VPS VIBRATIONS IN PHYSICAL SYSTEMS

DOI: 10.21008/j.0860-6897.2022.3.16
Vibrations in Physical Systems, 2022, 33(3), 2022316

Analysis of the Possibility of Mechanical Devices Supervision Based on the Measurement of the Vibration level and SVM Classifiers

Ryszard SCHOSSLER, **Marcin GROCHOWINA**, **Lucyna LENIOWSKA**

Uniwersytet Rzeszowski, Al Rejtana 16c, 35-959 Rzeszów

Corresponding author: Ryszard SCHOSSLER, email: ryszard.schossler@gmail.com

Abstract This paper presents the concept of diagnosing the technical condition of mechanical devices. The test is based on a non-invasive vibration analysis technique combined with the use of artificial intelligence method. The object of the research is an electric motor for which vibrations were recorded by a vibration sensor based on four 3-axis digital accelerometers and MPU-6050 gyroscopes. The effectiveness of classification methods using the two-class and one-class classification was compared. It has been shown that the use of an incomplete pattern of the vibration model and a single-class classifier allows for effective detection of anomalies in the operation of an induction motor. Satisfactory classification efficiency was achieved, despite the limitation of the teaching set only to the information obtained during the correct operation of the device. The described method is universal and can be used to diagnose the technical condition of many different types of technical devices.

Keywords: SVM classifier, vibration pattern, gyroscope, accelerometer, one-class classifier, two-class classifier.

1. Introduction

Nowadays, the study of the vibrational behavior of mechanical components plays a fundamental role in research. The safety of machines and the people working on them is a very important issue. To monitor the condition of machines, vibration analysis has been well developed and widely applied for the diagnostics of common devices failures [1]. The highest probability of detecting the resulting faults is during the operation of the devices under normal conditions. Modern machines are equipped with sensors to ensure work safety, but the manufacturer usually protects the product only for defects that he believes may occur. However, it is not possible to predict all possible cases against which it is necessary to protect oneself. Most often, additional security is added in subsequent versions or revisions of devices when a previously unforeseen error occurs.

Machine diagnostics is an area that is undergoing rapid development. New research problems emerge and methods are being developed that enable the support of diagnostic conclusions. In recent years, artificial intelligence-based advisory systems have played a special role.

The use of vibration analysis to detect irregularities in the operation of devices is the subject of many studies. Reports of their results can be found in an extensive literature database [2].

Several review papers have been published to summarize the vibration-based analysis approaches to monitor common gear failures [3]. They include investigating the relationships between gear surface features and vibration characteristics, and summarizing the current research progress of vibration-based gear wear monitoring. Vibration analysis, as an online technique, has been widely used to conduct condition monitoring for rotating machinery and bearing faults [4, 5]. The vibration-based rolling bearing monitoring was also studied by the authors [6] with of use the machine learning methods. The paper focuses on measurements of the acoustic signal generated by a rolling bearing that is utilized for the features extraction. Then the k-NN classifier is used for features selection and the classification and results suggested that this technique may be useful. In the vibration method, not only was the type of damage detected but also its size. Compared to the current measurement method, in which it was only possible to detect the type of damage, the vibration method is more effective.

In the work [7], using an accelerometer, differences in vibrations in a composite material with a honeycomb system were studied. The accelerometer collected vibration distribution data in a beam that had one rigid mounting point. The work compares the results of the distribution of vibrations, in which was assumed: there is no defect, the defect covers 10%, or 15% or 20% of the material under study, where the defect was holes occurring in the material. Vibration analysis is an effective tool for device surveillance; however, the signal can contain a lot of interference, which will cause the efficiency of damage detection to decrease drastically. That is why methods of denoise signals are often used in such studies. Denoising of signal has a positive effect on the quality of detection in the matter of efficiency and correctness. In the article [8], a comparison was made between two denoising methods depending on the content of the characteristic elements of the signal. The effectiveness of each method was presented depending on the type of signal measured.

In addition, an artificial intelligence-based approach has been used for the identification of damage in civil engineering structures [11]. This article presents a response-only structural health monitoring technique that uses cepstrum analysis and artificial neural networks (ANN) to identify damage in civil engineering structures.

The aim of this study is to present the results of implementing a noninvasive method of detecting anomalies in the operation of devices on the basis of vibrations recorded by a vibration sensor based on four 3-axis digital accelerometers and MPU-6050 gyroscopes. This method is based on the machine learning technique and uses SVM classifiers of one and two classes. The results suggest that this technique can be useful.

2. Materials and methods

2.1. Object of research

The object of the test to detect irregularities is a three-phase MEZ Mohelnice 4AP90S-2 motor with a power of 1.5 kW and a rotational speed of 1410 rpm. The study consisted of changing the voltage in one of the phases using an autotransformer. The connection diagram of the test bench is presented in Figure 1. The study of voltage asymmetry during the operation of three-phase systems is very crucial in terms of safety and service life of the device. Asymmetry of currents leads to torque pulsation, increased vibration, mechanical stress on the surface of the entire device, increased current losses, and overheating of the motor. It can be the cause of loosening of mechanical connections and contacts.

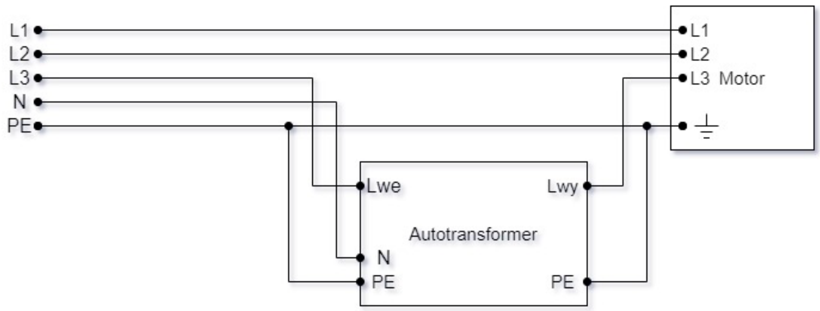

Figure 1. Diagram of connection of the tested system. L means live wire and the number tells which phase it is, N stands for neutral wire, PE is earth wire.

The tested engine was screwed to a metal base, to which four M8 screws had previously been welded. The metal base itself was placed on the table, but a material was placed between the elements to compensate transmission of vibrations from the engine to the entire test stand. Only one gyroscope attached to the upper part of the motor body was used to conduct the study. To compensate for interference of the collected data, the wire that connects the gyroscope to the vibration sensor was also attached to the motor body. Figure 2a represents the test bench and Figure 2b represents the MPU6050 sensor attached to the body motor.

 DOI: 10.21008/j.0860-6897.2022.3.16

a) b)

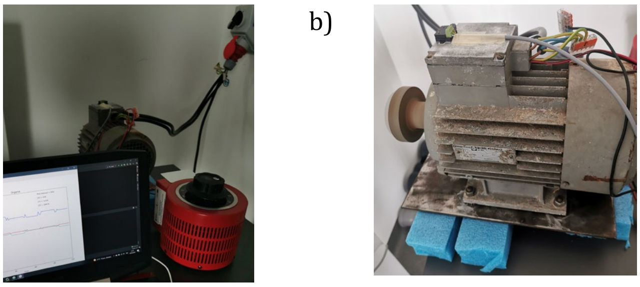

Figure 2. a) Test bench, b) Motor with MPU6050 sensor.

2.2. Measuring system

The data were recorded by a vibration sensor based on four 3-axis digital accelerometers and MPU-6050 gyroscopes. Accelerometers were connected to the STM32F446 microcontroller using the I2C bus. Communication between the computer and the device is carried out using UART (Figure 3). The device can be configured in terms of the number of channels recorded simultaneously and the sampling rate. For the purpose of the project, a single three-axis channel with a sampling rate of 400kS/s was used.

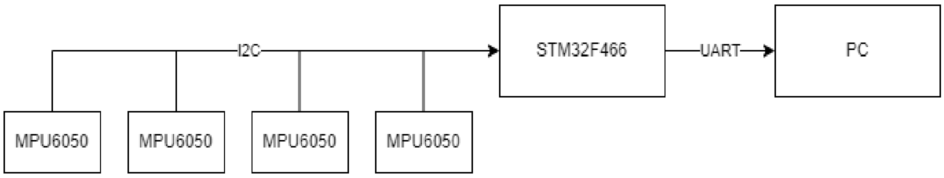

Figure 3. Flowchart of the vibration recording system

2.3. Data preparation

The data were recorded in several series. The first series is data collected during stable motor operation, when there is a balance of interfacial voltages. The second series was recorded when the equilibrium of interfacial voltages was not maintained but the values of interfacial voltages were unchanged over time. The last series of data is a case where the system was brought out of the equilibrium of interfacial voltages by smoothly changing the value of one of the phase voltages from 230V to 50V and again to 230V.

The data collected were divided into fragments with a length of 1024 samples. Subsequent fragments overlap with a shift of 64 elements from the beginning of the previous fragment (Figure 4). This treatment allows you to maximize the detection of anomalies in the signal.

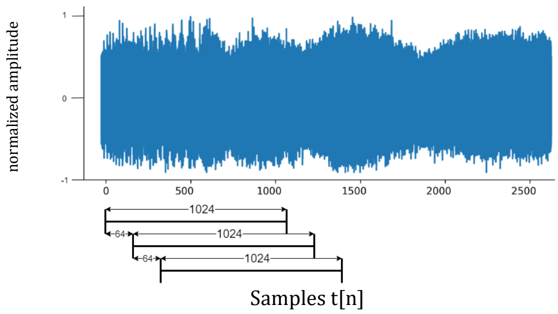

Figure 4. Signal sampling for FFT analysis.

Each fragment was subjected to the FFT calculation and normalization. The array with 513 FFT elements was divided into 16 tables of 32 elements each. An element with index 0 that specifies the value of the constant component of the signal has been rejected. By averaging each array according to the formula:

$$attribute_{an} = \frac{\sum_{i=0}^{31} fft[n*32+i]}{\sum_{i=1}^{512} fft[i]}, \tag{1}$$

 DOI: 10.21008/j.0860-6897.2022.3.16

where *an* represents an axis, *i* is sample, *n* is a fragment, allowing to obtained the attribute values of the object. The final result of the data processing is a vector composed of 16 attributes for each axis, giving a total of 48 attributes for each sensor.

The summary and processing of the signals recorded in the steady state engine operation are shown in Figure 5. Figures 5a, 5b, and 5c show the signal in the time domain collected from the MPU650 respectively for the X, Y, and Z axis. Figures 5d, 5e, and 5f represent the FFT of selected individual fragments of the signals. Figures 5g, 5h, and 5i show the values of attributes calculated from FFT from Figures 5d, 5e, and 5f. Figures 5j, 5k, and 5l show the values of the attributes in the time course for Figures 5a, 5b, and 5c, respectively.

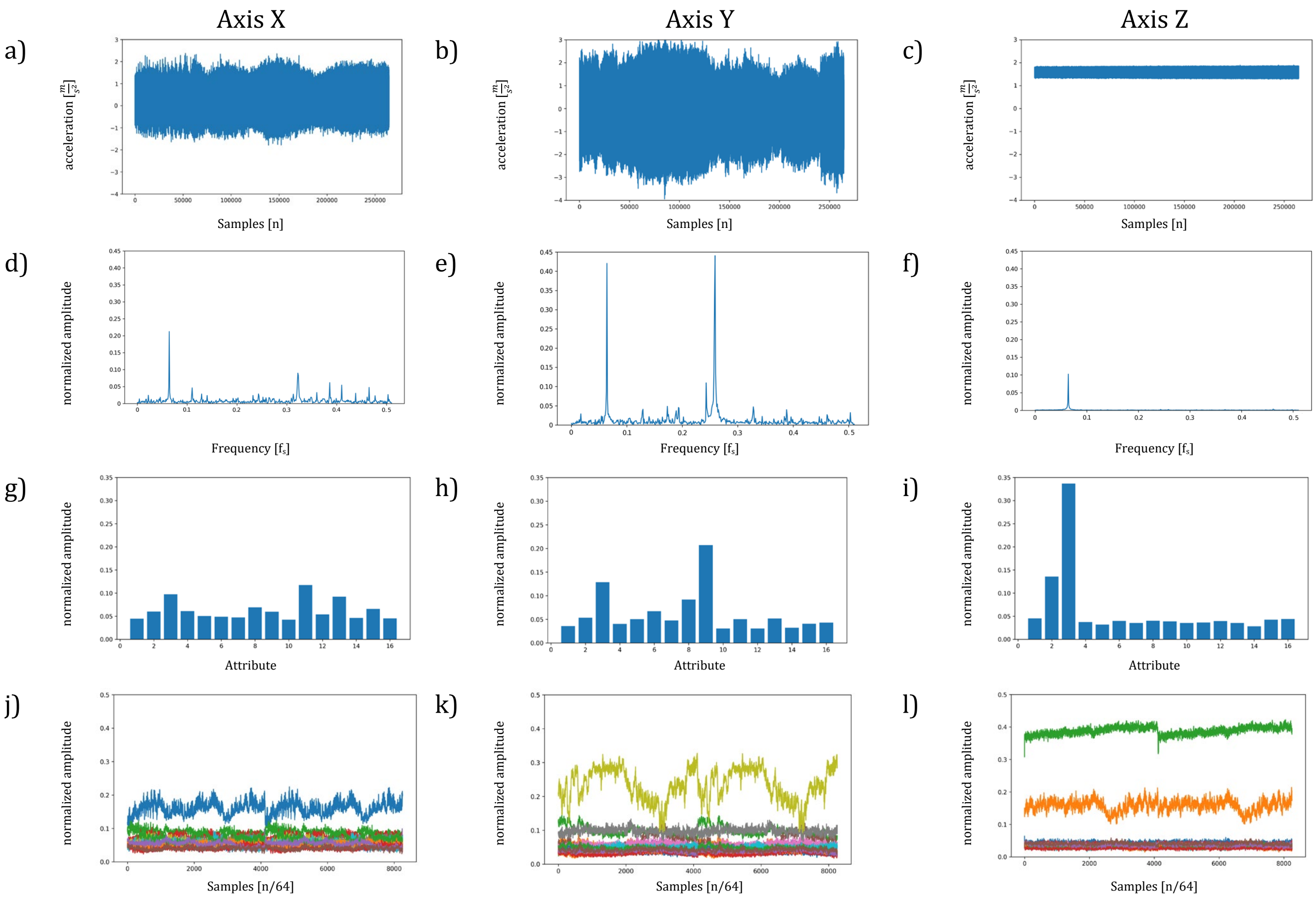

Figure 5. Signals recorded in the steady state of the engine operation. Sampling frequency f_s = 400 Hz.

3. Discussion

3.1. Attribute selection

Since the large number of dimensions of the obtained model makes it difficult to build an efficient functioning classification system, the process of reducing the dimension by selecting attributes was carried out. The selection of attributes was made in WEKA [9]. The first step was to see which attributes affect the effectiveness of the classification. Using the Gain Ratio algorithm [10], the validity of individual attributes for the effectiveness of the classification was determined, and Table 1 shows it.

The Gain Ratio is a modification of information gain that reduces its bias. The profit ratio overcomes the problem with information gain, taking into account the number of branches that would have formed before the division was made. Corrects the increase in information by taking into account internal information about the division. We can also say that the Gain ratio will add a penalty to the information profit according to formula:

$$GainRatio(T,a) = \frac{InformationGain(T,a)}{SplitInformation(X)} = \frac{-\sum_{i=1}^{n} P(T)logP(T) - (-\sum_{i=1}^{n} P(T|a)logP(T|a))}{-\sum_{i=1}^{n} \frac{N(t_i)}{N(t)} * \log_2 \frac{N(t_i)}{N(t)}}, \quad (2)$$

where T – random variable, a – set of attributes, X – discrete random variable, N(t_i) – number of times that t_i occurs, N(t) – set of events.

Table 1. Gain Ratio for every attribute used to create a classification model

Gain Ratio	Attribute name	Gain Ratio	Attribute name	Gain Ratio	Attribute name	Gain Ratio	Attribute name
0.45404	ay2	0.15188	ay14	0.06587	ax0	0.02822	az9
0.4532	ay8	0.14775	az15	0.05581	ay13	0.02695	ax14
0.44551	ay1	0.1355	ax15	0.05547	ax1	0.02608	ax12
0.29063	ay15	0.13319	ay5	0.05406	az10	0.02086	az7
0.26711	ay12	0.13218	ay0	0.05316	ay10	0.01749	ax7
0.23809	az14	0.11683	az11	0.0463	az6	0.01669	az3
0.22158	az8	0.11514	ax4	0.04549	az5	0.01643	ax9
0.21153	Ax8	0.10725	az2	0.04502	az13	0.01488	az4
0.18013	ay7	0.10243	ay4	0.04357	ax5	0.01371	ax11
0.17438	az1	0.09444	ax2	0.03936	az0	0.01084	ax13
0.16583	ax3	0.08684	ax10	0.03602	ay6	0.00916	ax6
0.16063	ay9	0.0861	ay3	0.03459	az12	0.0085	ay11

In order to determine the number of attributes in the final decision model, tests were carried out to check the classification effectiveness of subsets of attributes with the highest Gain Ratio value. Starting from the use of all attributes, remove the attributes with the lowest position in the ranking.

For a full set of 48 attributes, an accuracy of 83.64% was obtained, with 22 attributes, the accuracy drops to 82.63%, with 20 attributes to 82.6217%. Then the accuracy increases for 18 attributes to 82.63% and remains at this level up to 12 attributes. The level of accuracy increases when there are 7 to 12 attributes in the set and reaches the level of 83.64%, with 3 to 6 attributes in the set, the effectiveness decreased again. The next highest percentage of effectiveness turned out to be the use of only two attributes with the highest ranking value.

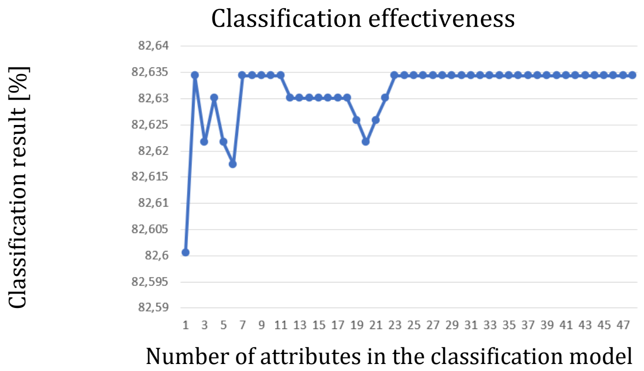

Figure 4. Effectiveness of classification.

Figure 6 shows a graph showing the variability of the accuracy value as a function of the number of attributes in the subset. Finally, the number of attributes in the subset was determined to 7, that is, the minimum number of attributes for which a stable maximum accuracy value was obtained.

3.2. Distribution of feature vectors in case space for SVM

3.2.1. Two-class model

The classic classification model assumes knowledge of at least two classes. In this particular case, it is the correct operation and work in the simulated fault mode. When the collected data is visualized (Figure 7), it is easy to see that the model has a greater accuracy of correct classification of data for the class of incorrect work than to the class of correct work. This phenomenon occurs because incorrect work partially coincides with the parameters of correct operation and there is noise in the measuring system. Therefore, in order to determine the correctness of incorrect work, it is necessary to average the classification results over a certain period of time.

3.2.2. One-class model

In the one-class model, the correct class is known. Therefore, it is not possible to select attributes. In the studied system, the knowledge obtained from the two-class model was used and the same set of attributes was used to obtain reliable results. In Figure 8 the distribution of vectors representing the correct operation of the device obtained by rejecting from the original data set the vectors representing incorrect work is presented. In a one-class model, the classifier can only estimate the vectors belonging of the studied to one class based on a fragmentary and incomplete model.

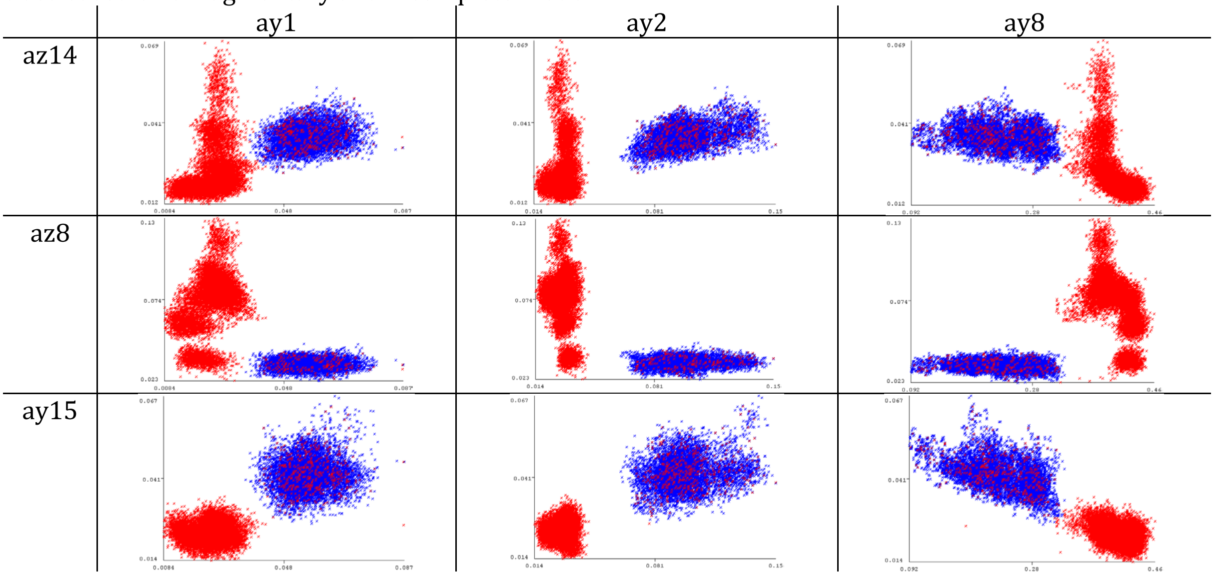

Figure 5. Distribution of vectors in the case space as a function of the features that form the basis of the classification system, the two-class model. Blue – positive class; red – negative class. Table header names - The first item shows which accelerometer the data come from, the second item shows which axis it is, and the third item shows the attribute number.

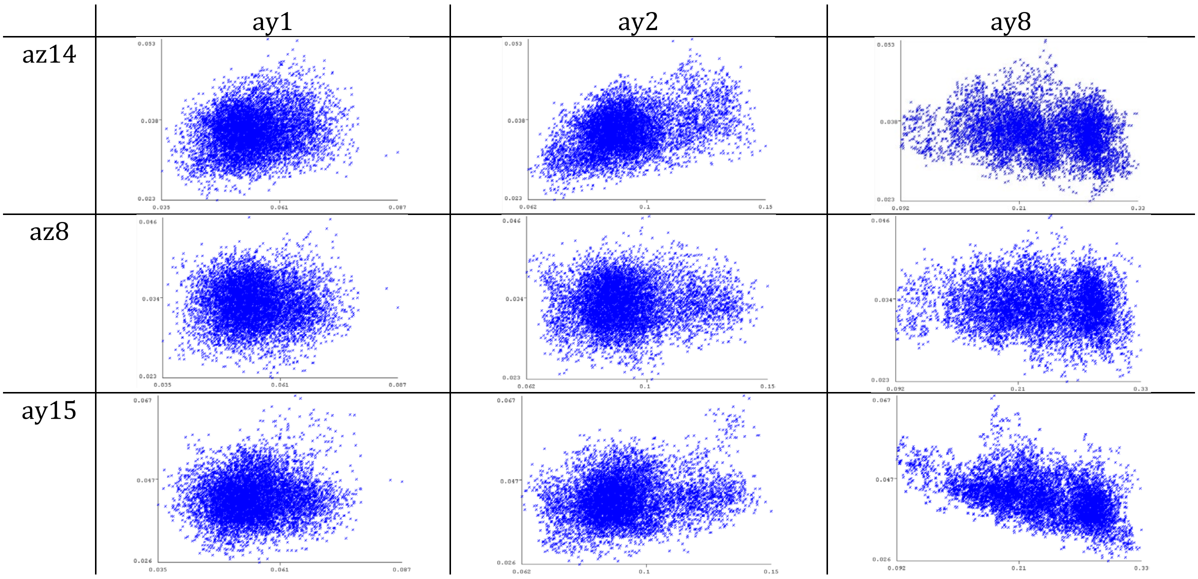

Figure 6. Distribution of vectors in the case space as a function of the features underlying the classification system, the single-class model. Table header names - The first item shows which accelerometer the data come from, the second item shows which axis it is, and the third item shows the attribute number.

 DOI: 10.21008/j.0860-6897.2022.3.16

3.3. Comparison of a one-class and two-class SVM classifier

The comparison of one- and two-class models was made on the basis of a series of data recorded in a system in which the value of one of the phase voltages was smoothly changed, thus simulating dysfunction in the system. The course of changes in the voltage value over time is presented in Figure 9a. In the first phase, the phase voltages were equal and the system worked in a steady state. Then the value of one of the phase voltages was smoothly reduced to 50V, after which it was again raised to 230V. In this way, dysfunction of varying degrees of severity was simulated. The classifier based on the two-class model detected the anomaly at an early stage, with a voltage difference of several volts. The uncertainty of the indications with a slight voltage difference was manifested by the instability of the classification result and oscillations between the values of 0 and 1 in the classifier (Figure 9b). This problem was eliminated by applying a filter with a moving average of length 64. The mileage has been smoothed and the indications of the system have been devoid of ambiguity (Figure 9c). However, the classifier based on the single-class model also detected anomalies, at a later, more advanced stage and with high uncertainty manifested by significant oscillations between the baseline values 0 and 1 (Figure 9d). As in the two-class model, the use of a low-pass filter improved the stability of the model's indications (Figure 10e). However, it can be noted that system dysfunction is detected with much larger differences in phase voltages than in the case of a two-class model. This means less sensitivity to dysfunctions that occur in the system.

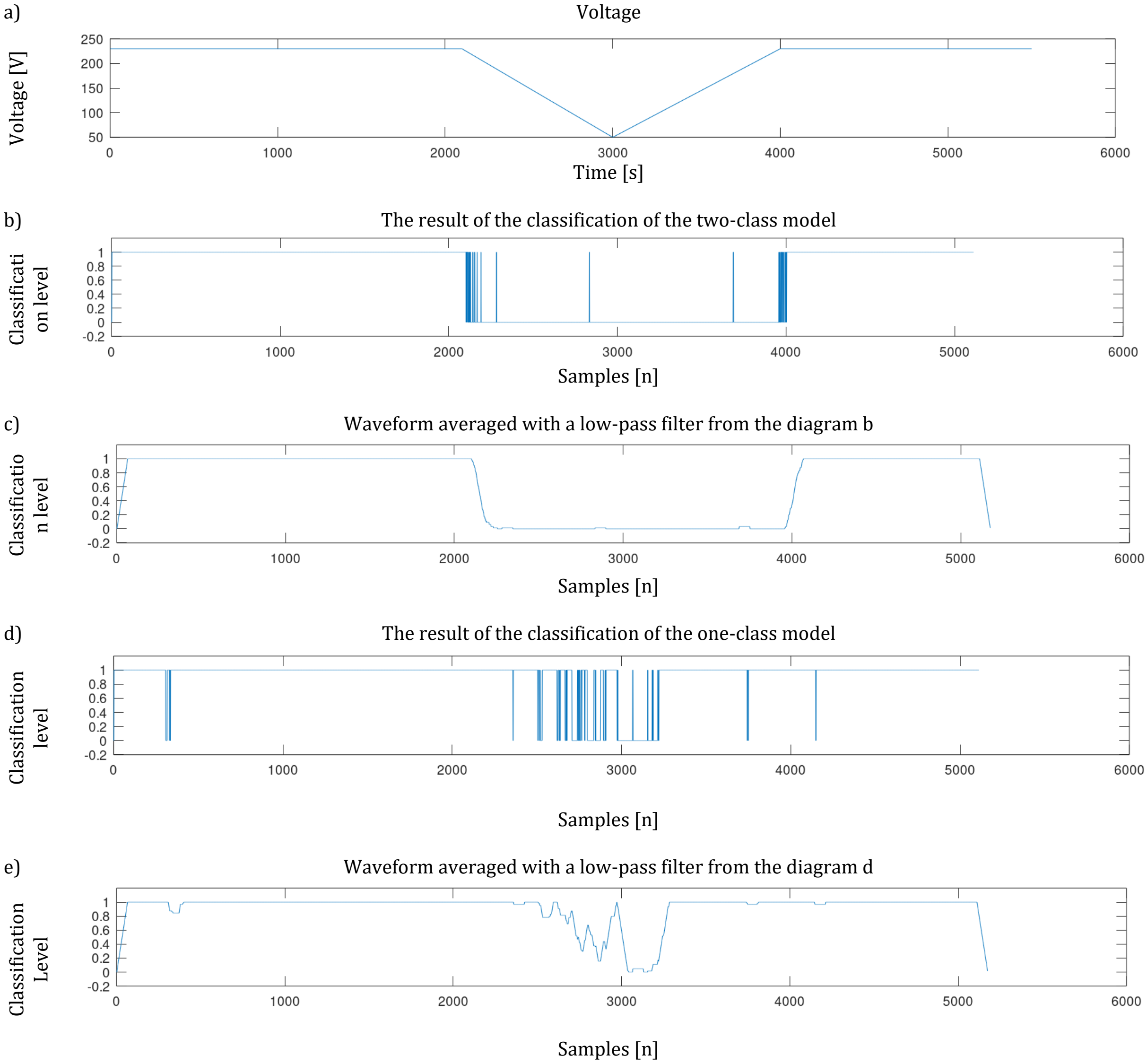

Figure 7. Comparison of the classification level of a one-class classifier with a two-class classifier Sampling frequency - 400 Hz.

4. Conclusions

The use of vibration analysis to detect irregularities in the operation of devices is the subject of many studies. In artificial intelligence research, a broad field is a direction that focuses on the expert's way of thinking. It results in specialized advisory systems based on various types of knowledge representations, and their important advantage is a quick decision. If they work properly, they detect, locate, and evaluate damage with minimal labor and cost.

The purpose of the work was to investigate the possibility of using SVM classifiers to detect device failure on the basis of recorded vibration signals. The tests show that both one-class and two-class SVM classifiers can effectively detect damage. The classification model built on the basis of a one-class SVM classifier positively classified the correctness and incorrectness of the operation of the tested object, achieving high efficiency of the model, having only one attribute class at the input. The level of real-time classification is satisfactory. The model is able to detect the incorrectness of the device's operation quite quickly with slight uncertainties in the result of the classification.

However, a one-class classifier performs much worse than a two-class SVM, although it is not enough to dismiss the idea of using it in this field of research. Systems based on single-class classification have the advantage of being able to detect unforeseen and unknown at the time of model construction. The cost is their lower sensitivity.

The experiment used a set of data with a reduced number of attributes using Gain Ratio methods and information obtained from the full data set of two-class classification. In single-class models, due to the incompleteness of the data set, it is impossible to apply this method of dimension reduction. The differences should therefore be considered if a single-class classifier is used on a full set, where it will not be reduced in terms of the number of features used to build the classification model.

Additional information

The author(s) declare: no competing financial interests and that all material taken from other sources (including their own published works) is clearly cited and that appropriate permits are obtained.

References

1. R.B. Randall; Vibration-based condition monitoring: industrial, automotive and aerospace applications; John Wiley & Sons 2021. DOI:10.1002/9780470977668
2. W. Fan, P. Qiao; Vibration-based damage identification methods: A review and comparative study. Struct Health Monit 2011, 10(1), 83-111.
3. Ke Feng, J.C. Ji, Qing Ni, M. Beer; A review of vibration-based gear wear monitoring and prediction techniques; Mechanical Systems and Signal Processing, 2023, 182, 109605. DOI:10.1016/j.ymssp.2022.109605.
4. R. B. Randall, J. Antoni; Rolling element bearing diagnostics a tutorial; Mechanical systems and signal processing 2011, 25(2), 485–520.
5. Y.-F. Li, M. Zuo, K. Feng, Y.-J. Chen; Detection of bearing faults using a novel adaptive morphological update lifting wavelet; Chinese Journal of, Mechanical Engineering 2017, 30, 1305–1313.
6. D. Gil, M. Grochowina, L. Leniowska; Detecting of the rolling bearing state based on acoustic signal and K-NN classifier; IEEE SPA 2019 – Signal Processing, Algorithms, Architectures, Arrangements and Applications, Conference Proceedings, Poznań, 2019, 246-249.
7. V.J. Suryawanshi, A.C Pawar, S.P. Palekar, K.A. Rade; Defect detection of composite honeycomb structure by vibration analysis technique, Materials Today: Proceedings 2020, 27, 2731-2735.
8. X.Chiementin, B.Kilundu, J.P.Dron, P.Dehombreux, K.Debray; Effect of cascade methods on vibration defects detection, Journal of Vibration and Control 2011, 17, 567–577.
9. A.K.Yadav, H,Malik, S.S.Chandel; Selection of most relevant input parameters using WEKA for artificial neural network based solar radiation prediction models; Renewable and Sustainable Energy Reviews 2014, 31, 509-519.
10. G.Meena, R.R.Choudhary; A review paper on IDS classification using KDD 99 and NSL KDD dataset in WEKA; International Conference on Computer, Communications and Electronics (Comptelix) 2017, 553-558.
11. U. Dackermann, W.A. Smith, R.B. Randall; Damage identification based on response-only measurements using cepstrum analysis and artificial neural networks; Structural Health Monitoring 2014, 13(4), 430-444. DOI:10.1177/1475921714542890