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ENGINE VALVE CLEARANCE DIAGNOSTICS BASED ON VIBRATION SIGNALS AND MACHINE LEARNING METHODS

DIAGNOSTYKA LUZU ZAWORÓW SILNIKA SPALINOWEGO Z WYKORZYSTANIEM SYGNAŁU DRGANIOWEGO I METOD UCZENIA MASZYNOWEGO*

A dynamic advancement of the design of combustion engines generates a necessity of introduction of strategies of operation based on the information related to their technical condition. The paper analyzes problems related to vibration based diagnostics of valve clearance of a piston combustion engine, significant in terms of its efficiency and durability. Methods of classification have been proposed for the assessment of the valve clearance. Experiments have been performed and described that aimed at providing information necessary to develop and validate the proposed methods. In the performed investigations, the vibration signals were obtained from a triaxial accelerometer located in the engine cylinder head. A parameterization of the obtained vibration signal has been carried out for the engine operating under different engine loads, rotation speeds and valve clearance settings. The parameterization pertained to the specific features of the vibration signals, the derivative of the vibration signal as a function of time as well as the envelope of this derivative. In the first approach, the authors developed a classifier in the form of a set of binary trees that additionally allowed distinguishing the features significant in terms of the identification of adopted classes. For comparison, the authors also developed classifiers in the form of a neural network as well as a k-nearest neighbors algorithm using the Euclidean metric. Based on the performed investigations and analyses a method of valve clearance assessment has been proposed.

Keywords: Combustion engine, diagnostics, vibration, machine learning.

Dynamiczny rozwój konstrukcji silników spalinowych generuje potrzebę wprowadzenia strategii eksploatacji jednostek napędowych, opartej na znajomości ich stanu technicznego. W artykule poddano analizie zagadnienia, związane z drganiową diagnostyką luzu zaworów tłokowego silnika spalinowego, istotnego ze względu na efektywność pracy silnika i jego trwałość. Zaproponowano wykorzystanie metod klasyfikacji do oceny poprawności luzu zaworowego. Przeprowadzono i opisano eksperymenty, które miały na celu dostarczenie informacji koniecznych do zbudowania i zweryfikowania zaproponowanych metod. W przeprowadzonych badaniach pozyskano sygnały drganiowe z trójosiowego czujnika przyspieszeń drgań zlokalizowanego na głowicy silnika. Dokonano parametryzacji uzyskanych przebiegów czasowych sygnału drganiowego dla silnika pracującego pod różnym obciążeniem, z różnymi prędkościami obrotowymi oraz z różnymi luzami zaworowymi. Parametryzacja dotyczyła zarówno cech sygnału przyspieszeń drgań, pochodnej przyspieszeń drgań względem czasu jak i obwiedni tej pochodnej. W pierwszym podejściu zbudowano klasyfikator w postaci zbioru drzew binarnych, który przy okazji pozwolił na wyodrębnienie istotnych, ze względu na przyjęte klasy, cech. Dla porównania zbudowano także klasyfikatory w postaci sieci neuronowej jak i algorytmu k – najbliższych sąsiadów z metryką euklidesową. Na podstawie przeprowadzonych badań i analiz zaproponowano metodę oceny luzu zaworowego.

Słowa kluczowe: silnik spalinowy, diagnostyka, drgania, uczenie maszynowe.

1. Introduction

Internal combustion engines are commonly applied in vehicles and stationary equipment. They convert the energy contained in the fuel into mechanical work of the rotating crankshaft and, like all mechanical equipment, are subject to wear and tear and aging. The engine durability is described with design properties and, to a great extent, depends on the conditions of operation and the nature of the loads. As the engine degradation processes advance (variable temperatures, tribological processes, cavitation, chemical and electrochemical corrosion, aging etc.) the reliability and efficiency parameters deteriorate. As a consequence, the object wears, fails or is withdrawn from operation for economic or environmental reasons. Ever since the beginning of combustion engines, it has been observed that one of the key problems having impact on the engine operation is its correct adjustment.

Degradation of the engine structure and engine incorrect adjustment may lead to the following phenomena in the internal combustion en-

gine: deterioration of the engine efficiency, reduction of power, related to the reduction of mechanical efficiency, thermal efficiency and filling coefficient, increase in the emission of toxic compounds in the exhaust fumes, and possible damage to the engine components.

Fig. 1a presents the differences in the fuel consumption for different valve clearance adjustments, and Fig. 1b presents the changes in the impact velocities of the valve against the valve seat allowing for the cam lift h). From the data shown in Fig. 1a, it follows that the changes in the valve clearance may lead to increased fuel consumption by the investigated internal combustion engine by approx. 9%, while the analysis of Fig. 1b leads to a conclusion that with the increasing valve clearance (lines: blue and green Fig.1b), the velocity of the impact of the valve against the valve seat grows, causing additional unwanted dynamic loads on the engine cylinder head of the engine.

There are many methods of diagnosing the technical condition of combustion engines. They can be divided into methods utilizing

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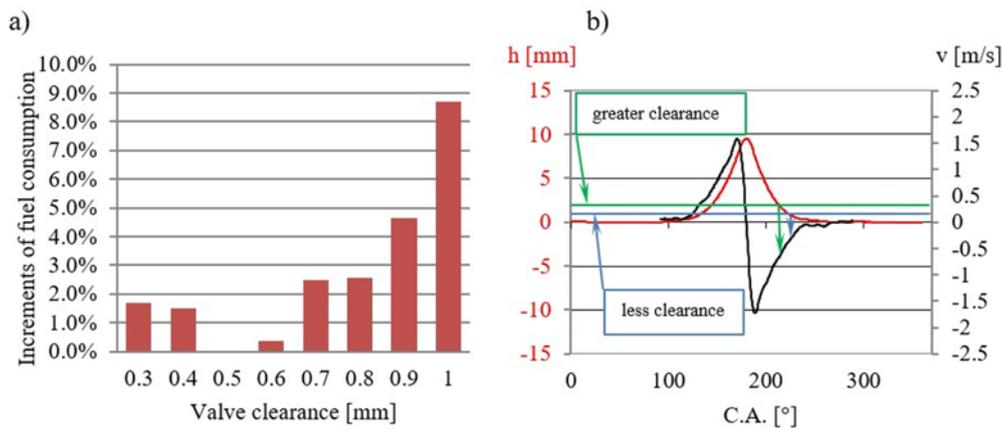


Fig. 1. a) Increments of fuel consumption as a function of valve clearance, b) cam curve (red line) and changes in the impact velocity of the valve against the valve seat in the engine caused by the changes in the valve clearance settings (vertical arrows: green and blue), C.A.– crankshaft angle, h – cam lift, v – velocity of the point on a cam

the operating processes (indicating, torque variations as a function of crankshaft angle, measurement of the exhaust fumes temperature and pressure above and underneath the piston, fueling parameters, exhaust opacity etc.) and residual processes (vibration, noise, thermal processes, electrical processes etc.). Based on the investigations into the operating processes, we may infer the overall condition of a combustion engine, while the residual processes carry information on the condition of individual subassemblies and kinematic pairs, which is why the residual processes are utilized as autonomous or auxiliary diagnostic methods. All methods based on vibration and noise analysis aiming at determining the technical condition of an object are called vibroacoustic diagnostics.

The engine timing mechanism, as one of the fundamental components of piston combustion engines, as a matter of the mere principle of its operation, is a source of vibroacoustic signal because the operation of the timing system, which includes such actions as valve opening and closing, cooperation of the cam with the valve lifters, canceling of the play between them etc. result in multiple impacts of the mating components, which naturally generates vibration. The use of vibration signals to diagnose the internal combustion engine timing system is presented in the following works:

Article [12] discusses the option of applying the distribution of the wavelet packet when filtering the acoustic signal of an internal combustion engine in order to diagnose excessive valve clearance. The authors have prepared an algorithm enabling selection of selected details and approximation of the wavelet analysis to low-frequency components, which constitute noise, as well as to high-frequency components, containing information about possible increase of the engine valve clearance. Then, based on selected components of the high-frequency acoustic signal, a method was developed for automatic detection of increased valve clearance, assuming that the energy share of the emitted acoustic signal should be determined when opening and closing individual valves. The authors of [13] have described research on the diagnosis of the condition of exhaust valves in large marine diesel engines. The tests were carried out on a four-cylinder two-stroke marine diesel engine with a piston diameter of 500 mm at MAN B&W Diesel Research Centre in Copenhagen, Denmark. The experiments involved three different states of the valve, two of which concerned artificially induced valve burnout situations. The basic monitoring measurements were vibration and structural stress waves, also known as acoustic emission (AE). The results showed that AE signals have a significant advantage over the other sensors involved, indicating sensitivity to both mechanical action and mechanical-smooth combustion. The recorded data has been pre-processed and the functions extracted using PCA (principal component analysis). On the basis of

a number of applied heuristics and statistics, the search for the optimal subspace of the main components was conducted. The selected feature space has been used to classify the condition of the exhaust valve by using both standardized neural feedback classifiers and linear discriminators. Article [28], however, calculates cone-kernel distributions (CKD) of vibration acceleration signals obtained from the cylinder head in eight different states of the camshaft mechanism and presents them in gray images. Non-negative matrix factorization (NMF) was used to decomposing multidimensional data, and neural network ensemble (NNE), which

has a better generalization capacity for classification than a single neural network, was used to make an intelligent diagnosis based on time-frequency distributions. On the basis of the experimental results, it has been shown that damage to the diesel engine's timing mechanism can be accurately classified using the proposed method. Paper [31] analyzes the issues related to vibration diagnostics of automatic clearance compensators for valves of internal combustion engines. Scientific experiments have been described and carried out to provide the information necessary to build and verify diagnostic models to assess the technical condition of those components of an internal combustion engine which are essential for engine performance and durability. Based on the obtained diagnostic model, an algorithm for evaluating the technical condition of automatic valve clearance compensators was developed. Whereas in [32] Wigner-Ville distributions (WVD) of vibration acceleration signals were calculated, which were recorded on the cylinder head in eight different valve train states and displayed in gray images. After their standardization, probabilistic neural networks (PNNs) were directly used to classify time-frequency images. In this way, the diagnosis of damage to the timing mechanism has been transferred to the classification of time-frequency images. Experimental results show that faults in diesel valve assemblies can be accurately classified using the proposed methods.

The application of various techniques of analyzing vibroacoustic signals to assess the technical condition of internal combustion engines was presented by the authors of the following works:

The authors of [1] have shown that the acoustic signals coming from a combustion engine are rich in information concerning the engine operation parameters and its condition. Unfortunately, this information is complex and has a lot of background noise. Based on the analysis of the measured parameters, they showed that engine failures caused by a drop in compression ratio, changes in injection pressure, changes in the exhaust system, changes in the suction and exhaust valve clearance can be diagnosed. The engine's technical condition was assessed on the basis of the analysis of changes in the rms value and the kurtosis of acoustic signals from each engine cylinder. The authors of [2] stated that acoustic signals caused by mechanisms often have to be described by non-linear models in the time domain. In the frequency domain, however, the linear model is in many cases sufficient to describe sound propagation channels. In the paper they compared the calculation methods in terms of accuracy, computation time and the possibility to perform tests during the operation of the facility. Article [3] presents a fast and automatic method of engine diagnostics based on one acoustic emission (AE) parameter. The method is based on a comparison of vibrations and AE energy with reference values

to determine whether the state of the engine is defective. The method was used in the test engine and proved to be satisfactory. Work [9] concerns the monitoring of large diesel engines by analyzing changes in crankshaft angular speed. The focus was on a 20-cylinder diesel engine with natural crankshaft frequencies in the operating speed range. Angular speed changes were modelled at the free end of the crankshaft. Modelling included both the dynamic behavior of the crankshaft and the moments of excitation. Since the engine is very large, the first crankshaft turning modes are in the low frequency range. A model with a flexible crankshaft is required. The moments of excitation depend on the pressure curve in the cylinder. The latter was modelled using a phenomenological model. The mechanical and combustion parameters of the model were optimized using real data. An automated diagnosis based on a system using artificial intelligence has been proposed. Neural networks were used to recognize angular velocity patterns under normal and faulty conditions. The reference patterns required at the training stage were calculated from a model, calibrated using a small number of actual measurements. Promising results were obtained. During the verification tests, damage consisting of a fuel leakage was successfully diagnosed. In [10], a coupled simulation of piston dynamics and engine tribology (tribodynamics) was performed using quasi-static and transient numerical codes to model piston impacts on the cylinder wall. Confirmation of suitability of the proposed methods was determined on the basis of experimental measurements carried out on a single-cylinder petrol engine in laboratory conditions by measuring the vibration acceleration of the engine block surface. The authors of [34] proposed a system for the diagnosis of damage to combustion engines using wavelet packet transform (WPT) and artificial neural network (ANN) techniques. Article [5] discusses the application of the ionic current sensor for detecting combustion resonance in a direct injection diesel engine. A modified glow plug is used to measure ionic current in addition to its main function of heating the combustion chamber. Comparison was made of combustion resonance determined from the signals of the ionic current sensor, cylinder pressure transducer and engine vibration sensor. It has been found that the ionic current signal can be used to determine synchronization, amplitude, frequency and duration of resonance. The sensor output can be used as a feedback signal to the ECU (electronic control unit) to minimize engine vibration and noise. Article [8] concerns state-of-the-art diagnostic strategies and techniques based on vibroacoustic signals which can be used to monitor and diagnose internal combustion engines (ICEs) both on the test bench and under operating conditions. This article presents for the first time a short summary of sound and vibration generation in ICE in the context of further discussion on vibroacoustic diagnostics. A review of monitoring and diagnostic techniques described in the literature using vibration and acoustic signals is also presented.

On the basis of the analysis of the achievements to date in the field of vibroacoustic diagnostics of internal combustion engine systems, it has been concluded that research was carried out on the application of parameters of vibration signals to assess the technical condition of internal combustion engine assemblies or processes occurring therein. The research concerned methodological issues (e. g. determination of engine operating conditions during vibration measurements, selection of measurement points) and modelling issues (building diagnostic models and their validation). In the investigations both simple methods of signal description (e.g. point measures) as well as highly advanced techniques of signal processing (e.g. artificial neural networks, time-spectrum analysis) were used. In the analyzed works on the vibration diagnostics of internal combustion engines, methods were recognized in which diagnostic models were based on responses of the object structure to impulse excitations. The analyses related to the responses provided a hint as to the optimal choice of the measurement point and possibly the frequency range to be covered by the analysis.

This paper presents a new approach to identification of valve clearance of an engine operating at different loads and speeds based on an appropriately processed vibration signal. A methodology of valve clearance class identification has been proposed based on the absolute vibration accelerations measured on the cylinder head and a supervised learning systems - classifiers. Such a solution allows an automatic assessment of the correctness of the valve clearance adjustment on an operating engine without the necessity of seeking a mathematical model describing the relation between the vibration signal and the valve clearance.

Classifiers, as supervised taught systems, are used in a wide range of areas to process very large data resources and automate the inference process. It is impossible to fully review the applications of these algorithms, or even their fields of application. For example, we can only mention such different areas as: prediction of students' exam results [6], monitoring of urban changes [11], classification of road roughness [15], segmentation of apple defects [19], intelligent system of rotor machine damage detection [20], classification of network traffic [24], or image processing and analysis [35]. There are many known attempts to use machine learning in machine and component diagnostics to determine the technical condition as well as the characteristics of the condition. For example, in [16] the use of a convolution network with some modifications for the classification of machine condition is considered. The authors presented promising results of the method on the example of signals from rolling bearings. In [18], the authors successfully used k-means clustering and classification using the SVM (Support Vector Machine) method to assess the state of wear of packaging machine blades. In [23], statistical distance measures were used to distinguish the states of damage to rolling bearings. The authors of [27] demonstrated the effectiveness of classification methods with respect to monitoring the condition of piston compressors installed in refrigeration equipment. Among others, neural networks were used here, but also extreme learning machines (ELMs). In the study on wind turbine diagnostics [29], time signal representations in the form of images were used, various texture characteristics were used and classified using these characteristics. A discussion of many machine learning methods in the context of general diagnostic applications can also be found in [17].

Machine learning methods were also used in the diagnostics of internal combustion piston engines. Paper [4] compares different classification methods used to identify the phenomenon of ignition loss. The authors of [7] diagnosed the state of the motor injectors using a vibration signal, discrete wavelet transform and neural network. In turn, in [21] the problem of engine cylinder shutdown was analyzed using the same methods. Many failures of the combustion engine were also identified using probabilistic methods [33]. However, the problem of non-optimal valve clearance was not considered here. In [14] classifications were used to identify many damages - including too small or too large valve clearance. The research was conducted using advanced methods of extreme machine learning. The analysis of the work shows that the accuracy of damage classification obtained by the researchers does not exceed 96%. It seems that it is desirable to find a simpler method for classification of clearance due to the possibility of its easy practical implementation in on-board diagnostics, therefore, in the opinion of the authors of this paper, further search and research in this direction is necessary. It is also important to maintain high reliability of the diagnosis despite the simplicity of the method.

The classification process can be technically carried out using a number of methods with specific properties and possibilities. Among a number of possibilities, you can mention classification trees, neural networks, distance classifiers, approximation classifiers, fuzzy classifiers, etc. There are three methods used in this paper which, according to the authors, are the easiest to implement in the on-board engine diagnostics: a classification tree, artificial neural networks MLP and a classifier of k-nearest neighbors.

The advantage of the tree structure is the human friendly way of representation of knowledge that can be obtained after the learning process. Another advantage is the lack of requirements for assumptions about the relationship between the dependent variable and the explanatory variables. In addition, the tree also allows distinguishing those diagnostic measures that are significant in the process of conditions classification. Those that will not be used by the algorithm are of no importance to the construction of the tree, hence, to the classification of the state or identification of malfunctions with the use of this method. Additionally, this method can be used in data sets containing numerous data shortages, which may be important in the case of databases from several sources.

Other classification methods used also in engine diagnostics are neural networks. Artificial neural networks, used here for classification, allow parallel processing of information. In the case of artificial neural networks, it is essential to optimize the network structure (number of hidden layers or number of neurons in the layers), which is an arduous process carried out mostly by trial and error method. The selection of input attributes is also important, which, in the case of classification trees, are built into the tree algorithm.

Another classifier used in this paper is the k-nearest neighbors classifier. Its advantage is undoubtedly the simplicity of implementation and easy-to-determine prediction of a given class. The downsides are the need to store big data in the memory and the need to optimize both the selection of parameter k, the measures of distance between the data and the set of attributes.

2. Methodology of research

The object of the investigations was a single cylinder research engine (SB 3.1) based on the SW 680 one. The SB 3.1 engine was designed for research purposes related to combustion and parameter assessment of SW 680 engines licensed from Leyland and manufactured in WSK Mielec. In the research engine, the following assemblies of the SW 680 engine were applied: connecting rod, piston with piston rings, cylinder sleeve, valves, timing system, injectors, cylinder head (adapted from the SW 680 engine). The design of the engine allows: measurement of the in-cylinder pressure, adjustment of the compression ratio in the range $\varepsilon = 14-20$, continuously variable onset of fuel pumping, continuous variable timing and changes in the balancing of the mass forces of the first order.

The investigations were carried out in two stages. In the first stage, impulse tests were performed aiming at identification of the resonance frequencies, which determined the measurement range and allowed determining the points of acquisition of vibration on the cylinder head. In the second stage, the vibration of the cylinder head was investigated for different settings of the valve clearance and the settings of the engine work point. Based on the results of the second stage, an algorithm of the valve clearance assessment in the investi-

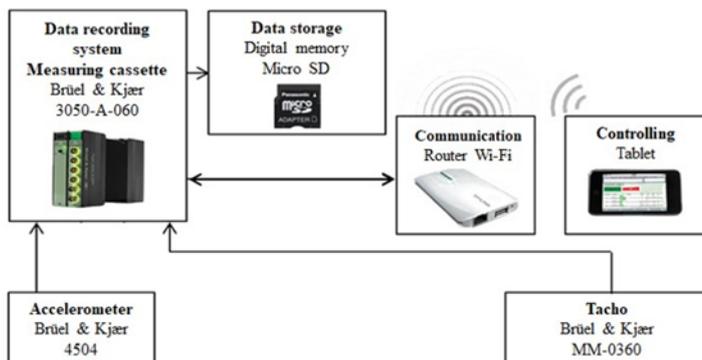


Fig. 2. Diagram of the system used for the measurement of the cylinder head vibration during engine operation

gated engine was developed. An overall diagram of the measurement system used for the recording of the vibration signals has been shown in Fig. 2.

The research methodology was developed based on the assumptions of an active experiment [22]. During the experiment the following were adjusted: valve clearance, engine load and speed while recording the vibration accelerations of the engine cylinder head.

The measurements were carried out according to the principle of three starts, i.e. each series of measurements was performed three times and between each series of measurements the engine was shut off. The described method was used to avoid incidental values of the parameters of the vibration signal characteristics.

Vibration transducers (type 4504) by Brüel&Kjær were selected based on suggestions in [26,30] and the linear frequency range of selected transducers was 18 kHz. During the investigations, signals in the range 0.1 Hz–25 kHz were recorded. The accelerometers were fixed on the cylinder head with a glue. When selecting the measurement spots for the impulse tests, a principle was adopted that a transducer should be located in an accessible area possibly closest to the point where the vibration signal related to the valve operation is generated [25]. The directions of the vibration measurement were adopted as follows: direction X parallel to the diameter of the cylinder, direction Z parallel to the axis of the cylinder, direction Y perpendicular to the previous two (Fig. 3a). The sampling frequency was set at 65536 Hz. For the recording of the vibration signals, PULSE multianalyzer by Brüel&Kjær was used. It allows a parallel recording of fast-varying processes on 6 channels with the dynamics of up to 160 dB.

The special orientation of the transducers has been shown in Fig. 3a and the exact location of their fitting in Fig. 3b.

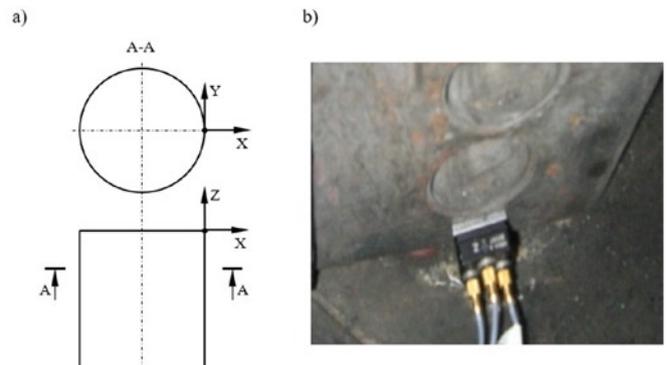


Fig. 3. a). Orientation of the directions of the vibration measurement on the cylinder head, b) view of the vibration transducer fitted on the cylinder head

The selection of the vibration measurement point was preceded by an analysis of the design of the cylinder head, the investigations described in [26] related to the determination of the influence of the diesel engine valve clearance on selected vibration parameters and the previously mentioned impulse tests consisting in hitting of the valves on the valve seats. The hits were carried out by removing of the reference shims from the valve stem and the valve lifter. This was repeated several times for each valve in order to eliminate incidental errors and to perform averaging. It was important to determine such a measurement point that would enable an assessment of the impact of each of the valves. Having performed the analyses of the impulse test results, a single point was selected. Given the dynamics of the signals recorded during the impulse tests, it was observed that direction X might carry the most information related to the valve clearance.

The tests on the operating engine were performed at the engine speed of 700 rpm, 1000 rpm, 1200 rpm, 1500 rpm, 1700 rpm and the engine load of 0 Nm, 22.5 Nm, 45 Nm, 67.5 Nm

and 90 Nm. The coolant temperature was 75°C. For the above-mentioned conditions, an acceleration signal recording in three directions was performed. An example portion of the recording in direction X of the vibration signal has been shown in Fig. 4.

In figure 4, we can observe a series of engine work cycles. The dominating phenomenon are the events related to the ignition, while the vibration related to the valve closing is more difficult to spot, particularly due to the low values of the valve clearance settings.

Prior to the analysis, the vibration signals were subjected to angular selection. This means that only those fragments were analyzed that were synchronized with the valve closing in terms of time or angle.

In practice, this can be easily made having appropriate marks on the flywheel or even based on the acceleration signal itself taking into consideration the threshold of the peak value generated during ignition and an appropriate time window. In this way, over 32 thousand time signal portions were obtained for different engine loads and speeds.

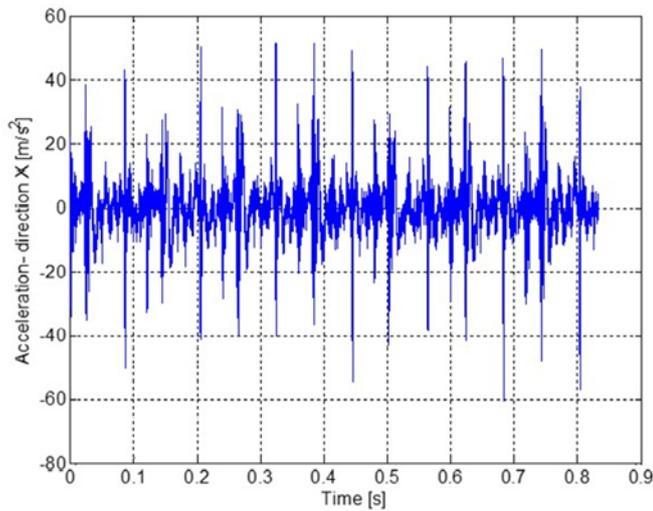


Fig. 4. Example waveform of the vibration acceleration recorded in direction X

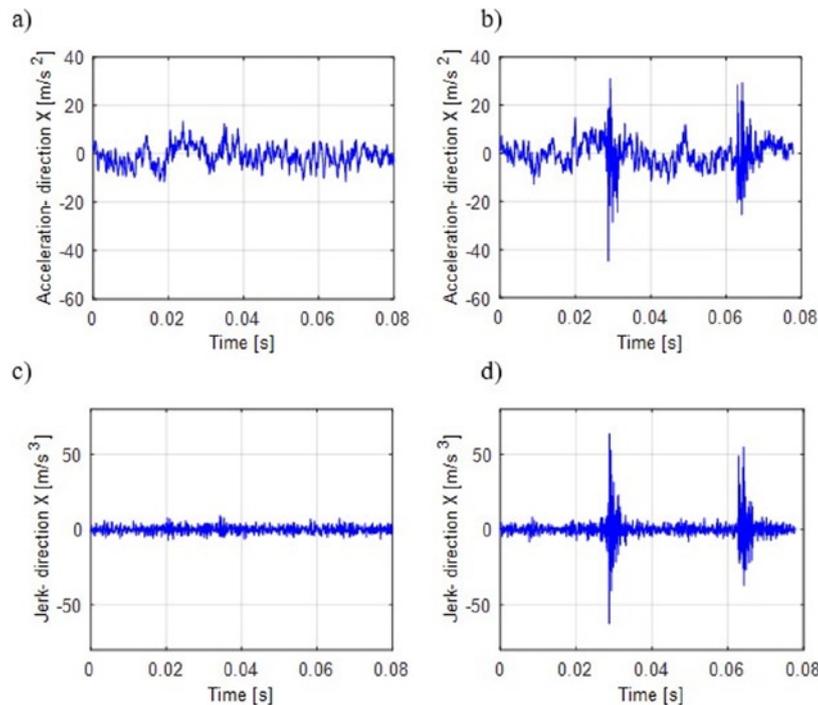


Fig. 5. Portions of tracings of accelerations (figures a, b) and the derivative of the vibration accelerations (figures c, d) related to the closing of the valves; figure a, c – clearance = 0.3 mm; figure b, d – clearance = 1.0 mm

Fig. 5 presents example portions of the recordings for the extreme values of the engine valve clearance of 0.3 mm and 1.0 mm.

In the case of a low value of the valve clearance setting, the moment of the valve closing is practically invisible (Fig. 5a) and in the case of extreme value of the valve setting, the said moment is easily discernible (Fig. 5b). We can clearly see the response of the system resulting from the impact of the valve on its seat. The most difficult to analyze are the indirect examples. It is noteworthy that individual portions differ from one another even for the same valve clearance setting, as shown in Fig. 4 and the obtained sets have a large spread. This is shown in Tab. 1 where the RMS values of the accelerations of selected signals and their standard deviations have been presented.

The design value of the valve clearance is 0.5 mm for the investigated engine. As results from the analysis of Tab. 1, due to an extensive spread of the results, correct determination of the valve clearance is impossible based exclusively on the effective value. It may be assumed that the determination of the valve clearance based on the amplitude measures themselves may have a significant level uncertainty. Given the above, it is substantiated to assess the signals using many measures and then select them in terms of their greatest information contribution to the identification of the class of a given valve clearance setting.

In order to emphasize the phenomena and reduce the impact of low frequencies, a rate of acceleration was also determined (jerk). Figures 5c and 5d present the tracings of this value corresponding to the presented waveforms of vibration accelerations.

In order to retrieve the most significant information from the isolated tracings, an envelope was determined of the signals using the Hilbert transform along with the magnitude of the analytical signal. Additionally, smoothing of the envelope was performed with the Brown's model of exponential smoothing:

$$\begin{cases} \hat{S}_1 = S_1 \\ \hat{S}_t = \alpha S_t + (1 - \alpha) \hat{S}_{t-1} \quad \text{dla } t > 1 \end{cases} \quad (1)$$

where: S_t – value of the original observations, \hat{S}_t – values of the observations after smoothing, α – smoothing coefficient (arbitrarily adopted as $\alpha=0.1$) and t – observation number.

Figures 6a and 6b present the obtained envelope of the waveforms from figures 5c and 5d and the envelope smoothed with the exponential smoothing model (figures 6c and 6d).

In order to train the classification system in distinguishing classes of valve clearance, a parameterization was carried out of the obtained portions of the tracings of the vibration accelerations, its derivatives and the smooth envelope. The obtained envelope was divided into two fragments corresponding to the time windows when the closing of the first and the second valves took place.

For the original acceleration signal, its derivative against time and the signal filtered in the frequency range above 2000Hz, the following signal measures were applied: abscissa of the center of gravity of the squared signal, regular and central moments of the first and second order, standardized moments of the same orders, RMS value of the signal, its peak, peak to peak value, average value, surface area under the curve, crest and form factors, peak to average value, as well as signal kurtosis. For the envelope, the counting of the samples was performed above the set levels (9 adopted levels)

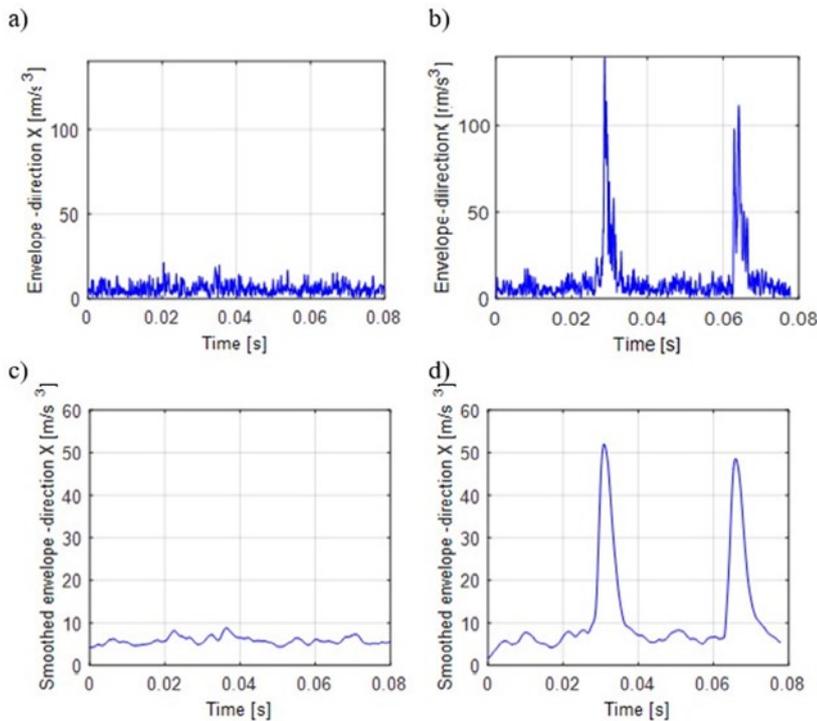


Fig. 6. Envelope of the signal of the acceleration derivative for two extreme cases of the valve clearance settings (figures a and b) and a smooth envelope (figures c and d); figures a, c – valve clearance setting = 0.3 mm; figures b, d – valve clearance setting = 1.0 mm

Table 1. Mean effective values of the accelerations and their standard deviations measured in the frequency range of up to 6kHz for different measurement directions and different engine valve clearance

| Clearance [mm] | Direction X | | Direction Y | | Direction Z | |
|----------------|------------------------------|-------------------------------------|------------------------------|-------------------------------------|------------------------------|-------------------------------------|
| | Average RMS m/s ² | Standard deviation m/s ² | Average RMS m/s ² | Standard deviation m/s ² | Average RMS m/s ² | Standard deviation m/s ² |
| 0,3 | 9.40 | 4.32 | 12.47 | 4.29 | 10.43 | 3.50 |
| 0,4 | 9.10 | 4.49 | 12.74 | 4.01 | 10.48 | 3.52 |
| 0,5 | 10.11 | 4.64 | 12.99 | 4.29 | 12.15 | 4.45 |
| 0,6 | 8.25 | 2.59 | 13.12 | 3.97 | 11.01 | 3.80 |
| 0,7 | 10.43 | 4.42 | 13.71 | 4.29 | 12.48 | 4.47 |
| 0,8 | 9.35 | 2.85 | 13.59 | 4.07 | 12.96 | 4.48 |
| 0,9 | 11.78 | 5.51 | 13.41 | 4.02 | 14.05 | 4.73 |
| 1,0 | 12.33 | 5.08 | 14.29 | 4.40 | 16.53 | 5.50 |

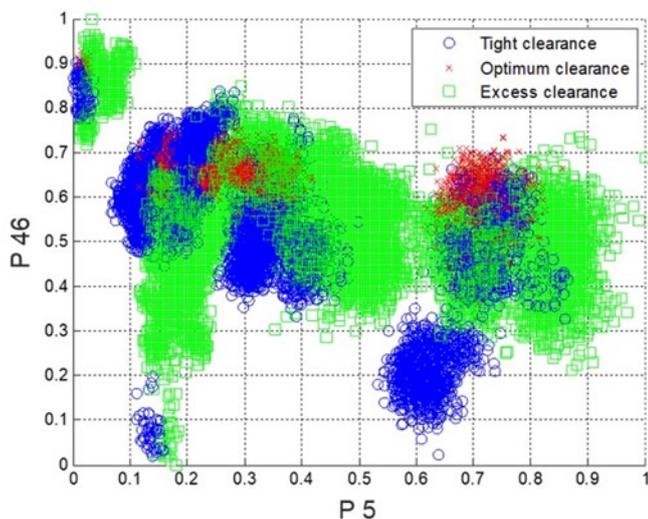


Fig. 7. Available training examples on a plane determined by two arbitrarily selected attributes

and the envelope was divided into two fragments related to the closing of the first and the second valve. The analyses were repeated for three recorded directions. Eventually, in excess of 300 parameters were generated. Additionally, the information related to the engine load and speed were considered as attributes. The available signal samples allowed generating 32054 training vectors. Compared to the number of parameters describing the training vectors, this is a set of small number of examples, hence, as described in the further part of the paper, a selection of diagnostic features was performed by reducing the training vectors to 15 parameters.

Each training vector was labeled in relation to the valve clearance setting and the data were divided into three classes: tight clearance (lower than 0.5 mm), optimum clearance (approx. 0.5 mm) and excess clearance (over 0.5 mm). Tab. 2 presents the number of available examples related to individual classes. As results from the table, the numbers of examples for individual classes vary widely, which determines the method of assessment of the results of classification errors.

Figure 7 presents the example space of features created by two standardized (min-max standardization) attributes marked P5 and P46.

3. Data analysis

In the paper, the authors propose a system of identification of valve clearance of an operating engine based

Table 2. Number of available examples representing classes

| Class | Number of examples |
|-------------------|--------------------|
| Tight clearance | 8160 |
| Optimum clearance | 4016 |
| Excess clearance | 19878 |

on the machine learning methods. To this end, three methods were compared: a set of three CART (Classification and Regression Tree) binary trees, using the OvA (one versus all) strategy, *k*-nearest neighbors classifier and a one direction MLP (multilayer perceptron) neural network with three outputs related to each of the classes. The classifier based on a set of three trees independently trained to recognize individual classes of valve clearance. The affiliation to a given class was determined by the positive response of one of the three trained classifiers. With such an approach, situations are possible when none of the classifiers give information at the output on the affiliation to a given class or more than one tree responds positively. A solution

was adopted that a lack of unanimous classification forces another. In practice, when a situation like this takes place, the recognition system will classify subsequent time portions omitting uncertain cases. One may also repeat the classification a number of times in real time and make a decision based on the significance of the majority of the recognitions of a given class. Given the large number of data generated by an operating engine, in a relatively short time, ignoring the uncertain classifications does not generate any problems in practice. A similar problem occurs in the proposed solution based on the neural network. Here, we can apply the approach, in which the affiliation to a given class is decided by a neuron in the output layer that gives the highest output value. It is unlikely that exactly the same value appears at more than one output. It may happen, however that the response at all network outputs will be on a relatively low level, which may be interpreted as an unrecognized case. Through trial and error, it was assumed that the value at the network output must exceed the threshold of 0.7 to accept the affiliation of a given case to a given class. If this value is not exceeded at any of the network outputs, it is assumed that an unrecognized case occurred and the action is the same as in the case of the set of classification trees.

In order to reduce the size of the feature vectors, it was determined which of the features were the most useful in the classification of the valve clearance. In the first place, a classification was made through the previously discussed classifier in the form of classifying trees. It is known that the tree construction algorithms apply a certain measure of goodness of the division and evaluate individual features based on this measure. In the applied algorithm, the Gini index was used as the measure of the division quality. Out of all available measures, only those were taken into account that were used to build the trees. Then, based on the subsequent step of the analysis, it was observed that some of these measures were significantly linearly correlated. Upon removing some of them from the set of data and performing tests, no significant growth of classification error was observed. At the end, a set of 15 features was obtained, whose further reduction resulted in a greater or smaller increase in the testing error. The final set of features included such measures as: RMS value and the coefficient of shape of the acceleration signal, normal and central moments of the first and second order of the acceleration signal, mean and maximum value, kurtosis from the acceleration signal derivative, number of samples above certain levels (of low values) of the envelope of the derivative of the acceleration signal and the filtered signal as well as engine speed. Majority of the measures selected by the tree construction algorithm pertained to the measurement directions X and Y. The information on the engine load turned out insignificant.

For comparison, the same features were applied for the other classifiers. Obviously, other methods of feature selection could also be applied here. It is possible that they would reveal other attributes that are better for different classifiers. Comparing different possibilities, however, was not the aim of these investigations.

In the k-nearest neighbors classifier, the value of parameter k was modified in the range 1 to 11 along with the measure of distance while observing the testing error. Eventually, parameter k=6 and Euclidean metric were adopted.

Similarly, the optimization of the MLP network was carried out by comparing the errors on the test set. The best results were obtained for the network with two hidden layers with 7 and 6 sigmoidal neurons

in individual layers. Increasing as well as decreasing of the number of neurons resulted in a growth of the learning error. For the learning process, the Levenberg – Marquardt gradient algorithm was applied.

Each time, the evaluation of the classifier errors was performed with the Hold-Out repeatable method for which 25% of examples as a test set and 100 test repetitions were arbitrarily adopted. It is noteworthy that this method has a tendency to overvalue the recognition error [17]. The obtained value of standard deviation during the repetition of the test allows determining how resistant a given classification algorithm is to the change of the training data. Such a solution also has its downsides as it is unlikely that during the tests, all sets of data will be depleted.

Due to a significant difference in the number of representatives of different classes, in order to compare the methods, a weighted classification error was calculated expressed with the formula:

$$\varepsilon = \frac{1}{K} \sum_{i=1}^K \frac{\sum_{j=1, j \neq i}^K a_{ij}}{K_i} \quad (2)$$

where: K – number of classes, K_i – number of elements in an i -th class, a_{ij} elements of the matrix of class distribution (confusion matrix) from outside of the diagonal.

Such a definition of error allows for the varied numbers of examples of different classes.

Table 3 presents the averaged results obtained during the tests of the compared methods while Tab. 4 presents matrices of the classes distribution. In the case of the neural networks as well as the k-NN classifier, results from the best classifiers have been presented (of the best selected network structure for the k-NN classifier of the optimum k parameter and distance measure). Due to the varied number of representatives of a given class, the number of errors was referred to the number of representatives of a given class.

From the comparison of the classifiers, it results that, out of the analyzed solutions of valve clearance identification for the investigated engine, the most advantageous is the set of binary classifiers. The k-NN classifier in the applied algorithm does not identify uncertain cases. This explains the greater classification error compared to other classifiers. ‘Difficult’ cases are classified and unrecognized cases are deemed uncertain. There is a possibility of introducing the nearest neighbors algorithm (k,l), for which, if there is an insufficient number of neighbors voting for a given class (fewer than l), the classification is deemed uncertain. Yet, this introduces another parameter l to optimize the classifier. As has been mentioned earlier in the paper, in the case of sets of trees and networks, uncertain classifications are rejected and the decision as to the class affiliation may be made based on subsequent signal samples. Upon rejecting of the uncertain classifications, the set of trees allows classifying the valve clearance with the accuracy of 99% despite the influence of different engine loads and speeds. In the case of other classifiers, the results are worse (approx. 98%) but acceptable, particularly, since, for the problem at hand, one may repeat the diagnosis in a short time.

The classifier based on classification trees was characterized by the highest resistance to change of the training set measured with the error standard deviation. All classifiers make the most errors in correct identification of the optimum valve clearance and it is most frequently

Table 3. Results of the classifiers tests

| Method | Average weighted error of classification [%] | Error standard deviation – measure of resistance of classifier to the training set [%] | Share of uncertain classifications [%] |
|--------------|--|--|--|
| Set of trees | 0.93 | 0.13 | 3.14 |
| k-NN (k=6) | 1.98 | 0.30 | 0 |
| MLP [7,6] | 1.73 | 0.70 | 3.27 |

Table 4. Matrix of the distribution of classes for the set of classification trees

| Recognized classes | | Real classes | | |
|--------------------|-------------------|---------------------|-----------------------|----------------------|
| | | Tight clearance [%] | Optimum clearance [%] | Excess clearance [%] |
| | Tight clearance | 99.4 | 0.4 | 0.2 |
| | Optimum clearance | 0.1 | 98.1 | 0.1 |
| | Excess clearance | 0.5 | 1.5 | 99.7 |

Table 5. Matrix of the distribution of classes for the k-NN classifier (k=6)

| Recognized classes | | Real classes | | |
|--------------------|-------------------|---------------------|-----------------------|----------------------|
| | | Tight clearance [%] | Optimum clearance [%] | Excess clearance [%] |
| | Tight clearance | 99.2 | 1.1 | 0.4 |
| | Optimum clearance | 0.4 | 96.0 | 0.8 |
| | Excess clearance | 0.4 | 2.9 | 98.8 |

Table 6. Matrix of the distribution of classes for the classifier in the form of a neuron network [7,6] (7 and 6 neurons in the hidden layers)

| Recognized classes | | Real classes | | |
|--------------------|-------------------|---------------------|-----------------------|----------------------|
| | | Tight clearance [%] | Optimum clearance [%] | Excess clearance [%] |
| | Tight clearance | 98.8 | 0.6 | 0.7 |
| | Optimum clearance | 0.2 | 97.1 | 0.4 |
| | Excess clearance | 1.0 | 2.3 | 98.9 |

confused with the excess valve clearance (1.5%, 2.9 % and 2.3 % of the cases of optimum valve clearance were classified as excess valve clearance). The best results in this respect has the set of classification trees. In the case of this classifier, out of the compared methods, the most successfully identified valve clearance was the excess one.

4. Conclusions

Following the performed analyses, a method can be proposed of classification of the engine valve clearance based on vibration signals measured on the cylinder head. For the engine under investigations this is successful with approx. 99%. Given the possibility of multiple repetition of the classification process almost in real time and selecting the most frequently occurring class, one may decide on the class of the valve clearance with a high level of certainty. In order to determine such a state for the investigated engine, as few as 15 easily

obtainable number parameters is sufficient. Obviously, for other type of engines, it will be necessary to perform the entire process of classifier construction.

In the paper, in order to solve the presented problem, the authors proposed an application of a set of three binary trees specialized in identification of each class of valve clearance. Such an approach allows an obtainment of relatively small classification errors (for the analyzed case) and automates the selection of **components** of the training vector. Additionally, the tree allows an easy generation of human friendly rules that are also easy to implement in a system that would operate autonomously.

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References

- Albarbar A, Ball A, Starr A. On acoustic measurement-based condition monitoring of internal combustion engines. *Insight: Non-Destructive Testing and Condition Monitoring* 2008; 50(1): 30-34, <https://doi.org/10.1784/insi.2008.50.1.30>.
- Albertson F, Bodén H, Gilbert J. Comparison of different methods to couple nonlinear source descriptions in the time domain to linear system descriptions in the frequency domain - Application to a simple valveless one-cylinder cold engine. *Journal of Sound and Vibration* 2006; 291(3-5): 963-985, <https://doi.org/10.1016/j.jsv.2005.07.046>.
- Arroyo J, Muñoz M, Moreno F, Bernal N, et al. Diagnostic method based on the analysis of the vibration and acoustic emission energy for emergency diesel generators in nuclear plants. *Applied Acoustics* 2013; 74(4): 502-508, <https://doi.org/10.1016/j.apacoust.2012.09.010>.
- Babu A K, Raj A A, Kumersan G. Misfire detection a multi- cylinder diesel engine: a machine learning approach. *Journal of Engineering Science and Technology* 2016; 11(2): 278-295.
- Badawy T, Shrestha A, Henein N. Detection of Combustion Resonance Using an Ion Current Sensor in Diesel Engines. *Journal of Engineering for Gas Turbines and Power* 2012; 134(5): 052-802, <https://doi.org/10.1115/1.4004840>.
- Ahmed A B, Elaraby I S. A prediction for Student's Performance Using Decision Tree ID3 Method. *India - World Journal of Computer Application and Technology* 2014; 2(2): 43-47.
- Czech P, Bąkowski H. Diagnosing of car engine fuel injectors damage using dwt analysis and PNN neural networks. *Transport Problems* 2013; 8(3): 85-91.
- Delvecchio S, Bonfiglio P, Pompoli F. Vibro-acoustic condition monitoring of Internal Combustion Engines: A critical review of existing

- techniques. *Mechanical Systems and Signal Processing* 2018; 99: 661-683, <https://doi.org/10.1016/j.ymsp.2017.06.033>.
9. Desbazeille M, Randall R B, Guillet F, El Badaoui M, et al. Model-based diagnosis of large diesel engines based on angular speed variations of the crankshaft. *Mechanical Systems and Signal Processing* 2010; 24(5): 1529-1541, <https://doi.org/10.1016/j.ymsp.2009.12.004>.
 10. Dolatabadi N., Theodossiades S., Rothberg S.J., On the identification of piston slap events in internal combustion engines using tribodynamic analysis. *Mechanical Systems and Signal Processing* 2015; 58: 308-324, <https://doi.org/10.1016/j.ymsp.2014.11.012>.
 11. Erbek F S, Özkan C, Taberner M. Comparison of maximum likelihood classification method with supervised artificial neural network algorithms for land use activities. *International Journal of Remote Sensing* 2004; 25(9): 1733-1748, <https://doi.org/10.1080/0143116031000150077>.
 12. Figlus T, Liščák Š, Wilk A, Łazarz B. Condition monitoring of engine timing system by using wavelet packet decomposition of a acoustic signal. *Journal of Mechanical Science and Technology* 2014; 28(5): 1663-1671, <https://doi.org/10.1007/s12206-014-0311-3>.
 13. Fog TL, Hansen LK, Larsen J, Hansen HS, et al. On condition monitoring of exhaust valves in marine diesel engines. *Neural Networks for Signal Processing IX, 1999. Proceedings of the 1999 IEEE Signal Processing Society Workshop 1999*; 554-563.
 14. Gao F, Lv J. Fault Diagnosis for Engine Based on Single-Stage Extreme Learning Machine. *Mathematical Problems in Engineering* 2016; 2016: 1-10, <https://doi.org/10.1155/2016/7939607>.
 15. Gorges C, Öztürk K, Liebich R. Impact detection using a machine learning approach and experimental road roughness classification. *Mechanical Systems and Signal Processing* 2019; 117: 738-756, <https://doi.org/10.1016/j.ymsp.2018.07.043>.
 16. Jia F, Lei Y, Lu N, Xing S. Deep normalized convolutional neural network for imbalanced fault classification of machinery and its understanding via visualization. *Mechanical Systems and Signal Processing* 2018; 110: 349-367, <https://doi.org/10.1016/j.ymsp.2018.03.025>.
 17. Korbicz J, Kościelny J M, Kowalczyk Z, Cholewa W (Eds.). *Models, Artificial Intelligence, Applications*. Springer-Verlag Berlin Heidelberg, 2004.
 18. Lahrache A, Cocconcelli M, Rubini R. Anomaly detection in a cutting tool by k-means clustering and support vector machines. *Diagnostyka* 2017; 18(3): 21-29.
 19. Leemans V, Magein H, Destain M F. Defect segmentation on 'Jonagold' apples using colour vision and a Bayesian classification method. *Computers and Electronics in Agriculture* 1999; 23: 43-53, [https://doi.org/10.1016/S0168-1699\(99\)00006-X](https://doi.org/10.1016/S0168-1699(99)00006-X).
 20. Lei Y, He Z, Zi Y. Application of an intelligent classification method to mechanical fault diagnosis. *Expert Systems with Applications* 2009; 36(6): 9941-9948, <https://doi.org/10.1016/j.eswa.2009.01.065>.
 21. Madej H, Czech P. Discrete wavelet transform and probabilistic neural network in IC engine fault diagnosis. *Eksplotacja i Niezawodność - Maintenance and reliability* 2010; 4(48): 47-54.
 22. Matzke W. *Four-stroke engine timing*, Warszawa: WKiŁ, 1967.
 23. Mechefske C K, Mathew J. Fault detection and diagnosis in low speed rolling element bearings Part II: The use of nearest neighbour classification. *Mechanical Systems and Signal Processing* 1992; 6(4): 309-316, [https://doi.org/10.1016/0888-3270\(92\)90033-F](https://doi.org/10.1016/0888-3270(92)90033-F).
 24. Nguyen T T, Armitage G. A survey of techniques for internet traffic classification using machine learning. *IEEE Communications Surveys Tutorials* 2008, 10(4): 56-76, <https://doi.org/10.1109/SURV.2008.080406>.
 25. Niziński S, Michalski R. *Diagnostics of technical objects*. Radom: Department of Vehicle and Machine Operation, Faculty of Technical Sciences, University of Warmia and Mazury in Olsztyn, Institute for Sustainable Technologies in Radom, 2002.
 26. Osiecki J, Ziemia S. *Basics of mechanical vibration measurements*, Warszawa: PWN, 1968.
 27. Potočnik P, Govekar E. Semi-supervised vibration-based classification and condition monitoring of compressors. *Mechanical Systems and Signal Processing* 2017; 93: 51-65, <https://doi.org/10.1016/j.ymsp.2017.01.048>.
 28. Qinghua W, Youyun Z, Lei C, Yongsheng Z. Fault diagnosis for diesel valve trains based on non-negative matrix factorization and neural network ensemble. *Mechanical Systems and Signal Processing* 2009; 23(5): 1683-1695, <https://doi.org/10.1016/j.ymsp.2008.12.004>.
 29. Ruiz M, Mujica L E, Alférez S, Acho L, et al. Wind turbine fault detection and classification by means of image texture analysis. *Mechanical Systems and Signal Processing* 2018; 107: 149-167, <https://doi.org/10.1016/j.ymsp.2017.12.035>.
 30. Serridge M, Licht T R. *Piezoelectric accelerometers and vibration preamplifiers*, Nearum: Brüel & Kjær, 1987.
 31. Szymański G.M., Tomaszewski F., Diagnostics of automatic compensators of valve clearance in combustion engine with the use of vibration signal. *Mechanical Systems and Signal Processing* 2016; 68-69: 479-490, <https://doi.org/10.1016/j.ymsp.2015.07.015>.
 32. Wang C, Zhang Y, Zhong Z. Fault diagnosis for diesel valve trains based on time-frequency images. *Mechanical Systems and Signal Processing* 2008; 22(8), 1981-1993, <https://doi.org/10.1016/j.ymsp.2008.01.016>.
 33. Wong P K, Zhong J, Yang Z, Vong C M. Sparse Bayesian extreme learning committee machine for engine simultaneous fault diagnosis. *Neurocomputing* 2016; 174: 331-343, <https://doi.org/10.1016/j.neucom.2015.02.097>.
 34. Wu J, Liu C. An expert system for fault diagnosis in internal combustion engines using wavelet packet transform and neural network. *Expert Systems with Applications* 2009, 36: 4278-4286, <https://doi.org/10.1016/j.eswa.2008.03.008>.
 35. Zhang H, Li J, Huang Y, Zhang L. A Nonlocal Weighted Joint Sparse Representation Classification Method for Hyperspectral Imagery. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 2014; 7(6): 2056-2065, <https://doi.org/10.1109/JSTARS.2013.2264720>.

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