set has been normalized in the same way as training data.

1. Introduction

Machinery and mechanical installations' condition monitoring has become a necessity with the rapid development of industrial automation. Due to the high cost of accidental interruptions generated by human errors or system failures, more intelligent and reliable manufacturing systems require related vehicle condition monitoring systems and the intervention decision to maintain and diagnose the malfunctions following based online measurements, dynamic response measurements periodically updated. In general, mechanical machining machines and operating conditions are monitored using vibration measurements generated during automated, technological processes or by online analyses of lubricating oils. The monitoring of lubrication conditions is recognized as an effective means of determining the health of gearboxes and transmission train components [1-6].

Mechanical vibrations occur due to imperfections and deviations generated both by the quality of the moving parts and lack of collinearity or coaxially. In addition, the degradation of lubricating oils is caused by altering the chemical or physical properties of these lubricants, Table 1, [7-13].

The role of an effective monitoring system, based on vibration intensity measurement and observation, is to provide singularities and abrupt increases/ decreases in vibration amplitudes in a certain period of observation and measurement. Undoubtedly, the signals contain the characteristics of the vibrations measured by several transducers or sensors, and it is infrequent to use a single transducer.

Therefore, such a system also involves numerical methods or algorithms for removing the noises from the signal components taken before the signal is used to process the information contained therein.

Table 1: Physical and chemical properties subject to degradation

Property	Definition of property
Viscosity at 40 and 100 °C	Contamination of the lubricant with other oils or oxidation thereof
Moisture, or water content	Verifying the presence of water
Insolubility	High-temperature indication in operation
Total Acid Number/ Total Base Number (TAN/TBN)	Acidity/ Alkalinity of the lubricant
Flashpoint	The presence of dissolved solvents and gases in the lubricant
Analyzes for the detection of wear results	Detection of wear-related elements in parts per million(ppm)
Particle counting (ISO count)	Detection of particle number, by size, in 100 cc

The success of a classification system depends significantly on the effectiveness of the extracted observation sequence to represent a particular condition or condition of the machine. Significant efforts have therefore been made in research works, the development of various techniques for extracting features, and monitoring the state of the machinery and installations. Characteristics extraction algorithms can be grouped, according to the basic methods used, into three main categories: the Principal Components Analysis, which is based on the identification of the axes on which data is most variable, the learning approach (Neural Networks, Pattern Classification, which have the advantages of superior learning, noise suppression, and parallel computational skills) and signal processing (Fourier transform, Hidden Markov Models or wavelet procedure, which allow the classification based on modulus maxima distribution), [14-26].

2. The Classification Learner application

This application allows you to approach the Feature Selection classification and establish Predictors Classes (in this study, the predictors are: column 16 (para_param: Param A used for oil degradation calculation), column 17 (oh_paramb: Param B used for oil degradation calculation) and column 18 (oh_paramc: Param C used for the oil degradation calculation) of the data file to be analyzed, see also Table 2, [27-29]:

Table 2- Parameters' definitions and symbols' significance

Crt. nr.	Parameter Symbol	• Significance of parameters
1	icm_rh	• Relative humidity of the oil (%)
2	icm_flow	• Oil flow (ml/min)
3	icm_temp	• Temperature of the sensor (°C)
4	icm_iso4	• Disaggregated ISO Cleanliness Code 4406:1999
5	icm_iso6	• Disaggregated ISO Cleanliness Code 4406:1999
6	icm_iso14	• Disaggregated ISO Cleanliness Code 4406:1999
7	icm_pc4	• Particle counter 4μ
8	icm_pc6	• Particle counter 6μ
9	icm_pc14	• Particle counter 14μ
10	fps_vcst	• Kinematic viscosity (cSt)
11	fps_v	• Dynamic viscosity (cPoise)
12	fps_density	• Density (g/cm ³)

13	fps_dielectric	• Dielectric
14	fps_temp	• Oil temperature (°C)
15	oh_temp	• The temperature of the sensor (°C)
16	oh_parama	• Param A used for oil degradation calculation
17	oh_paramb	• Param B used for oil degradation calculation
18	oh_paramc	• Param C used for oil degradation calculation
19	oh_od	• Oil degradation

From the same data file, column 19 (oh_od: Oil degradation, calculated using parameters oh_parama, oh_paramb, and oh_paramc, [27], [28]) is the basis of the learner classification response, used as the acceptance level of the application solution. The data contained in column 19, i.e., the values of the total oil degradation parameter were converted to binary values 0, corresponding to the values oh_od > 28 or 1, corresponding to the importance of oh_od < 28, i.e., a degraded quality grade oil to facilitate the classification the predictors, depending on the target responses. The application was developed successively for six classification models (Tree, Linear SVM, kNN, Linear Discriminant, Quadratic Discriminant, and Quadratic SVM), validated with PCA modelling in all six models. Response Classes generated by the application were 64. The highest accuracy, 99.7%, was obtained for the k-nearest neighbour (kNN) model. This technique, kNN, is, in fact, a remote function, which searches in a set of data and allows the graphical display of the closest "neighbour" based on a required query. The kNN search technique and kNN-based algorithms are widely used as reference learning rules. In addition, the relative simplicity of the kNN search technology makes it easier to compare the results from other classification techniques with kNN results, [1], [30-33], figure 1:

Model 1: Trained

Results

Accuracy 99.7%
Prediction speed ~220000 obs/sec
Training time 21.699 sec

Model Type

Preset: Fine KNN
Number of neighbors: 1
Distance metric: Euclidean
Distance weight: Equal
Standardize data: true

Feature Selection

All features used in the model, before PCA

PCA

PCA is keeping enough components to explain 95% variance.
After training, 1 components were kept.
Explained variance per component (in order): 99.6%, 0.4%, 0.0%

Figure 1.- The General kNN model characteristics after classification run

In the Classification Learner, a particular problem is creating a proper separation. This approach can be made by graphical representation using a scatter plot through graphic representation in a pair of predictors before training a classifier. Figure 2 shown a complete plot scatter, for two pairs of predictors, consisting of the data columns: oh_parama versus oh_paramb; oh_parama versus oh_paramc; oh_paramb versus oh_paramc. Note that, in the figures, the data columns correspond to the data in the file containing the collected data set, with the following correspondence: column_1 = oh_parama, column_2 = oh_paramb, column_3 = oh_paramc. It is easy to see, analyzing the six representations, that the chosen predictors are valid for the data classification: separation of data is good, the concentration of data sets in the two classes being remarkable.

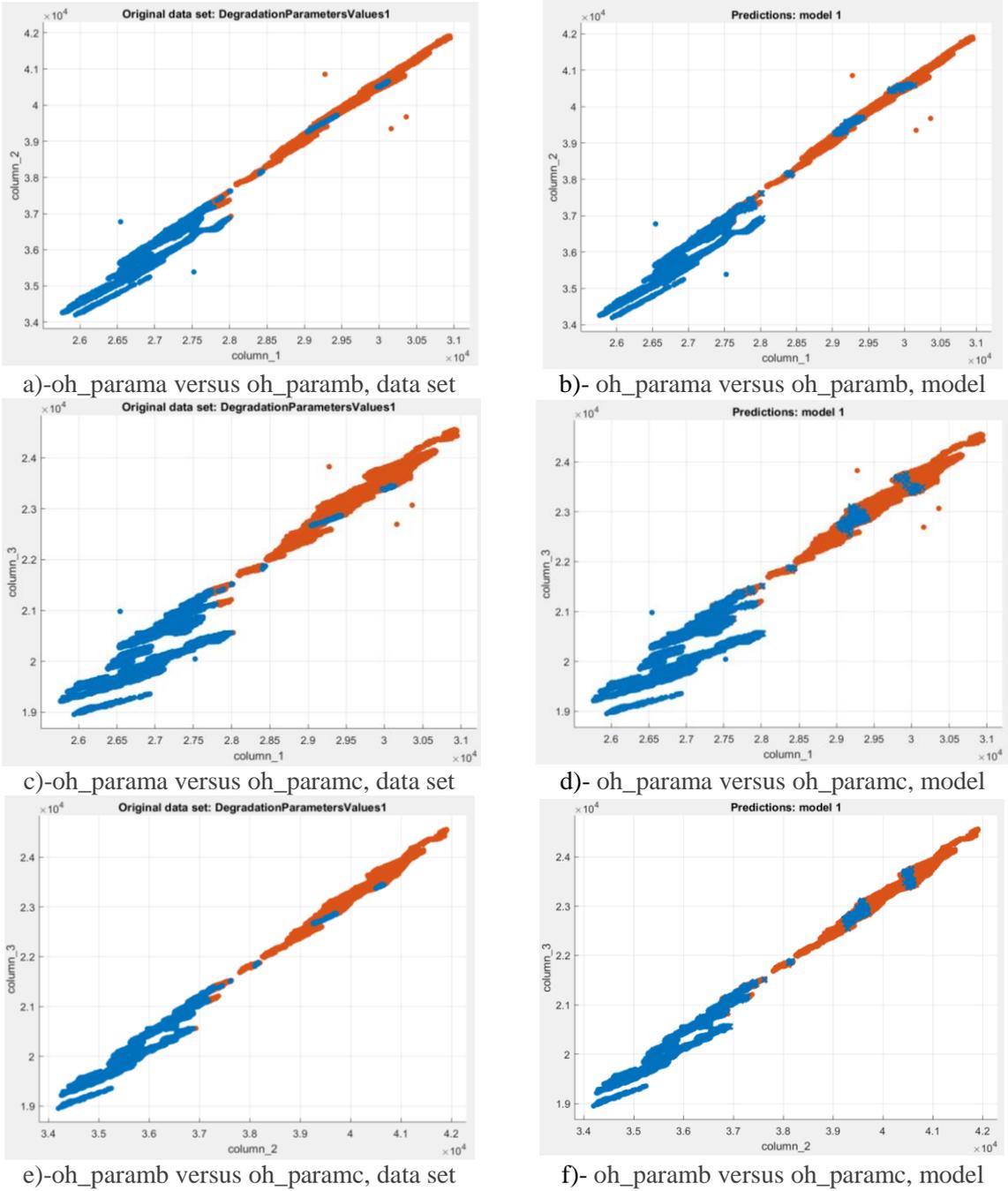


Figure 2-Scatter Plot for the data set and model predictions

The Confusion Matrix shown in Figure 3 and 4 describes a graphical method to help identify areas where the classifier had good results (diagonal area, green-colored):

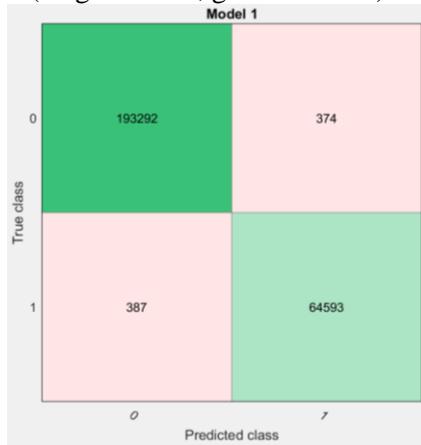


Figure 3- The confusion matrix, plotted using a number of observations

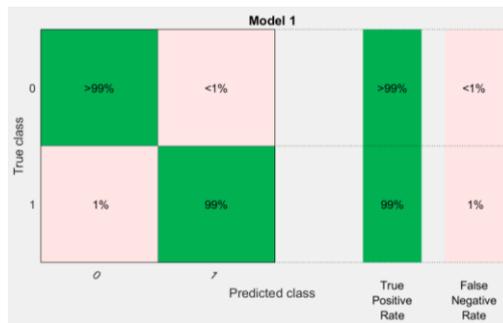
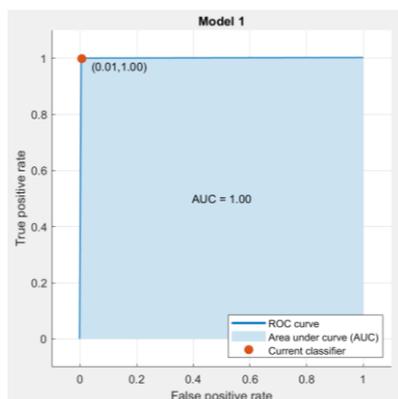
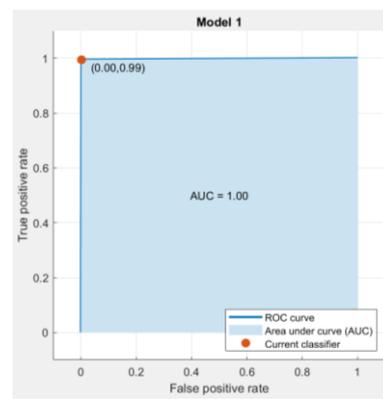


Figure 4- The confusion matrix, plotted using True Positive Rate and False Negative Rate options

A simple method to show the true positive rate versus the false positive rate for the currently selected trained classifier consists of plotting the Receiver Operating Characteristic (ROC) curve for each of the two classes, figure 5. One can select different classes in the plot. The marker on the plot, in figure 5, a), (0.01, 1) shows the performance of the currently selected classifier (class 0). The marker shows the values of the false positive rate (FPR: 0.01) and the true positive rate (TPR: 1.00) for the classifier 0, in this case, and in figure 5, b), the marker shows the values of the false the positive rate (FPR: 0.00) and the true positive rate (TPR: 0.99) for the classifier 1, respectively.



a)-Positive class: 0



b)-Positive class: 1

Figure 5- The receiver operating characteristic (ROC) curve for two classes

A decision, such as, which features to include in the classification, or which ones are excluded from the classification, respectively, can be determined by viewing the Parallel Coordinates Plot graphical representation. This graphical representation helps to understand the existing relationship between features and to identify useful predictors for different classifiers. You can thus view the training data and points unclassified or classified incorrectly. The latter is represented on the graph, always with dashed lines, figure 6:

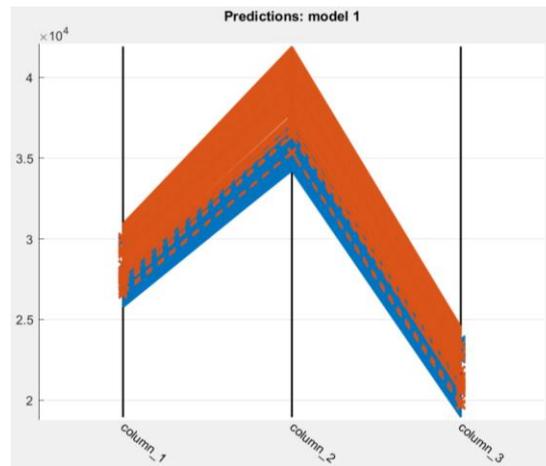


Figure 6- Parallel Coordinates Plot
(incorrectly classified points are represented with dashed lines)

3. Conclusions

Condition monitoring, diagnosis, and predicting the estimation of some output parameters for a technical system, respectively, can be framed in the "extrapolation" chapter as a mathematical, evaluation, testing and validation operation [27-29]. Doubtless, the time series for which mathematical operations of this kind can be applied are subject to errors due to the statistical nature of these mathematical classes. Therefore, a prediction is understood as an estimate of the values of a time function, based on values of a time series, values that can be, or can not be, affected by random errors. Thus, for example, a prediction problem could be expressed as follows: Given a series of time, $S(t)$, which consists of a set of values, and a random set of disturbing signals assimilated to a group of noise, $Z(t)$, it is proposed to estimate a future value, a prediction, therefore, $P(t+\tau)$, where τ is a positive constant, the forecast is also a continuous function of time.

This study was intended to show how to predict time series data using Artificial Intelligence techniques [3] on a set of data collected using direct/ indirect sensors and computational determinations based on empirical relationships. The data set contains 19 parameters, not all independent, whose values have been collected over six months or determined empirically. From this set, the data collected for three status parameters (which determines the degree of degradation of the lubricating oil) and a set of values corresponding to the set of target values were selected, the latter being used as a comparison element, training, learning, testing, and validation, respectively. The number of time steps is estimated at 258646 items. Outliers detection techniques have replaced missing or erroneous values by comparing the closest mean value set. The values with which these abnormalities have been replaced complies with the condition that they are interpolated linearly over a strictly determined range in the valid set of values.

To predict the values of the next steps of a sequence, the Classification Learner Technics has been approached by support vector machines (SVM) models. The answers obtained characterize and equate the training sequences with values changed by a step of the time. This means that at each step of the input sequence, the data structure learns to predict the output value at the next time step [1].

The prognosis process validating the time multiples values, the predictedAndUpdateState function in Matlab® [1] was used, which allows the anticipation of consecutive time steps to update the status of the network at each prediction. This experiment uses the data set collected within the National Program PN II project, ERA MANUNET: NR 13081221, [27], [28], [29]. These experiment models and analyzes at the same time the behaviour of a mechanical system, studying its behaviour based on data collected from applied sensors the hydraulic system of automatic machine lubrication. Computational determinations have been made for a small set of parameters to generate an estimate of the degradation state of the lubricating oil (A, B, C), respectively for the complete set of data (are used all 19 independent parameters, or not, collected during the experiment). The latter analysis required an excessive computational effort in the necessary resources, involving parallel computing techniques on an i7 computer with eight kernels. For this approach, it was also necessary to process the data provided by the last data column, which contains calculated estimations of the qualitative degradation of the oil (empirical determination, [34], [35]) so that the data column reflects the correct classification of the qualitative estimates as well as the values collected from the system sensors for the other parameters of the lubricating oil. In this sense, the last data column in the data set matrix contains binary values (0 and 1) for the two possible states of the oil in the plant: the logical value "1" corresponds to a degraded oil, and needs to be changed, respectively the logical value "0", represents a suitable quality oil, and can be used in the lubrication system. The data set is partitioned as follows: 70% of the data volume will be used for artificial network training, and 15% of the collected data set is used for network testing, and 15% of the dataset is used to validate the results. The working procedure states that the response values of the system are the network training data sequence [36]. Carefully prevent divergence of the forecast; it will be necessary to standardize the training data so that it has zero mean and unit variance.

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References

- [1] Statistics and Machine Learning Toolbox™ User's Guide, https://www.mathworks.com/help/releases/R2018a/pdf_doc/stats/stats.pdf, Accessed in February 2021.
- [2] Lihui Wang and Robert X. Gao (Eds.) Condition Monitoring and Control for Intelligent Manufacturing, 2006, Springer-Verlag.
- [3] David Ortiz, Carl Byington, Romano Patrick, Cody Ture, John Farnach, John Moffatt, Combined Lubrication Monitor for On-Line Gearbox Health Assessment, DOI: [10.1109/AERO.2011.5747563](https://doi.org/10.1109/AERO.2011.5747563), 2011, Aerospace Conference, **IEEE Xplore**.
- [4] Henry S. Teng, Kaihu Chen and Stephen C-Y Lu, Adaptive Real-time Anomaly Detection Using Inductively Generated Sequential Patterns, Conference Proceedings on Research in Security and Privacy, 1990., 1990, IEEE Xplore DOI: 10.1109/RISP.1990.63857
- [5] Chandola, V., Banerjee, A., and Kumar, V. 2009. Anomaly detection: A survey. ACM Comput. Surv., 2009, 58 pages. <http://doi.acm.org/10.1145/1541880.1541882>
- [6] Victoria J. Hodge and Jim Austin, A Survey of Outlier Detection Methodologies, Artificial Intelligence Review 22: 85–126, 2004, Kluwer Academic Publishers, DOI: 10.1023/B:AIRE.0000045502.10941.a9
- [7] George E. P. Box, Gwilym M. Jenkins, Gregory C. Reinsel, Greta M. Ljung, Time Series Analysis: Forecasting and Control, Fifth Edition, 2015, John Wiley & Sons.
- [8] G. E. P. Box & G. C. Tiao (1975) Intervention Analysis with Applications to Economic and Environmental Problems, Journal of the American Statistical Association, 70:349, 70-79, DOI: [10.1080/01621459.1975.10480264](https://doi.org/10.1080/01621459.1975.10480264).
- [9] Chang, Ih, George C. Tiao, and Chung Chen. "Estimation of Time Series Parameters in the

- Presence of Outliers." *Technometrics*30, no. 2 (1988): 193-204. DOI:10.2307/1270165.
- [10] Bovas Abraham, G. E. P. Box, "Bayesian Analysis of Some Outlier Problems in Time Series", 1979, *Biometrika* 66(2):229-236, DOI: 10.1093/biomet/66.2.229
- [11] Peter J. Rousseeuw, Annick M. Leroy, "Robust Regression and Outlier Detection", 1987, John Wiley & Sons.
- [12] Bernhard Schölkopf, Alex J. Smola, Klaus-Robert Müller, Nonlinear Component Analysis as a Kernel Eigenvalue Problem, *Neural Computation* 10(5):1299-1319, DOI: 10.1162/089976698300017467, 1998
- [13] Ryohei Fujimaki, Takehisa Yairi, Kazuo Machida, An approach to spacecraft anomaly detection problem using Kernel Feature Space, Conference: Proceedings of the Eleventh ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Chicago, 2005, DOI: 10.1145/1081870.1081917.
- [14] Daniel Peña, George C. Tiao, Ruey S. Tsay, *A Course in Time Series Analysis*, 2001, John Wiley & Sons, Inc., New York
- [15] Basu, S. & Meckesheimer, Automatic outlier detection for time series: an application to sensor data, Springer-Verlag London Limited, *M. Knowl Inf Syst* (2007) 11: 137. <https://doi.org/10.1007/s10115-006-0026-6>
- [16] Manahil Raza, Usman Qayyum, Classical and Deep Learning Classifiers for Anomaly Detection, 2019 16th International Bhurban Conference on Applied Sciences and Technology (IBCAST - 2019), DOI: 10.1109/IBCAST.2019.8667245
- [17] Rolf Isermann, Process Fault Detection Based on Modeling and Estimation Methods A Survey, Published in Elsevier- *Automatica*, Volume 20, Issue 4, July 1984, Pages 387-404, DOI:10.1016/0005-1098(84)90098-0
- [18] Gwidon W. Stachowiak, Andrew W. Batchelor, *Engineering Tribology*, Third Edition, 2005, Elsevier Butterworth-Heinemann
- [19] BC. Sharma and O.P. Gandhi, Performance evaluation and analysis of lubricating oil using parameter profile approach, *Industrial Lubrication and Tribology* 60(3):131-137, DOI: 10.1108/00368790810871057
- [20] Junda Zhu, David He, Eric Bechhoefer, Survey of Lubrication Oil Condition Monitoring, Diagnostics, and Prognostics Techniques and Systems, *Journal of Chemical Science and Technology* July 2013, Vol. 2 Iss. 3, PP. 100-115
- [21] NK. Myshkin and LV Markova, Online Condition Monitoring in Industrial Lubrication and Tribology, *Applied Condition Monitoring* 8, Springer International Publishing AG, 2018, DOI 10.1007/978-3-319-61134-1_1
- [22] Qingfei He, Guiming Chen, Xiaohu Chen, Chunjiang Yao, Application of Oil Analysis to the Condition Monitoring of Large Engineering Machinery, Published in 2009 8th International Conference on Reliability, Maintainability and Safety, *IEEE Xplore*, DOI: [10.1109/ICRMS.2009.5270033](https://doi.org/10.1109/ICRMS.2009.5270033)
- [23] Junda Zhu, Online Industrial Lubrication Oil Health Condition Monitoring, Diagnosis and Prognostics, Ph.D. Thesis, the University of Illinois at Chicago, 2013.
- [24] Saloka, G. and Meitzler, A., "A Capacitive Oil Deterioration Sensor," SAE Technical Paper 910497, 1991, <https://doi.org/10.4271/910497>.
- [25] A.H. Sihvola, J.A. Kong, Effective Permittivity of Dielectric Mixtures, *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING*. VOL 26, NO 4, 1988, pp 420-429, DOI: [10.1109/36.3045](https://doi.org/10.1109/36.3045).
- [26] B. Jakoby, M. J. Vellekoop, Physical sensors for water-in-oil emulsions, *Sensors and Actuators A* 110 (2004) 28–32, 2003 Published by Elsevier B.V., DOI:10.1016/j.sna.2003.08.005.
- [27] G. Adriani, M. Campatelli, M. Paoli, -Monitoil® - *Online sensors for efficient and cost-saving oil conditions' monitoring*, Mecoil Diagnosi Meccaniche s.r.l., Florence, Italy, http://www.mecoil.net/wp-content/uploads/2013/04/20120914-Articolo-colonne_Monitoil_eng.pdf

- [28] Grebenișan G., Salem N., and Bogdan S., *The lubricants parameters monitoring and data collecting*, MATEC Web of Conferences, **Volume** 126, 2017, <https://doi.org/10.1051/mateconf/201818403008>.
- [29] Grebenișan G., Salem N., and Bogdan S. -*An approach of classification and parameters estimation, using the neural network, for lubricant degradation diagnosis*, MATEC Web of Conferences, **Volume** 184, 2018, <https://doi.org/10.1051/mateconf/201818403009>.
- [30] Anveshan Bommareddi, *An Engine Oil Life Algorithm*, The Pennsylvania State University, Department of Mechanical and Nuclear Engineering, 2009
- [31] Enrico Zio, Giovanni Peloni, *Particle filtering prognostic estimation of the remaining useful life of nonlinear components*, 2010 Elsevier Ltd, *Reliability Engineering and System Safety* 96 (2011) 403–409, DOI:10.1016/j.ress.2010.08.009
- [32] Diego Galar Pascual, *Artificial Intelligence Tools: Decision Support Systems in Condition Monitoring and Diagnosis*, CRC Press Taylor & Francis Group, LLC, 2015
- [33] Qiang Miao, Viliam Makis, *Condition monitoring and classification of rotating machinery using wavelets and hidden Markov models*, ELSEVIER, Science Direct, *Mechanical Systems and Signal Processing* 21 (2007) 840–855, DOI:10.1016/j.ymssp.2006.01.009.
- [34] Qiang Miao, Hong-Zhong Huang, Xianfeng Fan, *A Comparison Study of Support Vector Machines and Hidden Markov Models in Machinery Condition Monitoring*, *Journal of Mechanical Science and Technology* 21 (2007) 607~615, DOI: 10.1007/BF03026965
- [35] Norbert Wiener, *Extrapolation, Interpolation, and Smoothing Of Stationary Time Series With Engineering Applications*, The M.I.T. Press Massachusetts Institute Of Technology Cambridge, Massachusetts, 1949.
- [36] Lotfi A. Zadeh and John R. Ragazzini, *An Extension of Wiener's Theory of Prediction*, 1950, IEEE Xplore, *Journal of Applied Physics* 21(7):645 – 655, DOI:10.1063/1.1699725