ATTEMPT TO UTILISE HISTOGRAM OF VIBRATION CEPSTRUM OF ENGINE BODY FOR SETTING UP THE CLEARANCE MODEL OF THE PISTON-CYLINDER ASSEMBLY FOR PNN NEURAL CLASSIFIER

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Abstract

The paper presents an attempt to evaluate the wear of piston-cylinder assembly with the aid of vibration signal recorded on spark ignition (SI) engine body. The subject of the study was a four-cylinder combustion engine 1.2 dm^3. Diagnosing combustion engines with vibration methods is specifically difficult due to the presence of multiple sources of vibration interfering with the symptoms of damages. Diagnosing engines with vibro-accoustic methods is difficult also due to the necessity to analyse non-stationary and transient signals [5]. Various methods for selection of usable signal are utilised in the diagnosing process. Changes of the engine technical condition resulting from early stages of wear are difficult to detect for the effect of mechanical defect masking by adaptive engine control systems [3]. According to the studies carried out, it is possible to utilise artificial neural networks for the evaluation of the clearance in piston-cylinder assembly. It was proven that it is possible to set up a properly operating neural classifier able to identify the degree of wear in the piston-cylinder assembly, based on the signal of vibration acceleration in the engine body. Faultless classification was successfully obtained with the use of probabilistic neural network with properly selected value of γ coefficient. At the same time, based on the experiments carried out, the crucial role was confirmed for the selection of proper method for pre-treatment of data intended for neural network teaching.

Keywords: diagnostics, combustion engines, artificial neural networks, vibration

1. Introduction

Diagnostic systems used in modern combustion engines are intended to localise the component or system which, due to natural wear or damage, can no longer perform as specified by its manufacturer. For engines, the highest efficiency of on-board diagnostics has been achieved in the field of toxic emission control. Some defects, however, such as the wear of cylinder bearing surface above the admissible limits, for a given engine, in many cases cause no reaction of the diagnostic system. In most cases, this is attributable to the algorithms for adaptation controls of combustion engines [6]. One of the methods for diagnostic data acquisition is to monitor the level of vibration generated by engine components.

The present paper describes an attempt to detect clearance in the piston-crank assembly by measuring the accelerations of body vibrations and, based on that, setting up models for probabilistic artificial neural networks.

2. Setting up the model for piston-cylinder assembly clearance

The major issue referred to in the literature related to methods of artificial intelligence is the method for creating data used in the process of neural network operations. The ability to set up models is the guarantee for a successful classifying process using neural networks [2, 4, 7 - 10].

Data in the experiments carried out is derived from time runs of the vibration accelerations in the engine body. The subject of tests was a Fiat Panda with SI engine 1.2 dm^3. The tests were carried out in Bosch FLA 203 roller bench. The vibration acceleration signal of the engine body was measured perpendicularly to the cylinder axis with a sensor placed at the 4th cylinder.

Vibration acceleration transducer type ICP 320C15 by PCB Piezoelectronics and data acquisition card NI PCI-6143 controlled by a program developed in LabView environment were used for the measurements. The signals were recorded at the velocity of 2500 rpm, at the sampling frequency of 40 kHz. During the tests, 23 runs of accelerations of the engine body vibration were recorded before the repair, and 27 runs of accelerations of the engine body vibration were recorded after the repair, including full operating cycles within the rotation angle of 0-720°. The engine repair involved the replacement of worn pistons which reduced the clearance in the piston-cylinder assembly.

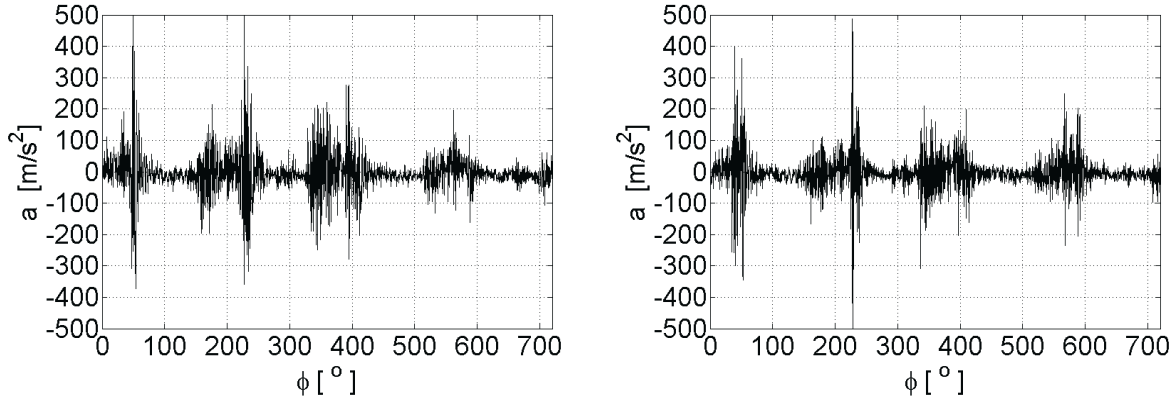Refer to Fig. 1 for examples of vibration signals recorded before and after the repair.

Fig. 1. Vibration acceleration runs recorded on the body before (a) and after (b)the engine repair

The analysis of time runs excluded the possibility to use them directly as the data for neural classifiers. The repair of the engine did not explicitly affect the character of changes in local measurements derived from the vibration signals. Both, the measurements of average position, differentiation, the group of slope measure and the distribution kurtosis of measurable variants of vibration accelerations in time domain did not allow the clearance in the piston-cylinder assembly to be explicitly identified.

According to the studies carried out to date, wherever the vibro-accoustic signal can be presented as a series of elementary events, the cepstrum analysis can be useful:

$$C(\tau) = \sqrt{\left|FFT\left[\log\left(G_{uu}(f)\right)\right]^2\right|}, \qquad (1)$$

where:

$G_{uu}(f)$ - densities of spectral power.

Occurrence of noise, especially of periodic nature, is possible to be identified with that analysis [1]. It allows to separate the series components respectively to the pulse response of the system and the initiation [11]. Series identity is used here in the time domain with the product of Fourier transforms in the frequency domain. For the diagnostics of technical facilities, the cepstrum analysis is used for all applications in which the change of state results in the appearance or disappearance of harmonics. Cepstrum was determined from the recorded accelerations of engine body vibrations.

Refer to Fig. 2 for examples of cepstrum derived from the vibration signal for two different states of the engine.
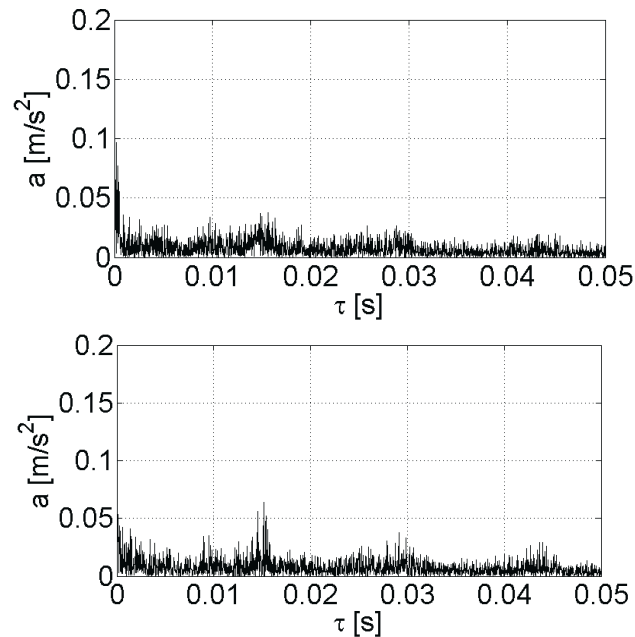
Fig. 2. Cepstrum of vibration accelerations recorded o the body before (a) and after (b)the engine repair

According to the studies, signal analysis in two selected representative frequency ranges is required to evaluate the piston-assembly wear. Therefore, in the next stage of model construction, the cepstrum range achieved was divided into 5 sub-ranges:

- sub-range I: 0 to 0.01 [s],
- sub-range II: 0.01 to 0.02 [s],
- sub-range III: 0.02 to 0.03 [s],
- sub-range IV: 0.03 to 0.04 [s],
- sub-range V: 0.04 to 0.05 [s].

Refer to Fig. 3 for separated cepstrum ranges for sample runs of engine body vibration before the repair, and Fig. 4 - after the repair.

A histogram was prepared to enable the description of the character of cepstrum changes for each sub-range. The limits of the histogram ranges were assumed by dividing the amplitude of cepstrum (determined for the maximum value of a given sub-range) into 5 equal parts. Based on the initial experiments, it was found that better results are obtained by assuming the value of the maximum cepstrum amplitude range, separately for signals recorded prior to and after the engine repair, than for the range determined based on all recorded signals, either before, or after the repair. The histogram ranges assumed for further experiments are as follows:

- range 1: 0 to 20% maximum cepstrum amplitude in a given sub-range,
- range 2: 20 to 40% maximum cepstrum amplitude in a given sub-range,
- range 3: 40 to 60% maximum cepstrum amplitude in a given sub-range,
- range 4: 60 to 80% maximum cepstrum amplitude in a given sub-range,
- range 5: 80 to 100% maximum cepstrum amplitude in a given sub-range.

Refer to Fig. 5 for an example of cepstrum histogram for accelerations of engine body vibrations with various clearance values in the piston-cylinder assembly.

For all recorded time runs of the accelerations of vibration measured prior to and after the engine repair, cepstrum histograms were determined according to the procedure described.

Another stage of the modelling process was to select only those ranges of cepstrum amplitude (range 1 - 5) and only such cepstrum sub-ranges (sub-range I - V) for which the separation for classes referring to the worn and new pistons was visible. Refer to Fig. 6 for a sample comparison

of cepstrum sub-range and histogram range for correct and incorrect classes separation.

As a result of selections which best separate the states prior to and after the engine repair, 15 comparisons between the cepstrum sub-range and histogram range were selected. Percent share of selected comparisons served as the input data for artificial neural networks.
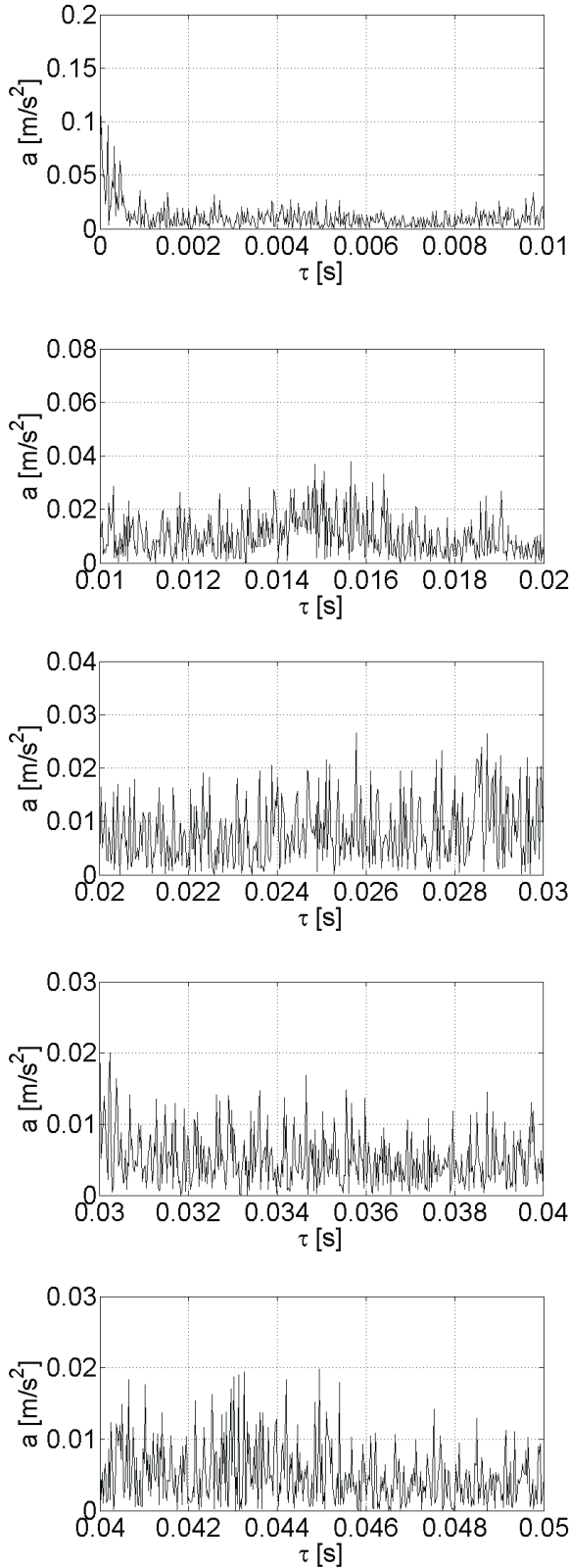

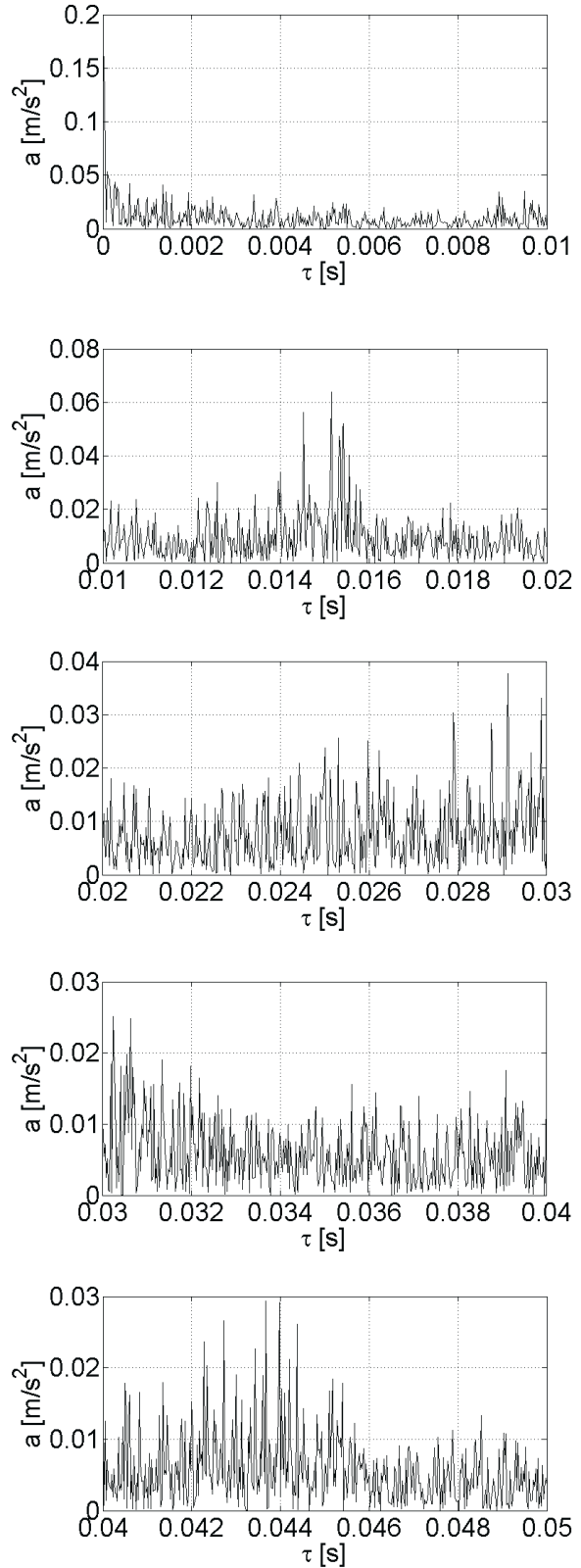*Fig. 3. Cepstrum ranges for vibration accelerations recorded o the body before the engine repair*

Fig. 4. Cepstrum ranges for vibration accelerations recorded o the body before after the engine repair
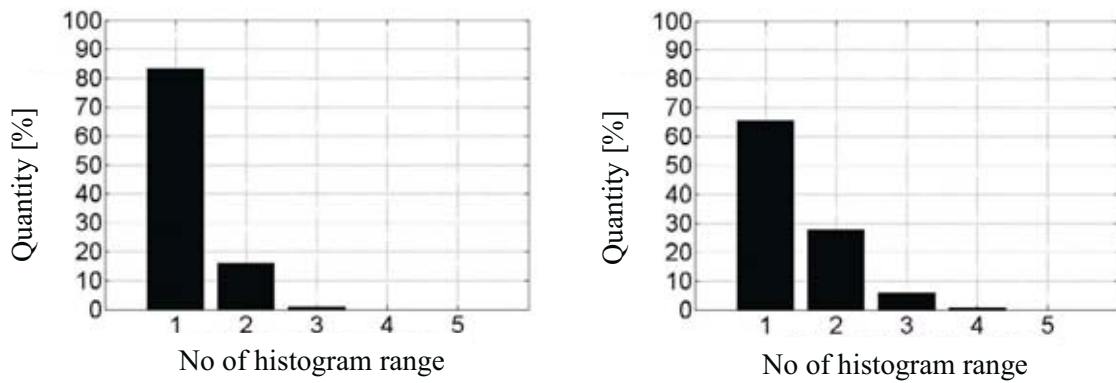
Fig. 5. *Sample cepstrum histogram of vibration accelerations recorded o the body before (a) and after (b)the engine repair*
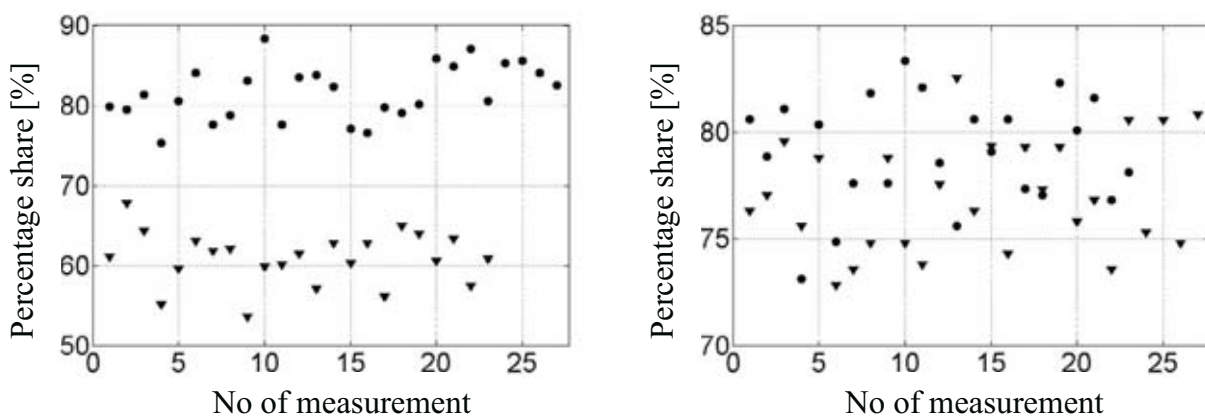

Fig. 6. *Sample comparison between the cepstrum sub-range and histogram range for the correct (a) and incorrect (b) separation of wear classes of the piston-cylinder assembly („triangle" – engine prior to repair, „circle"engine after repair)*

3. Neural classifier for the piston-cylinder assembly clearance

For the studies carried out, artificial neural networks of PNN type were utilised (Probabilistic Neural Networks). The probabilistic neural networks are used as the neural classifiers dividing the set of data into a determined number of output categories [4]. They are of three-layer structure: input, hidden and output layer [4, 10]. The number of hidden neurons equals the number of teaching samples, and the number of output neurons equals the number of classification categories. Each radial neuron models the Gauss function focusing on one teaching model. Output neurons sum up the output values of hidden neurons belonging to the class which corresponds to a given output neuron. The network output values are proportional to the nucleus estimators of the probability density function for various classes. Following the application of normalisation ensuring summing up to one, they produce estimation of the probability of belonging to individual classes [10]. While using such network type, proper smoothening coefficient γ should be selected [4, 10]. It represents the radial deviation of Gauss functions and is a measure of the range of neurons in the hidden layer [10]. This value, when too low, causes the loss of knowledge generalising property by the network, and, if too high, prevents the correct description of details [2]. Similarly to the radial networks, the value of γ coefficient is determined experimentally [2, 10]. One the greatest advantages of PNN type networks is their high learning speed, whereas their complexity [10] is the main drawback.

In the experiments carried out, the probabilistic neural networks had the following structure:
- number of input neurons: 15,

- number of output neurons: 2,
- number of neurons in the hidden layer: 50.

The input data represented the percent shares in selected subsequent cepstrum sub-range comparisons with the histogram ranges.

The neural network was expected to assign the recorded vibration signal to one of two classes corresponding to the engine prior to and after its repair.

50 time runs of the engine body vibration accelerations were divided into two equal parts and utilised for teaching and testing the performance of neural networks.

In the experiments aimed at the construction of a proper neural classifier of PNN type, the performance of the network for 86 various values of γ coefficient were checked.

The results of the effect of the γ coefficient on the classification error value are presented in Fig. 7.
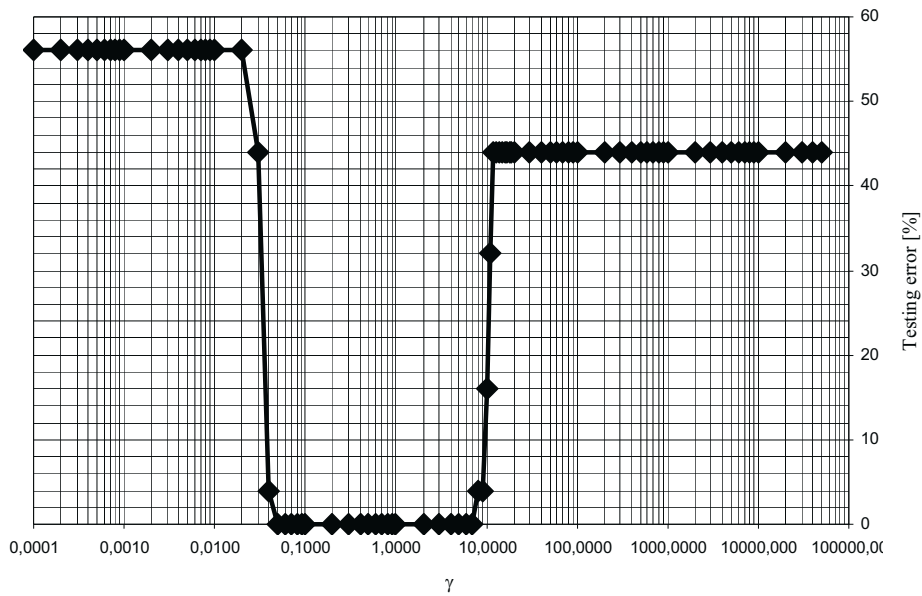

Fig. 7. The effect of the γ coefficient on the correctness of the PNN neural network classification

With the experiments carried out, it was possible to set up properly operating neural classifier. Such result was obtained for γ coefficient value within the range 0.05 - 7. For γ coefficient in the value range 0.0001 - 0.04 and 8 - 50000 significant increase of the classification error was noticeable.

4. Summary

With the studies carried out, it was proven that it is possible to set up a properly operating neural classifier able to identify the degree of wear in the piston-cylinder assembly, based on the signal of vibration acceleration in the engine body. Faultless classification was successfully obtained with the use of probabilistic neural network with properly selected value of γ coefficient.

At the same time, based on the experiments carried out, the crucial role was confirmed for the selection of proper method for pre-treatment of data intended for neural network teaching. The results obtained confirmed the usefulness of the cepstrum histogram of the acceleration of engine body vibration for that purpose.

The efficiency of OBD systems allowing the detection of engine mechanical defects masked by electronic controls in modern vehicles can be increased by the development of systems utilising probabilistic artificial neural networks.

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