19th IMEKO TC10 Conference
"MACRO meets NANO in Measurement for Diagnostics, Optimization and Control"
Delft, Netherlands, September 21–22, 2023

Analysis of the Faults in Ratchet Mechanisms in the Presence of Noise

Bartosz Połok[1], Piotr Bilski[2]

[1] *Warsaw University of Technology, Warsaw, Poland, b.polok@gmail.com, +48 222347644*
[2] *Warsaw University of Technology, Warsaw, Poland, piotr.bilski@pw.edu.pl, +48 601056969*

***Abstract* – The following paper presents the methodology of monitoring the state of the ratchet mechanisms in the presence of noise. The fault detection is based on the acoustic analysis of the signals generated by the revolving mechanism. Decision is made using machine learning methods, which accuracy is compared. The object of the analysis is the ratchet mechanism installed in the actual BMX-type bicycle. It was shown that the noise suppression approach is suitable for the applied diagnostic framework, leading to the high accuracy in detecting catastrophic faults, such as breaking the tooth inside the mechanism.**

Keywords – acoustic analysis, machine learning, fault detection in ratchet mechanisms, denoising.

I. INTRODUCTION

Processing of acoustic signals is the popular tool in the diagnostics of mechanical systems. Moving or rotating machinery often generates sound that can be used to determine its actual state. Magnetic bearings or centrifugal pumps are common objects of analysis [1,2]. One of the most significant problems during the fault detection is the environmental noise, degrading the sound quality. This is also the challenge for the Artificial Intelligence (AI)–based approaches, where the disturbances in data degrade the ability to accurately classify particular damages in the System Under Test (SUT). Therefore the important operation before the actual decision making may be implemented, among others, should be the noise elimination in order to suppress the unwanted components of the signal. This is the case for the ratchet mechanisms considered in the presented research.

Classification of faults in the uncertainty conditions is one of the pressing challenges for the modern, intelligent diagnostic procedures. There are multiple approaches tackling the noise and corrupted data, such as Support Vector Machines (SVM), Fuzzy Logic (FL), Rough Sets (RS) or Grey Systems (GS) [3]. They are all well established in the technical diagnostics domain (for instance, to detect cracks inside the induction motor [4]). and are often used where the real-world data are processed and the different types of disturbances pose a challenge for the accurate fault identification and location.

The following paper presents the methodology for diagnosing the state of the ratchet mechanism used in the bicycles in the presence of environmental noise. The measurement system used in the research was already tested in the laboratory conditions, proving its usefulness [5]. It is now optimized to tackle the acoustic disturbances, making it suitable for the real-world scenarios. This includes both denoising procedure and selection of the best fault detection and location approaches. It is demonstrated that the applied methodology is suitable for detecting the subset of catastrophic faults in the uncertainty conditions and can be implemented in the actual diagnostic system. Also, the importance of the presented research is that it is based completely on the real-world data, omitting computer-oriented simulations

The contents of the paper are as follows. The measurement system is briefly introduced in Section II. Next, the environmental conditions and acoustic noise characteristics making fault detection difficult are discussed. Experiments using various noise-resilient AI-based classification methods are described in Section IV. Results of the fault detection in various environmental conditions and using different AI-based classifiers are presented in Section V. Finally, conclusions drawn and future prospects are iterated in Section VI.

II. DATA AQUISITION AND PROCESSING SYSTEM

The measurement system used for the experiments was constructed [5] to record acoustic signals generated by the ratchet mechanisms [6] being part of the propulsion system in the BMX-type bicycle. Such a hardware is located inside the gear, responsible for rotating the wheel, thanks to the set of pawls based on the ratchet ring (Fig. 1). This way it is possible to transmit the force generated by the user to the gear, rotating the wheel and move the vehicle. Latching the pawl against the teeth generates the characteristic sound, based on which the attempt to determine the actual state of the system may be made. The considered faults included disabling particular pawls, which drives the number of detectable categories. For instance, in the 4-pawl ratchet there are four faults possible (respectively, one, two, three and four pawls disabled) with one nominal state (all elements operating correctly). This is the catastriphic fault, as taking out the pawl changes the structure of the propulsion system. Parametric faults could be considered (aimed at the gradual teeth or pawls wearing detection), but as they are more difficult to implement in the actually working system, the are not considered here.

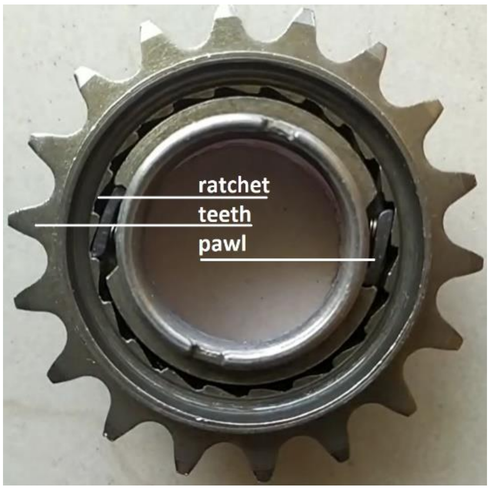

Fig. 1. Construction of the diagnosed mechanism

The measurement (Fig. 2) system contains mechanical and electronic modules and was built to operate the mechanism and acquire acoustic data from it. The ATMega 328P microcontroller-driven DC motor allows for rotating the bicycle wheel so the "click" sounds made by the pawls moving along the ratchet can be recorded. The reed switch attached to the wheel allows for counting the number of revolutions (which is important, as the analyzed signal is periodic). For the particular mechanism the number of sounds generated during the single revolution is constant, so counting them may be used as the fault indicator. The electronic part (implemented using the Personal Computer – PC) is resposnible for the sound acquisition thanks to the microphone located close to the wheel. The sampled sound pattern is also processed there, concluded with the fault detection and location procedure.

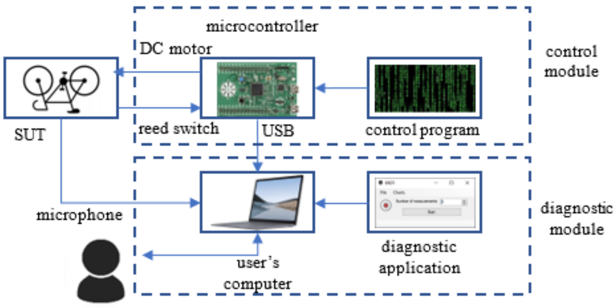

Fig. 2. Architecture of the diagnostic system

The motor control software was written in C++ (one of the standard techniques for programming microcontrollers), while the PC-based diagnostic part was prepared in Python, using popular libraries for data processing, such as scikit-learn. The system is constantly optimized to increase efficiency and decrease the occupied memory. Modifications are made in both software and hardware parts, so it could be applied in practical applications.

III. ENVIRONMENTAL NOISE CHARACETRISTICS

The system allows for the data acquisition in the sound spectrum range (between 20Hz and 20kHz). The samples can then be analyzed in the time, frequency and mixed domains. Finding the optimal set of features (extracted from the collected samples) is a crucial task for the diagnositcs of ratchet mechanisms. In a real-world scenario the additional problem is the quality of the recorded sound. This strongly influcences the subsequent steps, i.e. data collection for the training data sets, machine learning procedure and decision making by the selected classifiers.

Initially, all recordings were done in the anechoic chamber, where any noise was suppressed and external sound eliminated. In the actual system's application, multiple sources of disturbances are possible. These include both the white (related to other machinery operating in the background, etc.) and the color noise (due to the narrow band phenomena). Besides the time-invariant stochastic processes, short-time events may also occur (including human voice, short pitches of the key falling, etc.). This means that the disturbances may overlap on the useful signal during the whole recording time or have a short duration (like the sound of the door closing). In Fig. 3 two scenarios of the ratchet mechanism operating with the Additive White Gaussian Noise (AWGN) [7] of different power are presented. The noise was generated by the software and combined with the recorded sounds of the ratchet. This allows for the controlled insertion of the disturbances into the original acoustic signal, depending on its power:

$$\boldsymbol{x_n} = \boldsymbol{x} + \alpha \cdot \left|\max \boldsymbol{x} - \min \boldsymbol{x}\right| \cdot N(0,1) \qquad (1)$$

where *N(0,1)* is the normal random distribution with the unit variance and $\alpha \in (0,1)$ is the coefficient determining the noise power depending on the signal's dynamic range. This way the desired Signal-to-Noise ration is determined.

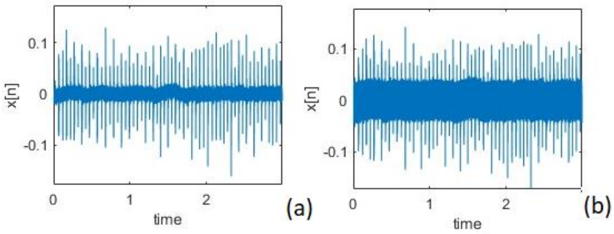

Fig. 3. White noise superimposed on the analyzed acoustic signal for α=0.05 (a) and α=0.4 (b)

Fig. 4 presents how the short disturbance influences the ability to count "clicks" and makes the diagnostcs difficult.

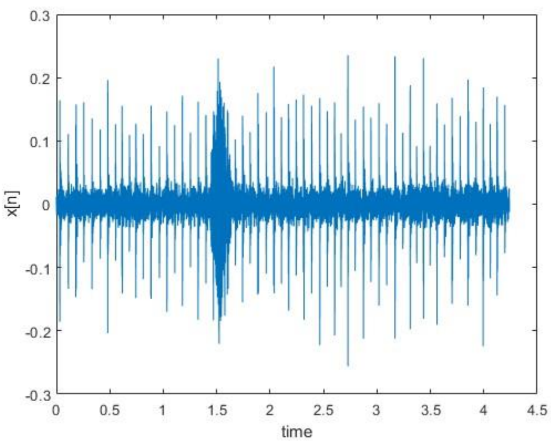

Fig. 4. Analyzed acoustic signal with the short-time disturbance

The main challenge for the diagnostic system is now to maintain the high accuracy (which was achieved in the more "user-friendly" conditions [5]) in the case of worse quality of sound samples. This may be done either by the de-noising procedure, or applying the more sophisticated classifier [8]. Both approaches were tested during the experiments.

The data sets used for training the intelligent module were created by testing the selected bicycle hubs in the noisy conditions in two locations with different acoustics, where various background sounds could be recorded. These included the underground garage with, respectively, concrete walls, and different hardware present inside (such as garden machinery, bike, etc.). Besides recording the ratchet sound, additional tracks were recorded independently, containing short events, such as coughing, hands clapping, moving the keys, yelling. These could be later added to the useful patterns, making the fault detection more challenging.

IV. DATA SETS AND PROCESSING METHODS

Each recording (stored in the file) contains the full revolution of the wheel, where multiple pawl "clicks" are present. Assuming such a signal is provided to the input of the diagnostic software, the key features are next extracted and the vector undergoes the analysis leading to the classification outcome.

The important aspect now is the training and testing the AI-based methods to verify its accuracy on data including phenomena described in Section III. The data partitioning was applied, consisting in separation of the generated sound files into the exclusive subsets, one of which (T) being used for the evaluation. The cross-validation process is repeated N times (here $N=5$). Each sound file is represented by the single feature vector (example) $\boldsymbol{v}$:

$$v = \{v_1 \quad \cdots \quad v_m \quad c\} \tag{2}$$

This way each recording is represented only once and belongs either to the training or to the testing set (but not both). Each vector contains the elements obtained from the time- frequency and wavelet-based analysis of the original pattern:

- number of pawl "clicks" per a single wheel revolution
- energy of four subsequent "clicks" (as the number of pawls in the examined ratchets was 4)
- duration of four subsequent "clicks"
- volume and width of scalograms for these four "clicks"
- magnitude and frequency of the spectral pitch of three odd and three even "clicks"

This way 32 features are collected in each example, supplemented with the category number (indicating either nominal state of the SUT or the index of disabled pawl).

The sets were filled with data from multiple hubs of the same type, but with different state of wearing. This makes knowledge extracted from data closer to the real-world scenarios. Overall, all data sets contain 600 files (examples). Their number and variability (3 different hubs and 2 recording conditions) allows for verifying generalization abilities of the system (as the number of hubs for bicycles is very large and it is not possible to consider all of them in the training data).

The classifiers applied for the experiments were selected to tackle the uncertainty conditions. They include:

- Decision Tree (DT) – the traditional rule-based approach, where the main hyperparameters are the method of the test selection for the node
- Random Forest (RF) [9] – extension of DT into multiple trees, trained on various subsets of the training set L. Here the main hyperparameter is the number of generated trees.
- Artificial Neural Network (ANN) [10] – the simple and multilayer perceptron architectures aimed at classification. In the first case it is the single-layer network with the hyperbolic tangent activation function, while the second scenario includes hidden layer, with number and the number of neurons in each of them are hyperparameters
- K Nearest Neighbors (kNN) – metrics-based classifier, where k examples from the set nearest to the currently analyzed vector decide about the fault category. Hyperparameters include the distance metrics and the number of neighbors.
- Naïve Bayes Classifier (NBC) – statistical approach where the probabilities are calculated as the frequencies of the attribute values occurrences.
- Support Vector Machine (SVM) [11] – the method similar to ANN, but based on the kernel function transformation (to increase the classification accuracy). The main hyperparameters include the kernel function and its coordinates (for instance, the width of the Radial Basis Function).
- Ada boost – the gradient boosting method,

increasing the chance of correctly classifying the "difficult" data.

- Quadratic Discriminant Analysis [12] – the simple statistical classifier that assumes the attributes in the analyzed set fall into the Gaussian distribution, which is the basis for constructing the separating quadratic-type hyperplane.
- Gaussian Process – the classifier also assumes the Gaussian distribution of attributes in data. Similarly to SVM, the type of the applied kernel is important.

In each case the classifier is trained on one set and tested on the other. The quality measure was accuracy:

$$acc = \frac{|v: \quad h(v)=c(v)|}{|T|} \cdot 100\% \tag{3}$$

where $h(\boldsymbol{v})$ is the SUT state proposed by the diagnostic system, while $c(\boldsymbol{v})$ is its actual category. Verification of the classifiers is done using the available data as follows:

The classifier is trained on the "clear" recordings and with the simulated noise added to them. It is then tested on the separate recordings with the noise included and also short-pitched environmental disturbances. The aim of the experiments is to check if the previously effective classifiers will maintain the fault detection accuracy after introducing the disturbances. Also the robustness and versatility while analyzing different hubs (of the same type but in different exploitation state) and environmental conditions was tested.

V. EXPERIMENTS

This section contains results of experiments for the selected classifiers. They were divided into particular stages, for estimation of the classifiers' usefulness.

A. Initial selection of classifiers

The first one was to select the optimal classifiers for the task. Average results for the preliminary evaluation are in Fig. 5.

The most effective is RF containing 100 trees (over 75%), with the QDA behind it (72.2%). The last classifier with the acceptable accuracy (i.e. above 50%) is DT. The remaining classifiers are not efficient enough to be used further. Note that SVM and AB underperform, though their structure considers uncertainty conditions. Introduction of more versatile data (including more hubs witch pawls and testh in different wearing states – though still opertional) led to the decrease of the accuracy, especially if the noise power is higher than the one present in the training data. For the presented featurs the rule-based methods seem to be more suitable for the correct fault identificatio, while RF additionally tackles the uncertainty conditions.

Further improvement of the classifiers' performance can be done through the thorough, time-consuming hyperparameters' optimization. Improvement is especially expected for SVM, neural network and Ada boost.

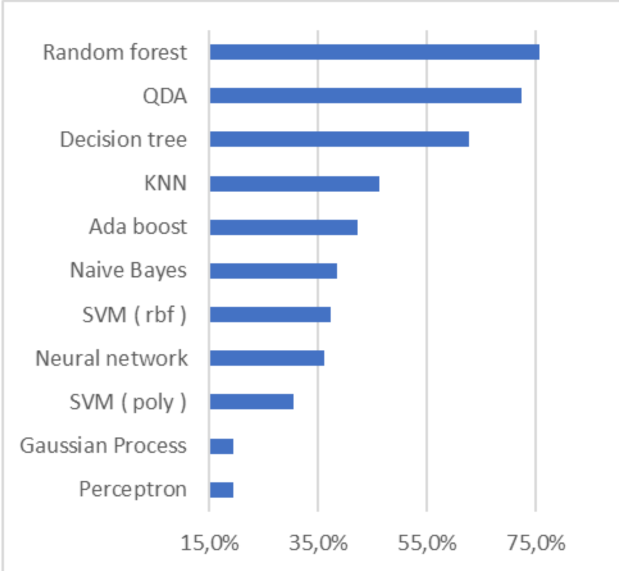

Fig. 5. Comparative analysis of the selected classifiers' accuracy

B. Change in the data selection for training

The new mode of the training data set preparation was employed to obtain more reliable results and verify generalization ailities of the proposed classifiers. Four approaches of generating training and testing data from the recorded files have been tested:

M_1 – a single vector $\boldsymbol{v}$ is generated from each file in both sets (T and L).

M_2 – a single vector $\boldsymbol{v}$ is generated from each file in L while all possible vectors are generated from each example in T.

M_3 – all possible examples are generated for a single file in L, with only one example in the single file from T.

M_4 – all possible examples are generated for each file in both L and T.

Everytime only one example is extracted from the single file, there is no threat of putting the same run into both sets (and therefore decreasing the generalization abilities).

For the experiment, the specific set T was created, by putting inside a single file for each hub with each possible fault. This way the set eith 45 files was created, while 555 files were put into L. Fault identification results for the classifiers selected from Section V.A using all four methods presented above are in Table 1. As before, the values here are averages for 5 trials.

Table 1: Comparison of fault identification results for different methods of creatintg data sets from recordings.

	M_1	M_2	M_3	M_4
DT	66,7%	82,2%	74,9%	84,4%
RF	80,0%	88,9%	91,9%	97,8%
QDA	64,4%	80,0%	70,6%	80,0%

RF is still the best classifier, though its accuracy depends on the data set preparation. The worst case is still the first method, (i.e. one example per file), because there is no redundancy between L and T. Similarly, the amount of training data influences the accuracy as knowledge from larger sets is better explored for DT and RF.

C. *Influence of the white noise to the fault detection accuracy*

This experiment consisted in verifying the influence of noise on the fault detection accuracy. For top 3 classifiers from section V.A the testing sets were modified by adding to the recoirdings the noise with increasing power (expressed by different values of α – see (1)), while the training examples remained “clear” (i.e. with the minimal amount of the white noise present). Results for DT and four dfferent methods of extracting examples from files are in Fig. 6, for RF are in Fig. 7, while for QDA – in Fig. 8. Outcomes confirm individual accuracies of the particular classifiers.

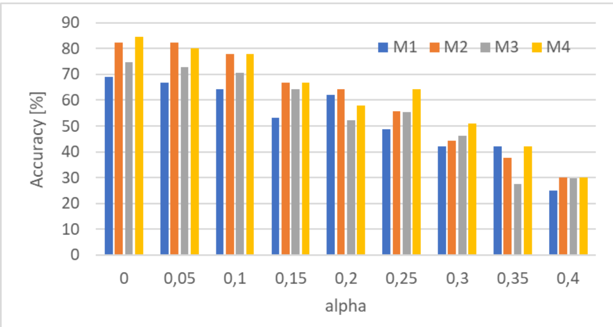

Fig. 6. Influence of the noise on the diagnostic accuracy of DT

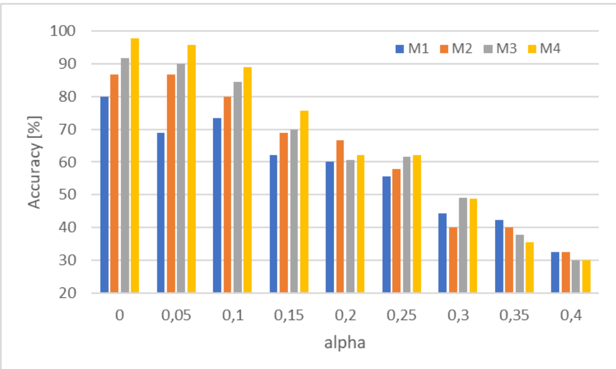

Fig. 7. Influence of the noise on the diagnostic accuracy of RF

In all cases the noise with α above 0.25 makes fault classification very difficult (as accuracy falls below 50%). This is the practical hint about the minimal required conditions of sound recordings if the “clear” (noiseless) data are used for training. The white noise affects at least some part of the time-based symptoms, making them detectable incorrectly. The solution for that phenomenon may be denoising procedure, assuming the crucial components for the feature extraction are not degraded. Another approach would be to intorduce the noise to the training set as well, which should improve accuracy for detecting faults in the presence of noise at least of the same power as used during the training.

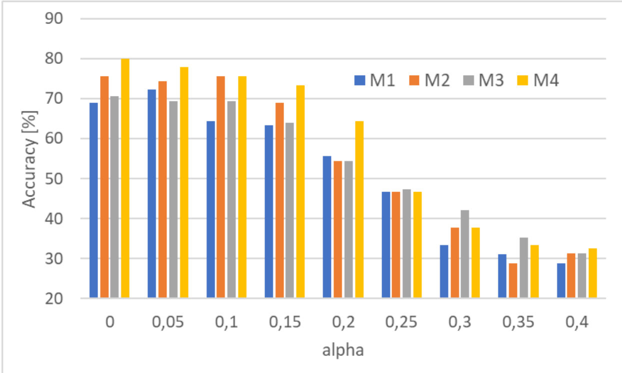

Fig. 8. Influence of the noise on the diagnostic accuracy of QDA

D. *Influence of the short-timed disturbances on the fault detection accuracy*

In this experiment to the original acoustic signal short-time disturbances are added. The latter were generated as the separate files, containing sounds with relatively short duration but high power. This means only part of the recording is affected (for instance, in one revolution period of the wheel). Therefore if methods M_1 and M_2 are used, the accuracy is higher, because less examples are extracted from the recording and they are less affected by such disturbances. Alternatively, introducing multiple examples from the single file improves the algorithms’ performance. Results for all classifiers are in Fig. 9.

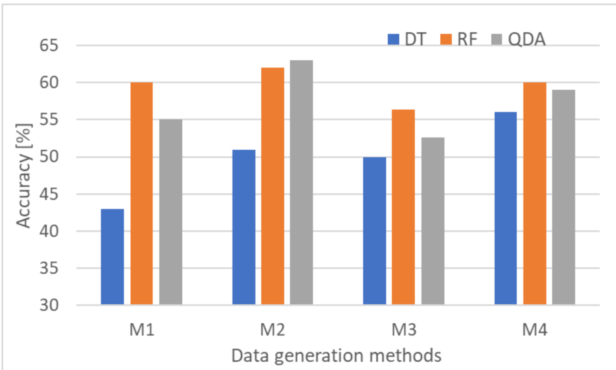

Fig. 9. Influence of the short-time disturbances on the classifiers accuracy

Overall, occurrence of these disturbances has negative impact on the ability to distinguish faults. In practice it is more reasonable to leave out recordings containing such events and repeat them until the correct data acquisition may be performed. If this is not an option (for instance, because of the recurring problems with isolating the recording system from the background influence), only the symptoms robust against such effects should be selected (though the accuracy of the classification would still be degraded).

VI. CONCLUSIONS

The presented research shows the applicability of the acoustic analysis for the catastrophic fault identification in the ratchet mechanisms. The main problem considered in this work was to evaluate the influence of the background disturbances (seen as both the white constant noise and the short-time sound) on the fault detection and identification abilities. The second aim was to propose different data selection methods on the generalization abilities of the selected classifiers. Multiple algorithms have been applied in the scheme to compare their accuracy and to select the most promising approaches.

It was determined that the noise poses a significant problem for the diagnostic procedure. In the case of the ubiquitous white noise, a lot depends on its power compared to the useful signal. To some extent there is no need to implement the denoising, as the correct symptoms can be extracted from the acoustic pattern. After exceeding the threshold power, the denoising might be required, or training the system with the noisy data (examples created from the AWGN-affected signals). The disturbances of short duration are more difficult to tackle, as even their occasional occurrence may significantly affect the ability to extract features accurately. In this case either another set of robust features should be applied, otherwise the sound recording must be repeated. The latter is practically easier to perform, but not always possible.

The future research will be devoted to introduce additional classifiers and optimizing them, especially in the noisy conditions with the increasing power of the disturbance. Also, more complex approaches, such as classifier fusion should be tested [13]. Finally, denoising procedures and their influence on the ability to select the features properly should be evaluated.

REFERENCES

[1] **Albraik A., Althobiani F., Gu F., and Ball A.:** Diagnosis of Centrifugal Pump Faults Using Vibration Methods**,** *Journal of Physics: Conference Series*, 2012 Vol. 364, DOI:10.1088/1742-6596/364/1/012139.

[2] **da Silva G. M., Pederiva R.:** Fault diagnosis of active magnetic bearings, *Mechatronics*, Vol. 84, 2022, DOI:https://doi.org/10.1016/j.mechatronics.2022.102801.

[3] **Tay F. E.H., Shen L.:** Fault diagnosis based on Rough Set Theory, *Engineering Applications of Artificial Intelligence*, Vol. 16, 2003, pp. 39-43, DOI:https://doi.org/10.1016/S0952-1976(03)00022-8.

[4] **Gundewar, S.K., Kane, P.V.:** Condition Monitoring and Fault Diagnosis of Induction Motor, Journal of Vibration Engineering & Technologies 9, 2021, pp. 643–674 DOI:https://doi.org/10.1007/s42417-020-00253-y

[5] **Połok B., Bilski P.:** Intelligent diagnostic system for the rachet mechanism faults detection using acoustic analysis, *Measurement*, Vol. 183, 2021, DOI:https://doi.org/10.1016/j.measurement.2021.109637.

[6] **Burgreen D.:** The Thermal Ratchet Mechanism, *Journal of Fluids Engineering*, 1968, 90(3), pp. 319-324, DOI:https://doi.org/10.1115/1.3605098.

[7] **Lyon R. H.:** Sound Radiated by Machines, *Machinery Noise and Diagnostics*, 1987, pp. 121-159, DOI: https://doi.org/10.1016/B978-0-409-90101-6.50008-5.

[8] **Schäfer P.:** The BOSS is concerned with time series classification in the presence of noise, *Data Mining and Knowledge Discovery*, 2015, 29(6), DOI:10.1007/s10618-014-0377-7.

[9] **Aldrich C. and Auret L.:** Fault detection and diagnosis with random forest feature extraction and variable importance methods, *IFAC Proceedings Volumes*, Vol. 43, 2010, pp. 79-86, DOI:https://doi.org/10.3182/20100802-3-ZA-2014.00020.

[10] **Widodo A., Yang B.-S.:** Support vector machine in machine condition monitoring and fault diagnosis, *Mechanical Systems and Signal Processing*, Vol. 21, 2007, pp. 2560-2574, DOI:https://doi.org/10.1016/j.ymssp.2006.12.007.

[11] **Becraft W. R.:** Diagnostic applications of artificial neural networks, *Proceedings of 1993 International Conference on Neural Networks* Nagoya, Japan, 1993, pp. 2807-2810 vol.3, doi: 10.1109/IJCNN.1993.714307.

[12] **Guo S. and Tracey H.:** Discriminant Analysis for Radar Signal Classification, *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 56, no. 4, pp. 3134-3148, 2020, DOI: 10.1109/TAES.2020.2965787.

[13] **Li W., Hou J., and Yin L.:** A classifier fusion method based on classifier accuracy, *2014 International Conference on Mechatronics and Control (ICMC)*, Jinzhou, China, 2014, pp. 2119-2122, DOI:10.1109/ICMC.2014.7231940.