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Piotr CZECH[1]

DIAGNOSING FAULTS IN THE TIMING SYSTEM OF A PASSENGER CAR SPARK IGNITION ENGINE USING THE BAYES CLASSIFIER AND ENTROPY OF VIBRATION SIGNALS

Summary. Today's systems for diagnosing the technical condition of machines, including vehicles, use very advanced methods of acquiring and processing input data. Presently, work is being conducted globally to solve related problems. At the moment, it is not yet possible to create a single procedure that would enable the construction of a properly functioning diagnostic system, regardless of the selected object to be diagnosed. Hence, there is a need to conduct further research into the possibility of using already developed methods, as well as their modification to other diagnostic cases. This article presents the results of research related to the use of the Bayes classifier for diagnosing the technical condition of passenger car engine components. Damage to the exhaust valve of a spark ignition engine was diagnosed. The source of information on the technical condition was vibration signals recorded at various measuring points and under different operating conditions of the car. To describe the nature of changes in the vibration signals, the entropy measures were determined for the decomposed signal using the discrete wavelet transform is proposed.

Keywords: internal combustion engines, diagnostics, Bayesian classifier, pattern recognizing, spark ignition internal combustion engine, exhaust valve of the internal combustion engine

[1] Faculty of Transport and Aviation Engineering, The Silesian University of Technology, Krasinskiego 8 Street, 40-019 Katowice, Poland. Email: piotr.czech@polsl.pl. ORCID: 0000-0002-0884-8765

1. INTRODUCTION

Very dynamic development of automotive technology has been observed over the last years. Currently produced vehicles are characterized by high power and speeds as car manufacturers aim to optimize the mass and weight of vehicles [7, 18, 20, 23, 28]. These two factors may cause a rise in the level of vibrations and noise generated by vehicles, which is caused by the fact that part of the energy processed by the vehicle is always emitted to the environment in the form of vibroacoustic phenomena. Presently, used design methods do not give a full guarantee of the construction of a structure with predetermined vibroactivity [7, 18, 20, 23, 28].

Among the methods of solving vibroacoustic problems, the following stages can be distinguished:

- experimental identification of vibroacoustic phenomena of working machines,
- development of models of vibroacoustic phenomena,
- development of theoretical and experimental methods of studying models,
- development of methods for calculating vibroacoustic states,
- setting the design principles for low-emission machines,
- experimental verification of experiments results on prototypes and in production,
- development of standards determining acceptable vibroacoustic conditions of machines.

Vibrations may cause disturbances in the correct operation of the machine and other devices and reduce their durability and reliability. In addition, it should be mentioned that mechanical vibrations are often a working factor deliberately introduced by machine builders as an indispensable element for the implementation of technological processes. They are also a valuable source of information, as, through them, one can assess the technical condition of the machine and its build quality [1, 9-11, 27, 32-34].

In recent years, methods of non-invasive diagnostics of technical conditions in which vibrational and acoustic signals emitted during work are used have been developed around the world [1, 9-11, 27, 32-34].

The diagnostic process, aimed at identifying the technical condition of the object, is carried out usually during the normal operation of the object, and it can be done at any stage of its life. Occurrence of damage to the machines or deterioration of their operational status is recognized based on the symptoms, which are represented by the features of diagnostic signals [17, 21, 29, 31, 38, 39, 40, 42-44, 45].

It should be considered that the vibrations produced in one of the elements can be transmitted and cause vibrations in a completely different, remote element. For example, vibrations generated by the crankshaft system of a car engine can be transferred by attaching the engine to the chassis members, then the bodywork, and by fixing the hinges to the boot lid, causing it to resonate. In this case, despite the source of vibration being at the front of the vehicle, vibrations with the highest intensity – in the form of vibrations or noise – will reach the vehicle user from a completely different angle.

Research is being carried out to find the appropriate tools to support the process of vibroacoustic diagnostics of objects' conditions through experiments related to the application of new algorithms of registration, ordering and processing of data according to specific rules, enabling the classification of states. The different characteristics and determinants of such tasks to a specific object mean that despite the existence of many proven methods, there is still a need for further research in this area.

2. RESEARCH PROBLEM

According to the trade literature for car service plants [6, 13, 15, 25, 36], the repair of the timing gear is an expensive and time-consuming operation. For example, some of the valve failures that occur lead to serious failures of the entire engine, and the repair itself may be unjustified for economic reasons.

The combustion engine timing system is responsible for controlling the start and end of the filling process with fresh load and exhaust gas outlet. This must be in full synchronization with the movement of the piston, which depends on the position of the crankshaft. The movement of the intake and exhaust valves, on the other hand, is caused by the rotation of the camshaft, which is driven by the engine's crankshaft.

The timing system must also provide a refrigerant flow field to maintain proper flow rates. The flow field depends on the dimensions of the valve seat, valve plug and valve stem and changes its value with the valve lift. The lift and diameter of the intake valves are increased to improve cylinder filling. It should be noted, however, that valves with a smaller diameter deform less and remain tight for longer [6, 13, 15, 25, 36].

Exhaust valves are particularly exposed to harsh working conditions, as they have to operate at temperatures of up to 700^{o}C. The valve plug is the most heat-loaded. Cyclically, heat is removed therefrom through the valve face to the seat and head when the valve is closed and continuously through the valve stem and guide. The intake valves operate under much milder conditions.

During the long-term use of an engine, one of the basic operating factors negatively affecting its operation by changing the conditions of heat exchange in the elements surrounding the combustion chamber is carbon deposit (Figure 1). The process of carbon deposit formation is influenced by many factors, which include, among others [6, 13, 15, 25, 36]:

- incomplete combustion of too heavy fuel,
- presence of asphalt and resin substances in the fuel,
- presence of unsaturated hydrocarbons and sulfur compounds,
- the content of mineral impurities that create ash during the combustion process,
- combustion of engine oil due to leakage in the cylinder space.

Fig. 1. Examples of valve damage resulting from carbon deposits [14]

Exemplary results of numerical calculations of temperature distributions, temperature gradients and stresses in the exhaust valve of the internal combustion engine can be found in [14, 16, 19].

The valves must be characterized by [6, 13, 15, 25, 36]:

- good heat conductivity,
- resistance to work in impact conditions,
- corrosion resistance,
- abrasion resistance.

The automotive industry literature [6, 13, 15, 25, 36] provides the following as causes of valve failures:

- thermal or mechanical overloads,
  - plastic deformation of the valve head,
  - changes in the material structure of valves,
  - thermal corrosion of the hollow valves,
  - corrosion pitting on valve faces,
  - surface cracks,
  - break off of the valve stem,
  - burnout of the hollow valves.
- disruptions in the operation of the valve drive system,
  - failure of the camshaft drive,
  - defective valve stem mounting,
  - eccentric thrust of the rocker arm,
  - too tight valve guide,
  - valve guide too loose,
  - no rotation of the valve during operation,
  - too intense valve rotation.
- errors in closing the valves,
  - too large valve clearance,
  - too small valve clearance,
  - deformation of the valve seat.
- incorrect selection of valve material.
- faulty assembly of valves,
  - misalignment of seat and valve guide,
  - wrong valve clearance,
  - valve marking.
- construction defects,
  - defective shape of the valve disc,
  - defective shape of the valve stem foot.
- defects in workmanship,
  - overheating during forging,
  - the disadvantages of stelliting,
  - the disadvantages of heat treatment,
  - the disadvantages of chrome plating,
  - the defects of hardening the valve's foot,
  - faulty fiber path.
- material defects,
  - inclusions and contamination of the material,
  - surface defects,
  - defects in the structure of the material.

The most common cause of valve failure is [6, 13, 15, 25, 36]:

- heat or mechanical overload: 38%,
- workmanship defects: 22%,
- timing system failures: 10%,
- material defects: 9%,
- defective assembly and operation: 8%,
- structural defects: 7%,
- other: 6%.

To prevent valve damage, the instructions for auto mechanics give the following guidelines [6, 13, 15, 25, 36]:

- valve clearance must be precisely set,
- control times must be precisely set,
- after replacing the toothed belt or the chain, the tensioner should also be replaced,
- after machining the cylinder head, check the return position of the valves,
- the valve spring must be properly seated during installation,
- new washers for valve seats should be used,
- new locks of the valve spring should be used,
- the valve guide and the valve face must be parallel,
- only parts specified by the manufacturer should be used,
- when installing the engine, all foreign bodies must be removed from the combustion chamber and the fuel supply system.

3. BASICS OF BAYESIAN CLASSIFIER OPERATION

In technical diagnostics systems, statistical methods are included in the group of possible to use pattern classification methods [8, 21, 26, 37, 41]. In this research, the possibility of using one of such methods – the Bayes classifier, was checked. The operation of the Bayes classifier is based on the Bayes theorem [2-4, 12, 30, 35].

According to the theory of probability:

$$P(Y/X) = \frac{P(Y \cap X)}{P(X)} \tag{1}$$

$$P(X/Y) = \frac{P(Y \cap X)}{P(Y)} \tag{2}$$

where:
$P(Y/X)$ – probability of Y event occurring if X event happened,
$P(X/Y)$ – probability of X event occurring if Y event happened,
$P(Y \cap X)$ – probability of simultaneous occurrence of the event Y and X,
$P(X)$ – probability of X event,
$P(Y)$ – probability of Y event.

Transforming (1) and (2), we get:

$$P(Y \cap X) = P(Y/X) \cdot P(X) \tag{3}$$

$$P(Y \cap X) = P(X/Y) \cdot P(Y) \tag{4}$$

Hence:

$$P(Y/X) = \frac{P(X/Y) \cdot P(Y)}{P(X)} \tag{5}$$

Formula (5) is called the Bayes rule.

At the same time, the total probability is:

$$P(X) = P(X/Y_1) \cdot P(Y_1) + P(X/Y_2) \cdot P(Y_2) + \cdots + P(X/Y_n) \cdot P(Y_n) \tag{6}$$

Assuming that *Y* represents a given class, and *X* is a set of data attributes defining the selected class, depending on the number of classes and attributes, the Bayesian rule can be written in the form:

- for one class and one attribute:
-

$$P(Y/X) = \frac{P(X/Y) \cdot P(Y)}{P(X/Y) \cdot P(Y) + P(X/\bar{Y}) \cdot P(\bar{Y})} \tag{7}$$

where:

$P(\bar{Y})$ –probability of an event opposite to *Y*,

- for *N* classes and one attribute, the probability of the *K* class:

$$P(Y_K/X) = \frac{P(X/Y_K) \cdot P(Y_K)}{\sum_{i=1}^{N} P(X/Y_i) \cdot P(Y_i)} \tag{8}$$

- for *N* classes and *M* attributes, the probability of *K* class:

$$P\big(Y_K/(X_1, X_2, \cdots, X_M)\big) = \frac{P\big((X_1, X_2, \cdots, X_M)/Y_K\big) \cdot P(Y_K)}{\sum_{i=1}^{N} P\big((X_1, X_2, \cdots, X_M)/Y_i\big) \cdot P(Y_i)} \tag{9}$$

If the independence of the attributes is assumed, formula (9) can be written as:

$$P\big(Y_K/(X_1, X_2, \cdots, X_M)\big) = \frac{P(X_1/Y_K) \cdot P(X_2/Y_K) \cdot \cdots \cdot P(X_M/Y_K) \cdot P(Y_K)}{\sum_{i=1}^{N}\big(P(X_1/Y_i) \cdot P(X_2/Y_i) \cdot \cdots \cdot P(X_M/Y_i) \cdot P(Y_i)\big)} \tag{10}$$

The highest value of the probability of a specific class occurrence means that the belonging of the input data described by the accepted *X* attributes belongs to that class.

4. DESCRIPTION OF THE RESEARCH EXPERIMENT

The test object was a passenger car spark ignition internal combustion engine with a capacity of 1,6 dm^3.

This research aims to develop a method for diagnosing damage to the exhaust valve of an internal combustion engine based on vibration signals generated by the engine.

In this study, registered signals for accelerators of the engine head close to:

- the intake valve of the first cylinder,
- the outlet valve of the first cylinder,

- the outlet valve of the fourth cylinder,
- the gearbox.

The measurements were made on a car dynamometer at various driving speeds. Vibration signals were recorded for:

- third gear,
- fourth gear,
- fifth gear,

at engine rotational speeds of:

- 2000 rpm,
- 3000 rpm,
- 4000 rpm.

In the experiments for registration of vibration signals, a multi-channel National Instruments registration equipment was used. The recorder allowed for synchronous sampling at a frequency of 50 kHz. PCB Piezotronics Accelerating Transducers were used in the measurements. An application developed in the LabView environment was used to control the data acquisition system.

During the conducted tests, the vibration signals of the efficient internal combustion engine and engine with a damaged outlet valve were recorded. Damage to the outlet valve was made up by performing the incision of its valve climb (Figure 2).

Fig. 2. Modeled damage to the spark ignition engine exhaust valve

Examples of recorded vibration signals of an efficient and damaged internal combustion engine of a passenger car are shown in Figure 3.

The recorded vibration signal was processed with the use of a discrete wavelet transform (*DWT*) [21, 24]. Signal analysis selected for these experiments can be defined as:

$$DWT = \int_{-\infty}^{+\infty} \psi(t) \cdot x(t) dt \tag{11}$$

where:

$x(t)$ – registered vibration signal,

$\psi(t)$ – base wavelet.

The result of the analysis is to obtain a multi-level signal decomposition $x(t)$ for high-frequency $d_j(t)$ and low-frequency components $a_j(t)$:

$$x(t) = a_J(t) + \sum_{j=1}^{J} d_j\,(t) \tag{12}$$

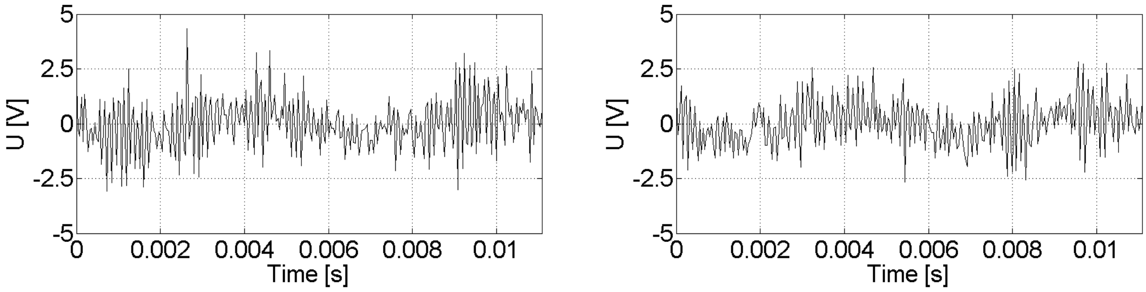

Fig. 3. Vibration signal of the engine without damage (left) and with a damaged exhaust valve of the combustion engine (right)

The occurring changes in the vibration waveforms in the decomposed approximation and detail signals were described by the entropy of the signal:

$$E_{sh} = -\sum x^2(t) \cdot \log\big(x^2(t)\big) \tag{13}$$

For the construction of the patterns, the number of decomposition levels and the type of the base wavelet also had to be assumed. The usefulness of 52 base wavelets and 10 levels of decomposition were checked in this research. Wavelets from the following family were used:

- haar,
- daubechies,
- biorthogonal,
- coiflets,
- symlets,
- reverse biorthogonal,
- discrete Meyer.

Depending on the assumed number of decomposition levels, the size of the pattern was from two for 1 decomposition level to eleven for 10 decomposition levels. The experiments were checked for the impact that the correctness of the diagnostic classification has on the size of the pattern used.

The diagnostic classification consisted in determining whether the vibration signal was registered for the internal combustion engine in good technical condition and the internal combustion engine with damage in the timing system.

The Bayes classifiers were constructed with the use of patterns created for 10 variants of the pattern size, and each variant was checked for 52 base wavelets.

According to the assumptions made during this research, in equation (10), the number of attributes is from 2 to 11 (X_1,X_2 or X_1,X_2,X_3 or ... or X_1,X_2,X_3,...,X_{11}), while the number of classes is 2 (Y_1 or Y_2).

In conducting this research, 400 different sets of teaching and testing patterns were used. Two hundred examples were used to learn the diagnostic models. The examples included 100 patterns for each of the recognized classes. The same number of patterns was used in the process of testing the diagnostic models.

An example of the distribution of data used in the process of learning and testing the diagnostic models is shown in Figure 4.

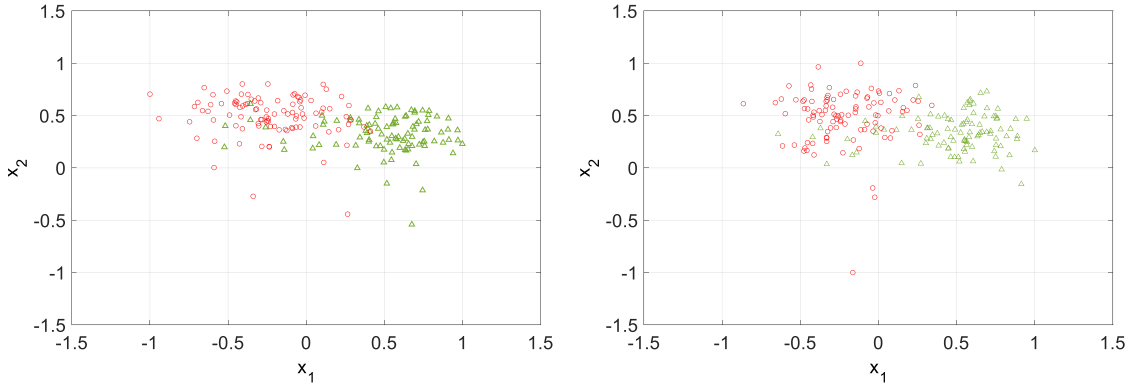

Fig. 4. Sample distribution of data used in the learning process (left) and testing (right)

In the conducted tests, the correctness of the operation of the diagnostic models using vibration signals registered in various measurement locations and for various operating conditions, as well as patterns obtained with different base wavelets at a different number of decomposition levels of vibration signals, were checked.

5. RESULTS OF RESEARCH EXPERIMENT

During the experiment, the operation of classifiers using patterns derived from vibration signals recorded in a specific place (4 measuring points: 1st cylinder exhaust valve, 1st cylinder inlet valve, 4th cylinder outlet valve, gearbox) was checked for an engine operating at a specific gear (3 gears), and at a fixed speed (3 speeds).

The influence of the selection of the wavelet on the correctness of the pattern classification in the testing process, depending on the place of vibration signal registration, is shown in Figures 5 and 6.

The figures show the distribution of the number of cases for which the classifiers were characterized by the minimum testing error value using a given base wavelet (regardless of the selected gear – 3 gears, engine rotational speed – 3 speeds, pattern size – 10 variants of decomposition level). The best base wavelet would have several cases equal to 90. However, such a situation did not occur in the experiment.

When analyzing the presented results, it can be noticed that regardless of the selected place of vibration signal registration, the best wavelet used in the pattern building process is the discrete Meyer wavelet.

Furthermore, the presented figures also show that the best measurement place among the tested during the experiment was the area of the exhaust valve of the 1st cylinder. This may be because the measurement, in this case, was carried out closest to the place where the simulated failure occurred.

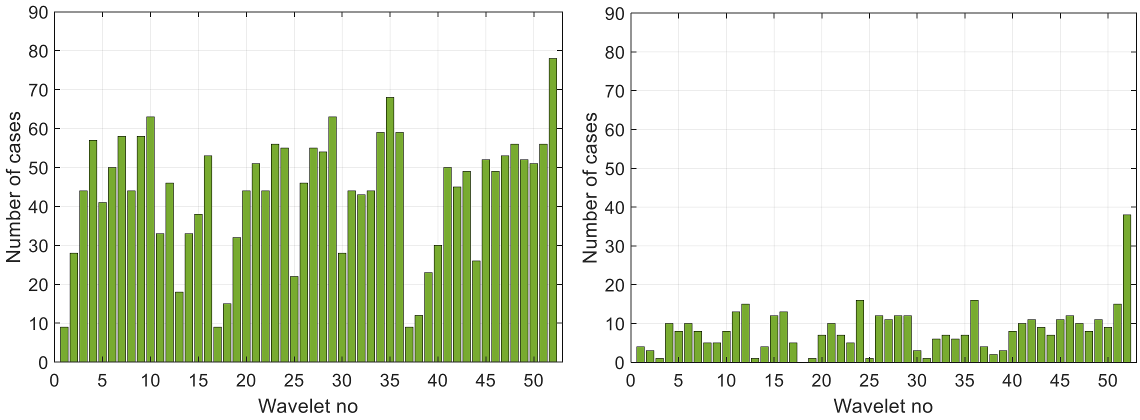

Fig. 5. Influence of the selection of the wavelet on the correctness of the classification for the patterns obtained from the signals recorded in the vicinity of the outlet valve of the 1st cylinder (left) and the 4th cylinder (right)

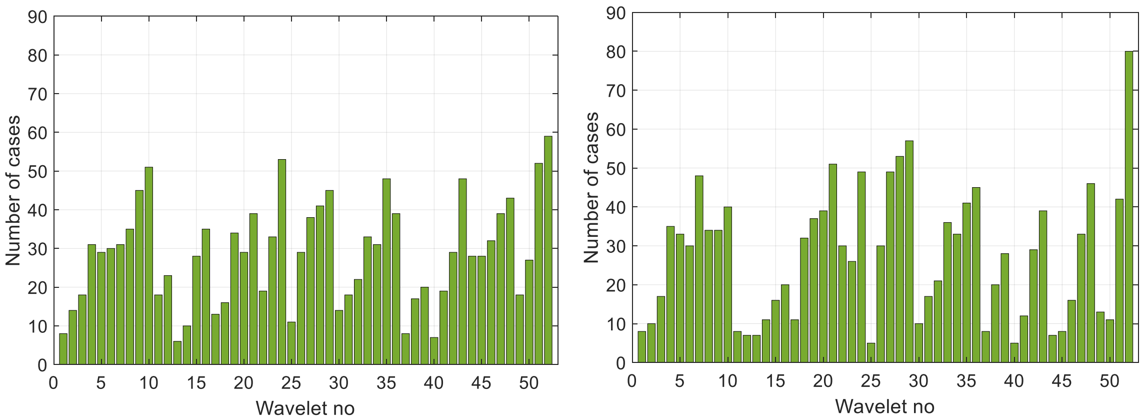

Fig. 6. Influence of the selection of the wavelet on the correctness of the classification for the patterns obtained from the signals recorded in the vicinity of the inlet valve of the 1st cylinder (left) and gearbox (right)

Interestingly, similar results were obtained during the research on the detection of damage to the gasket under the head of a spark ignition internal combustion engine, as presented in [5].

Figure 7 shows the influence of the selection of the wavelet on the correct classification of the pattern in the testing process, regardless of the place of vibration signal registration.

The best base wavelet would have several cases equal to 360. Such a situation did not occur in the experiment. Consequently, the best wavelet was the discrete Meyer wavelet.

Figures 8 and 9 show an exemplary influence of the pattern size, that is, the selected number of decomposition levels, on the correctness of the classification result.

In the case of the Bayes classifier models, which were characterized by a greater error, it was possible to notice a tendency of the test error to decrease with the increase of the pattern size, that is, the selected number of decomposition levels. For variants of models with low values of test errors, it is not possible to unequivocally determine the influence of the pattern size on the obtained result. A summary of the best results obtained is shown in Table 1.

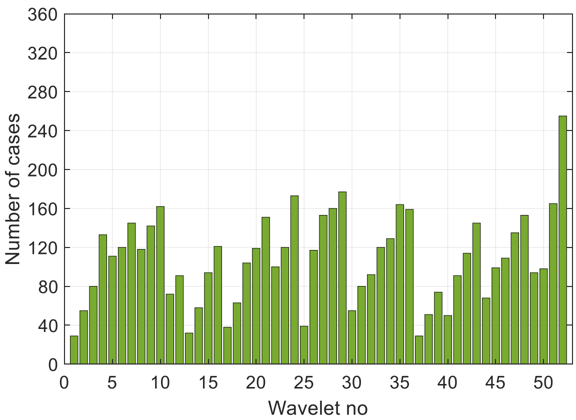

Fig. 7. Influence of the selection of the wavelet on the correctness of the classification, regardless of the place where the vibration signal is measured

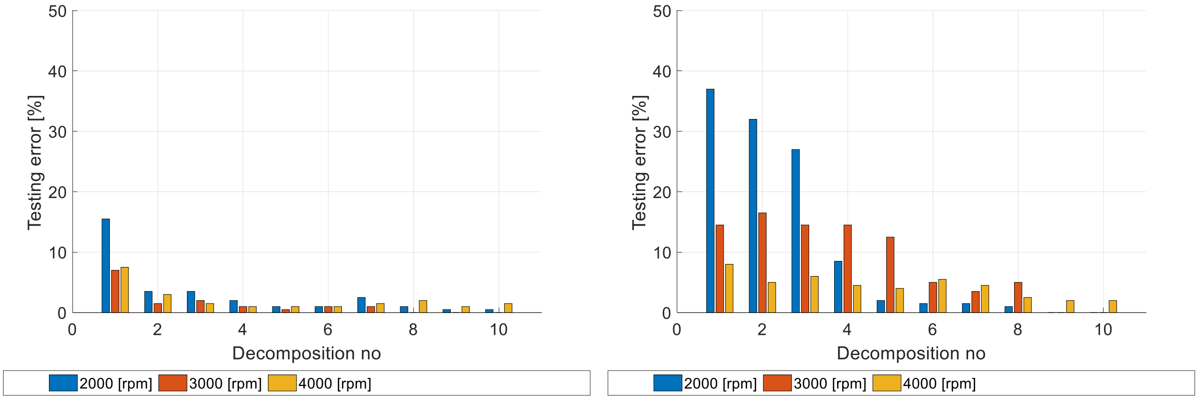

Fig. 8. An example of the impact of the selection of the number of decomposition levels on the classification result for the patterns obtained from the signals recorded in the vicinity of the exhaust valve of the 1st cylinder (left) and 4th cylinder (right)

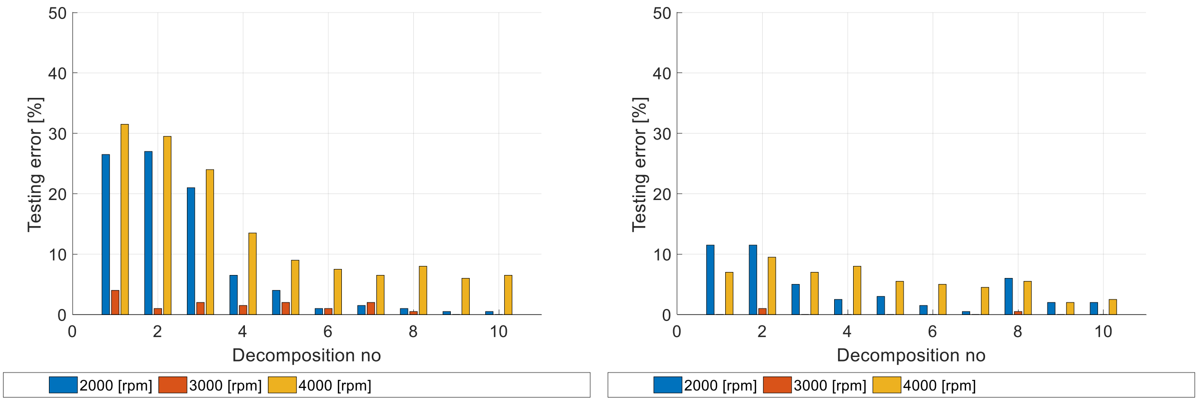

Fig. 9. An example of the impact of the selection of the number of decomposition levels on the classification result for the patterns obtained from the signals recorded around the inlet valve of the 1st cylinder (left) and the gearbox (right)

Also, in this case, the obtained results are consistent with those presented in [5] and concerning the diagnosis of the occurrence of damage to the gasket under the head of a spark ignition car internal combustion engine.

Tab. 1.

Summary of the best obtained results

No.	**Measurement location**	**Gear no. [-]**	**Engine rotational speed [rpm]**	**Test error [%]**
1	Intake valve of the 1st cylinder	3	2000	0,5
2	Intake valve of the 1st cylinder	3	3000	0
3	Intake valve of the 1st cylinder	3	4000	6
4	Intake valve of the 1st cylinder	4	2000	3
5	Intake valve of the 1st cylinder	4	3000	4
6	Intake valve of the 1st cylinder	4	4000	1,5
7	Intake valve of the 1st cylinder	5	2000	8,5
8	Intake valve of the 1st cylinder	5	3000	0
9	Intake valve of the 1st cylinder	5	4000	0
	Outlet valve of the 1st cylinder	3	2000	0,5
	Outlet valve of the 1st cylinder	3	3000	0
	Outlet valve of the 1st cylinder	3	4000	1
	Outlet valve of the 1st cylinder	4	2000	0
	Outlet valve of the 1st cylinder	4	3000	1
	Outlet valve of the 1st cylinder	4	4000	0
	Outlet valve of the 1st cylinder	5	2000	0
	Outlet valve of the 1st cylinder	5	3000	0,5
	Outlet valve of the 1st cylinder	5	4000	0
	Outlet valve of the 4th cylinder	3	2000	0
	Outlet valve of the 4th cylinder	3	3000	0
	Outlet valve of the 4th cylinder	3	4000	2
	Outlet valve of the 4th cylinder	4	2000	16
	Outlet valve of the 4th cylinder	4	3000	6
	Outlet valve of the 4th cylinder	4	4000	7
	Outlet valve of the 4th cylinder	5	2000	6
	Outlet valve of the 4th cylinder	5	3000	3
	Outlet valve of the 4th cylinder	5	4000	4,5
	Gearbox	3	2000	0,5
	Gearbox	3	3000	0
	Gearbox	3	4000	2
	Gearbox	4	2000	5
	Gearbox	4	3000	9,5
	Gearbox	4	4000	6,5
	Gearbox	5	2000	14
	Gearbox	5	3000	7
	Gearbox	5	4000	1

The conducted experiments allowed to confirm the usefulness of Bayes classifiers in the diagnostic process of the technical condition of the spark ignition engine timing system. Following the conducted experiments, faultless or almost flawlessly operating Bayes classifiers were built.

6. CONCLUSIONS

During their operation, all technical objects are a source of vibrations and noise. One should be aware that the generation of the vibroacoustic phenomena by operating technical objects is not synonymous with their poor technical condition. A certain level will always be present and must be considered as the nominal one. Only the difference between the model of a machine that is working properly or in good technical condition, and the actual case that occurs, will indicate possible damage to the elements.

Difficulties in using vibroacoustic signals for diagnostic purposes, among other things, are the result that they are generated simultaneously in various parts of a working machine. There are many different generation sources of vibroacoustic processes in internal combustion engines. The consequence of this is the high complexity of the resultant signal used for diagnostic purposes.

To use vibroacoustic signals to diagnose the state of a technical object, they must be appropriately processed in advance in the domain of time, frequency or both time and frequency. The purpose of signal processing is to obtain estimates that are highly correlated with the monitored phenomenon.

One of the methods used to pre-process vibroacoustic signals is the wavelet analysis. Wavelet analysis is one of the methods usually used in vibroacoustic diagnostics today. It enables the linear decomposition of the examined vibroacoustic signal using any basis function with a finite and short range, in which it takes values other than zero. A properly selected wavelet allows isolating the proper signal from random disturbances. Such disturbances after transformation are represented by coefficients with small values. Such coefficients are removed from the distribution by a threshold function. A properly selected wavelet is understood as a wavelet that is consistent with the character of the tested signal. The greatest advantage of wavelet analysis is the ability to freely define the parameters of the analysis. This is accomplished by selecting the base wavelet and the scale range.

In the conducted experiments, the discrete wavelet transform (DWT) was used as a method of pre-processing the recorded vibroacoustic signals. The character of changes in the vibroacoustic signals was described using the entropy of approximation and the details of the vibration signal. Patterns developed in this way were used to build a technical condition classifier of a spark ignition engine timing system. The possibility of using Bayesian classifiers to diagnose the occurrence of damage was tested. The exhaust valve crack was modeled in the tests as an undesirable condition. During the tests, the influence of the selection of the place of vibration measurement, the operating conditions of the working internal combustion engine, and the type of base wavelet used in the pattern construction process were checked.

The results obtained in this research confirm the possibility of using Bayes classifiers to diagnose the technical condition of the spark ignition engine timing system used in passenger cars. Finally, based on this research, it was possible to obtain flawlessly working Bayes classifiers.

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