Identification of Technical Condition of Valve Clearance Compensators Using Vibration Measurement and Machine Learning

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Abstract

The dynamic development of internal combustion engine design and requirements for high reliability generates the need to apply a strategy of their operation based on the current technical condition. The paper concerns vibration diagnostics of automatic compensators of valve lash of a combustion engine. It presents the course of an active experiment conducted in order to develop a methodology for identifying the state of compensators based on measures of vibration signals measured at the engine head. Based on the results of the experiment, a classifier was developed in the form of a decision tree, which with high accuracy identified the technical condition of the compensators. The set of simple rules obtained thanks to the built up trees allows for easy implementation of the diagnostic system in practice.

Keywords: vibroacoustic diagnostics, combustion engine, machine learning

1. Introduction

One of the key problems affecting the correct operation of an internal combustion engine is the correct setting of control parameters. Incorrectly set control parameters may cause: deterioration of the effectiveness of the internal combustion engine, decrease in its mechanical efficiency, thermal efficiency and filling ratio, increase in toxic compounds emission in exhaust gases, increase in the probability of failure of internal combustion engine components. One of the most important control parameters is valve clearance (between valve stem and lever or other valve actuating element). The data presented in [1] show that increasing the valve lash may cause an increase in fuel consumption of the tested internal combustion engine by up to approx. 9%.

Automatic valve backlash compensation eliminates the need for periodic adjustment. This solution, however, has its drawbacks, because the introduction of additional masses into the engine timing system increases the inertia forces, and the additional device increases the probability of failure, because it is often connected in series in the kinematic chain of the camshaft system. The consequence of damage to the automatic valve lash compensator is an uncontrolled increase in valve lash resulting in the phenomena described above and which may lead to damage to other components of the internal combustion engine timing system, e.g. burning of valve faces or valve seats, knocking out valve faces. Therefore, it is also necessary to evaluate the clearance (state of adjustment) of engines equipped with automatic valve clearance compensators.

One of the possible approaches to state classification in technical diagnostics is the use of machine learning methods. In order to apply such methods, it is necessary to have a large set of teaching examples covering all recognized state classes. This requirement is difficult to meet in the case of individual objects, but it should not be a problem in the case of internal combustion engines of a given type produced in large numbers. It is also important that taking into account the relatively repetitive cycle of engine operation, we are able to obtain a large number of examples in a relatively short time from one object. Usually in diagnostics it is particularly difficult to obtain examples related to a faulty condition, because in many cases it may be associated with the occurrence of an unacceptable failure. However, in case of identification of incorrect operation of a valve lash compensator it is possible to perform an active experiment, obtaining a large set of examples in a short time.

Classification methods are used in many different fields. One could mention here, for example, the analysis of texts, power engineering, medicine, image identification, transport, hydrology, agriculture, computer science, mechanical engineering, economics and many others [2-11].

The use of classifiers in the diagnosis of machines, equipment, processes or tools has been described in many publications - for example [12-25, 37]. Classification methods were also used in the diagnostics and modelling of processes in internal combustion engines [9, 26-28]. The classification process can be carried out using many methods [29-32]. One can mention here: neural networks, deep neural networks, classifiers based on different distance measures (dissimilarity), regression (e.g. logistic regression), set of induced rules, set of fuzzy rules, etc. One of the widely used methods are CART classification and regression trees developed by Breiman in 1984 [29, 31, 32].

Unquestionable advantages of trees are their simplicity of construction, easy interpretation of the acquired knowledge, which can be easily transformed into a set of classification rules, versatility, performance and the selection of important input features built into the tree construction algorithm that affect the correct prediction of the class [29, 32]. Thus, the tree allows you to identify those diagnostic symptoms that are relevant to the process of state classification. Of course, the trees also have their drawbacks, such as a large number of necessary teaching examples, sometimes unnecessarily complicated decision limits, which can lead to overtraining the classifier or high sensitivity to a small variance in the set of training data [32].

The effectiveness of the classification can be increased by using families of classifiers. It turns out that a large set of independent classifiers, each of which gives slightly better results than random classification, can work out correct decisions by majority voting [32]. Averaging the forecasts developed by many trees improves the stability of the classifier. Such methods as bagging and boosting apply here. The idea of creating a family of classifiers and voting can be applied to different methods, but they are particularly important for classification trees, giving, according to the literature, a significant improvement in results compared to a single tree. Boosting algorithms are among the best classification algorithms, which do not require any preliminary preparation of data [32]. An important method based on the family of classification trees is the random forest method. Random forests combine poorly interdependent trees into a family. In this method, classifiers are built based on input vectors drawn with a replacement from the set of available examples (as in the bagging method). The size of the pseudo-sample drawn is the same as the size of the whole training set. Additionally, in each node a sampling of only some of the attributes of the input vector is made without replacement, and based on the drawn attributes, the quality measure of data division in the node is evaluated. In this way, a greater variety of trees is obtained, which leads to a lower variance of the model. The classification of data is based on the principle of majority voting on the basis of many independent trees constructed in this way [32].

2. Methodology of testing

The object of research concerning the assessment of the technical condition of automatic valve lash compensators was the a8C22 engine, which is used, among others, for propulsion of diesel locomotives, generator sets and as an auxiliary engine of vessels. The engine uses the classic timing system, the diagram of which is shown in Figure 1a. The test engine heads have four valves. The lever timing system of the test engine head is shown in Figure 1b. The adjustment of valve clearance in this engine is carried out in two stages: the first stage is the initial mechanical adjustment, the second stage is carried out by automatic (hydraulic) valve clearance compensators.

The research was carried out in two stages. In the first stage, impulse tests were conducted to determine the vibration acquisition points on the internal combustion engine head. In the second stage the vibrations of engine heads for various configurations of failures of automatic valve lash compensators were tested. The methodology was developed based on the assumptions of an active experiment [33, 34]. The input parameters were the changes in the states of automatic valve lash compensators of the internal combustion engine timing system. The controlled parameters were the internal combustion engine load and crankshaft speed. The output parameters were the accelerations of vibrations of the engine head.

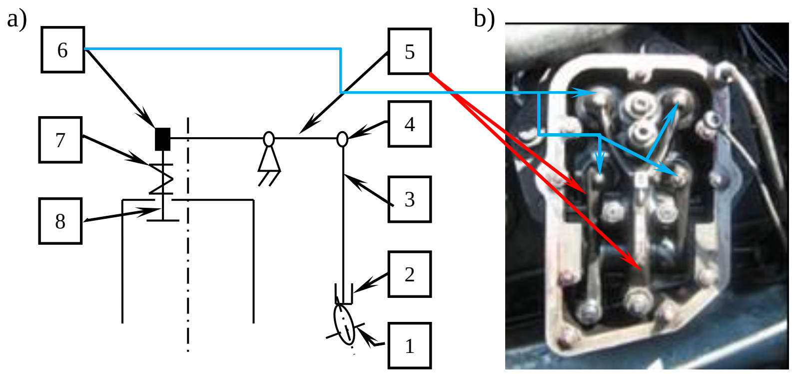


Figure 1. a) diagram of the timing system used in the engine; 1 – camshaft, 2 – tappet, 3 – push rod, 4 – screw valve lash adjustment mechanism, 5 – rocker arm, 6 – automatic valve backlash compensator, 7 – valve spring, 8 – valve; b) engine head timing system

Measurements were made in accordance with the principle of three starts, i.e. each series of measurements was made three times and between each series of measurements the engine was shut down. The method described above was used in order to avoid random values of parameters of vibration signal characteristics.

The general scheme of the measurement system used to record vibration signals during impulse tests is shown in Figure 2.

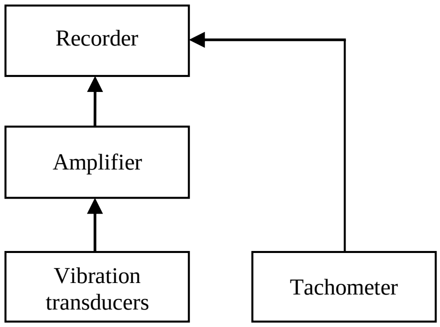


Figure 2. Diagram of the measuring system used for measuring engine head vibrations during operation [1]

Brüel&Kjær type 4504 vibration acceleration transducers have been selected based on the guidelines contained in [35], and the linear frequency response of the selected transducers was up to 18 kHz. During the tests, signals in the 0.1 Hz-25 kHz band were recorded. The vibration measurement directions were as follows: X direction parallel to the cylinder diameter and set at 45° to the crankshaft axis, Z direction parallel to the cylinder axis, and Y direction perpendicular to the other two. The sampling rate was set to 65536 Hz. To record vibration signals, a Brüel & Kjær PULSE multi-analyzer was used, which enables recording of fast alternating signals in parallel on 17 channels with dynamics up to 160 dB.

The vibration transducers were mounted on the combustion engine head with glue. When choosing the measurement locations, the principle was adopted that the transducer should be as close as possible to the place of vibration signal generation associated with the operation of the valves and in an accessible place [36]. The selection of the vibration measurement point was preceded by an analysis of the head design, research on the influence of diesel engine valve clearance on selected vibration parameters and impulse tests consisting in hitting valves on valve seats. The impacts were carried out by removing the gauge block placed between the valve stem and the lever. This was repeated several times for each valve to eliminate random errors and perform the averaging process. It was important to establish a vibration signal measurement point that would allow the impact of each valve to be assessed. Considering the dynamics of the signals recorded during the impulse tests, it was decided that the signals registered in the X, Y and Z directions will be taken into account for the testing of the correctness of the operation of the automatic valve clearance compensators.

Tests of the working engine were carried out at: crankshaft speed of 500 rpm, no external load (drive unit's own resistance), and coolant temperature maintained at 75°C.

Figures 3 and 4 show exemplary cut-out fragments of the time signal relating to the closing moments of the inlet and exhaust valves for the working and faulty condition of the compensator. The cut out fragments were obtained based on information about the position of the shaft identified by a marker.

The waveforms in Figures 3 and 4 show clear responses of the system to the stimulation by hitting the valve on the valve seat. In the case of the exhaust valve, another fading signal can also be seen, but in a slightly lower frequency range (see the time-frequency analysis in Figure 5). Since the origin of the individual fragments of the structure response associated with the exhaust valve closure was not identified, it was decided to consider the whole section together. At this stage it is also difficult to determine why the signals associated with each valve are significantly different when the compensator is operating correctly. Minor signal shifts in time for the sample waveforms in working and faulty conditions of the compensators result from unevenness in the motor speed. In the case of an inlet valve, the identification of a compensator malfunction is very simple based on the simplest estimates, while in the case of an exhaust valve it is not so obvious.

a)

b)

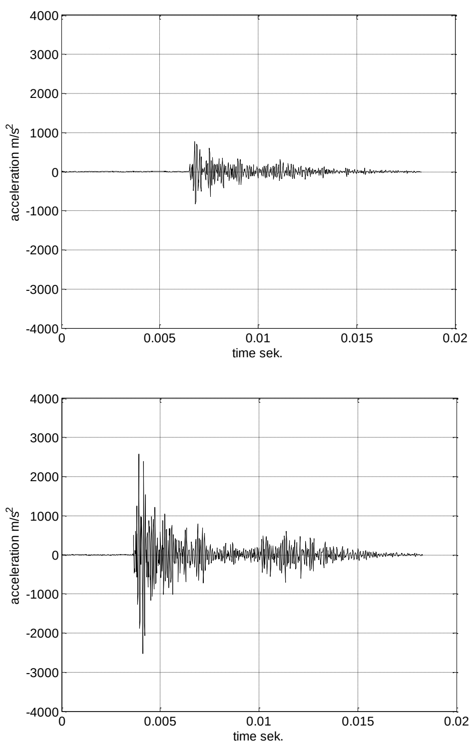
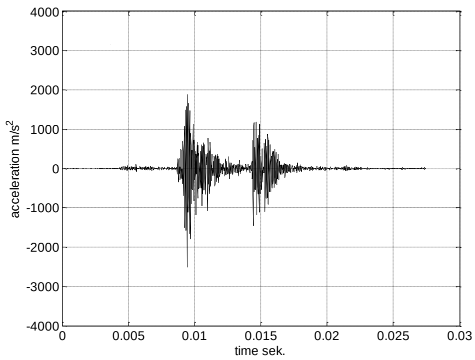


Figure 3. Cut-out sequences associated with inlet valve closing - measuring direction X; a) correctly functioning compensator; b) incorrectly operating compensator

a)



b)

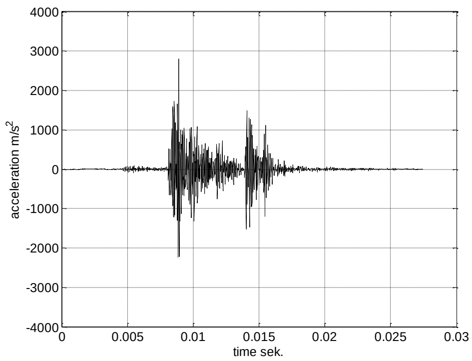


Figure 4. Cut-out sequences associated with exhaust valve closing - measuring direction X; a) correctly functioning compensator; b) incorrectly operating compensator

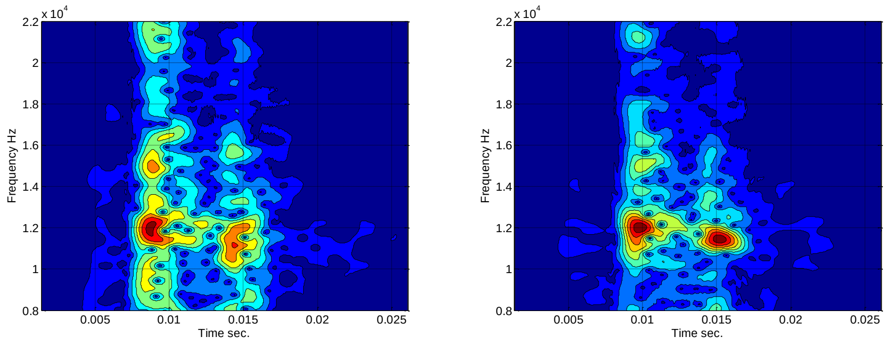


Figure 5. Short-Time Fourier Transform for the signals shown in Figure 4

Table 1 shows the rms values of vibration accelerations determined on the cut-out fragments of the signal for individual cases. As one can see, in the case of the inlet valve, distinguishing the state of the compensator is very simple on the basis of even the rms value calculated in the whole band, and any possible mistake in determining the class is very unlikely. In the case of signals concerning the exhaust valve, the consideration of the rms value alone may not be sufficient to delimit the classes. An attempt can be made to laboriously obtain other measures that would give better distinguishability here. Another solution is to determine multiple measures and use a learning system based on examples, which itself will choose the right measures from the set of proposed ones.

Table 1. Rms values of vibration accelerations
determined on the cut-out sections of the signal for individual cases

Data set	RMS [m/s^2]	Three times the standard deviation RMS [m/s^2]
Inlet valve – compensator in working order	98.8	18.6
Inlet valve – compensator out of order	266.1	80.4
Exhaust valve – compensator in working order	252.3	117.3
Exhaust valve – compensator out of order	355.2	75.9

3. Data analysis

Due to the lack of precise identification of phenomena and the difficulty in constructing an explicit model combining vibration signal estimates and the compensator state class, as well as due to the need to use several measures simultaneously to determine this state, an approach based on machine learning, specifically using classification trees, was applied. From the obtained recordings of acceleration waveforms, appropriate sections were cut out, obtaining examples of correct operation and compensator malfunction determining the inlet and exhaust valve operation. Table 2 summarizes the number of cases obtained.

Table 2. Summary of the number of cases obtained

Data set	Number of examples
Inlet valve – compensator in working order	489
Inlet valve – compensator out of order	374
Exhaust valve – compensator in working order	371
Exhaust valve – compensator out of order	492

In the first stage of construction of the classifier, the obtained waveforms were parameterized. On the basis of the analyzed signals the following parameters were determined in the band up to 32 kHz: coordinates of the center of gravity of the waveform, abscissa of the center of gravity of the signal square, rms value in the whole band, ordinary, central and central normalized moments of the first and second order, upper peak, lower peak, and interpeak value. In addition, the rms values of the signal were determined in 10 separate frequency bands (the width of each band was about

3.2 kHz). The division of the measurement band into 10 intervals was arbitrary. All the measures were determined for the three measuring directions X, Y, Z obtaining a total of 72 features. As an output two possible states were assumed: the compensator is in working order and technically inoperative. Further steps have been taken separately for signal fragments related to the inlet and exhaust valves. The CART (classification and regression tree) binary tree based in the assessment of the quality of the division on Gini index was used as the classifier. The next step was to optimize the parameter defining the minimum number of examples in a leaf. For this purpose, a cross validation test for k = 10 (10 fold cross validation on the training data) was used. The minimum number of observations in a leaf was being changed from 1 to 10. The classification error was averaged. Figure 6 shows the obtained dependence of the classification error on the minimum number of observations in the leaf for data related to the more difficult case - the classification of the condition of the exhaust valve.

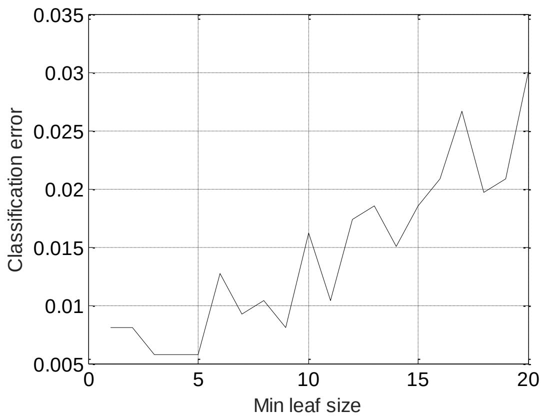


Figure 6. The dependence of the classification error on the minimum number of observations in the leaf for the data related to the classification of the exhaust valve

The optimal values of the hyperparameter in question turned out to be 1 (for signals concerning inlet valve closing, and 4 (or 5) for exhaust valve closing). The features of the input vectors present in trees were also identified. It turned out that in the case of the inlet valve, one feature was sufficient to unambiguously determine the state class - the abscissa of the center of gravity of the signal square calculated over the entire band and the X direction. The state distinction for inlet valve related signals is obvious and does not actually require a multi-feature approach. For signal sections related to the closing of the exhaust valve, two rms values calculated in the appropriate bands proved to be the dominant features. The rms value of the vibration acceleration signal measured in the X direction for the band from 6.4 to 9.6 kHz (i.e. in the band not coinciding with that with maximum amplitudes - see Figure 5) and the rms value of the vibration acceleration signal measured in the Z direction for the band from 3.2 to 6.4 kHz proved to be important.

Table 3 presents the average values of the classification error obtained by means of the aforementioned cross-validation test for individual signal sections, as well as for classifiers based on all features and on features limited to the best ones. It should be noted that during the construction process the algorithm selects the most important features due to the quality of data division in a given node. However, it may turn out that for some of the pseudo-samples drawn during the cross-validation test, these may be different features. Therefore, both cases of tree construction, based on all available features and limited to the most relevant ones, may give a different assessment of the classification error.

Table 3. Average values of the classification error for individual cases

Identification of the state	Average classification error [%] for all features	Average classification error [%] for the most important features
Compensator – inlet valve	0.0	0.0
Compensator – exhaust valve	0.9	0.8

As shown in Table 3, the identification of the compensator malfunction for the inlet valve is error-free and, as mentioned above, requires only one signal feature. For the exhaust valve, the error is less than 1% regardless of whether the best features or all available ones will be used to build the classifier. It turns out that the smaller testing error, i.e. related to the pseudo-sample not used at the moment for construction of the classifier, can be obtained taking into account only two features, from which the tree must be built.

4. Conclusions

The proposed methodology may be used to build a system for identification of valve lash compensators malfunctions. It should be noted that the classification of the state of the compensators based on the vibration acceleration signal and simple signal measures can be determined with negligible error and, in addition, based on a small number of measures. The built trees enable to generate simple diagnostic rules (one rule to determine the state of the inlet valve backlash compensator and a set of two rules for the second case), which in a very simple way allows the implementation of the solution in a simple system in terms of hardware construction. Even more accurate results with an exhaust valve compensator can be obtained by classifying several successive engine work cycles and, in case of contradictions, selecting the class that has been identified the most frequently. During motor operation, a very large number of repetitions of this state recognition can be achieved. The only difficulty in the construction of the system is the need to mount a marker determining the position of the shaft, but in modern engines such information is available in the engine ignition control systems.

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