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HENRYK MADEJ*, PIOTR CZECH**

Application of the histogram of the vibration spectrum of an engine block for setting up the clearance model of the piston-cylinder assembly for PNN neural classifier

K e y w o r d s

Diagnostics, combustion engines, artificial neural networks, vibration.

S ł o w a k l u c z o w e

Diagnostyka, silniki spalinowe, sztuczne sieci neuronowe, drgania

S u m m a r y

The paper presents an attempt to evaluate the wear of piston-cylinder assembly with the aid of a 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 especially 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 a 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 masked 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.

* Silesian University of Technology, Faculty of Transport, 8 Krasińskiego St., 40-019 Katowice, e-mail: henryk.madej@polsl.pl
** Silesian University of Technology, Faculty of Transport, 8 Krasińskiego St., e-mail: piotr.czech@polsl.pl

1. Introduction

Diagnostic systems used in modern combustion engines are intended to localise the component or system that, 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 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, 6-15].

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 the roller bench. The vibration acceleration signal of the engine body was measured perpendicularly to the cylinder axis with a sensor placed at the 4^{th} cylinder. The vibration acceleration transducer type ICP and data acquisition card 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 0-720º. The engine repair involved the replacement of worn pistons that reduced the clearance in the piston-cylinder assembly.

Refer to Figure 1 for examples of vibration signals recorded before and after the 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 (Table 1). 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.

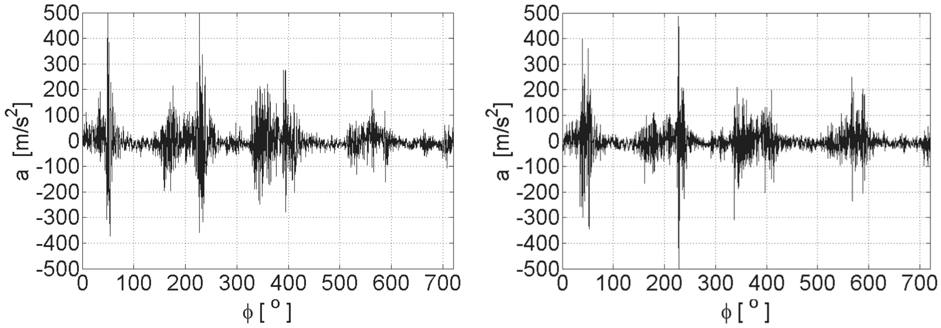

Fig. 1. Vibration acceleration runs recorded on the body before (a) and after (b) the engine repair
Rys. 1. Przebiegi przyśpieszeń drgań zarejestrowane na korpusie przed (a) i po (b) naprawie silnika

Table 1. Selected measures obtained from vibration accelerations
Tabela 1. Przykładowe miary wyznaczone z sygnałów czasowych

	Name of measure	**Value of measure for engine**		**Δ [%]**
		before repair	**after repair**	
1	Root mean square $X_{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_i(t) - \overline{X}\right)^2}$	101.2600	95.3200	5.8611
2	Mean value $\overline{X} = \frac{1}{N}\sum_{i=1}^{N}\lvert x_i(t)\rvert$	50.2920	48.3720	3.8175
3	Mean absolute deviation $X_{MAD} = \frac{1}{N}\sum_{i=1}^{N}\lvert x_i(t) - \overline{X}\rvert$	49.9510	48.1990	3.5063
4	Kurtosis $K = \frac{\frac{1}{N}\sum_{i=1}^{N}\left(x_i(t) - \overline{X}\right)^4}{\left(X_{RMS}\right)^4}$	13.8170	14.1390	-2.3309
5	Crest factor $CF = \frac{X_{peak}}{X_{RMS}}$	9.8759	10.4910	-6.2260
6	Clearance factor $CLF = \frac{\overline{X}}{\left(\frac{1}{N}\sum_{i=1}^{N}\sqrt{\lvert x_i(t)\rvert}\right)^2}$	1.3834	1.3769	0.4678
7	Shape factor $SF = \frac{X_{RMS}}{\overline{X}}$	2.0133	1.9706	2.1247
8	Impulse factor $IF = \frac{X_{peak}}{\overline{X}}$	19.8840	20.6730	-3.9690

Refer to Figure 2 for examples of spectrum derived from the vibration signal for two different states of the engine.

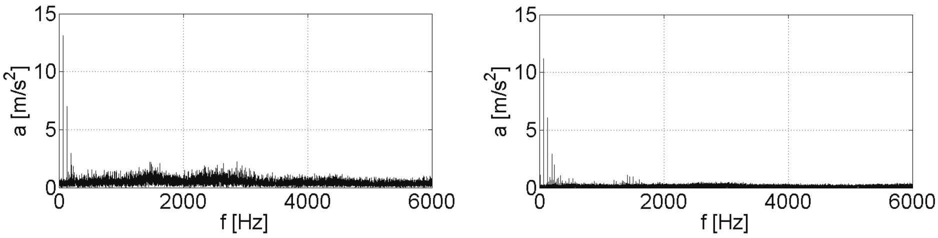

Fig. 2. Spectrum of vibration accelerations recorded o the body before (a) and after (b) the engine repair
Rys. 2. Widmo przyśpieszeń drgań zarejestrowanych na korpusie przed (a) i po (b) naprawie silnika

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 spectrum range achieved was divided into 40 sub-ranges, 500 [Hz] width each.

A histogram was prepared to enable the description of the character of spectrum changes for each sub-range (Figure 3). The limits of the histogram ranges were assumed by dividing the amplitude of spectrum (determined for the maximum value of a given sub-range) into 5 equal parts. The histogram ranges assumed for further experiments were as follows:

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

Refer to Figure 4 for an example of spectrum histogram for accelerations of engine body vibrations with various clearance values in the piston-cylinder assembly.

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

Another stage of the modelling process was to select only those ranges of spectrum amplitude (range 1 – 5) and only such spectrum sub-ranges (sub-range 1 – 40) for which the separation for classes referring to the worn and new pistons was visible. Refer to Figure 5 for a sample comparison of spectrum sub-range and histogram range for correct and incorrect classes separation.

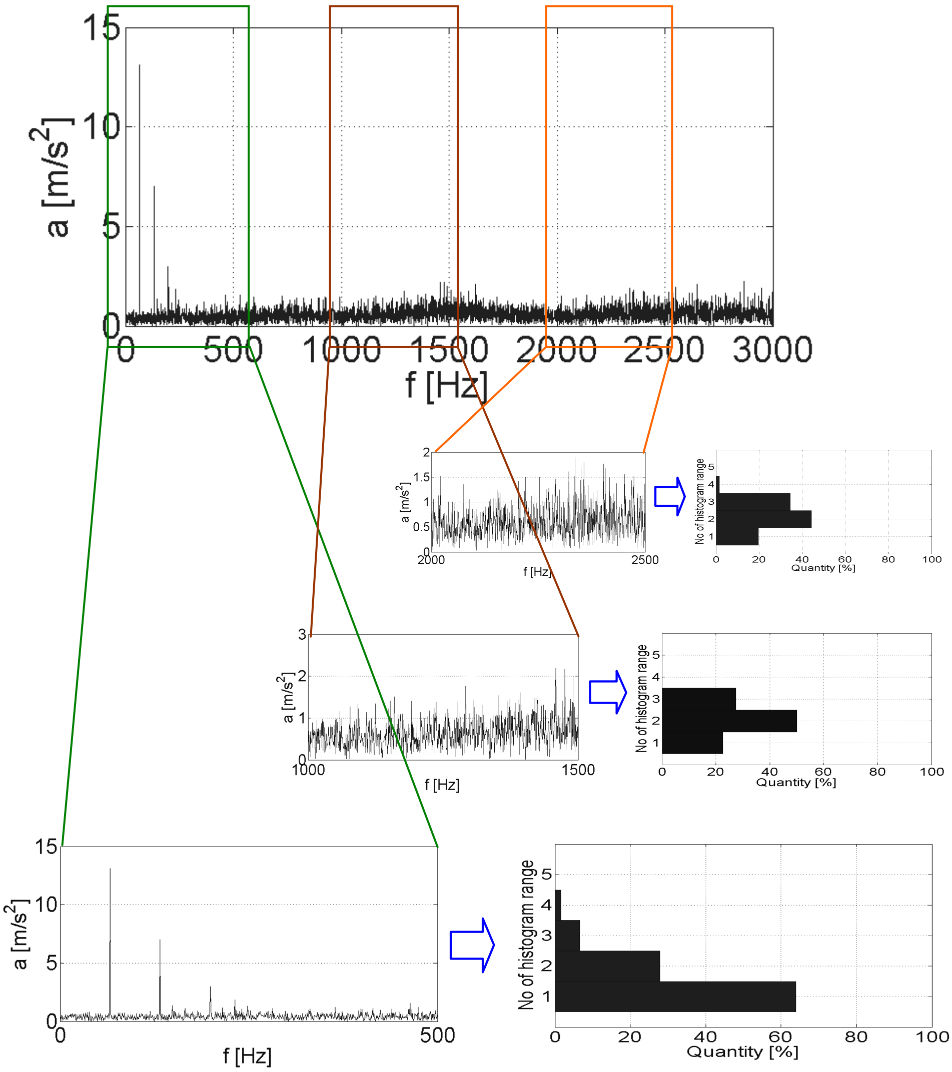

Fig. 3. Procedure of spectrum histograms determination
Rys. 3. Schemat działania przy budowie histogramów

As a result of selections that best separate the states prior to and after the engine repair, 17 comparisons between the spectrum sub-range and histogram range were selected. The percentage share of selected comparisons served as the input data for artificial neural networks.

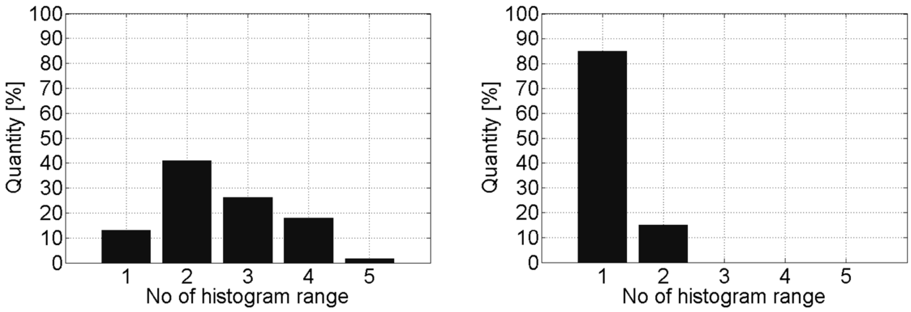

Fig. 4. Sample spectrum histogram of vibration accelerations recorded on the body before (a) and after (b) the engine repair

Rys. 4. Przykładowy histogram widma przyśpieszeń drgań zarejestrowanych na korpusie przed (a) i po (b) naprawie silnika

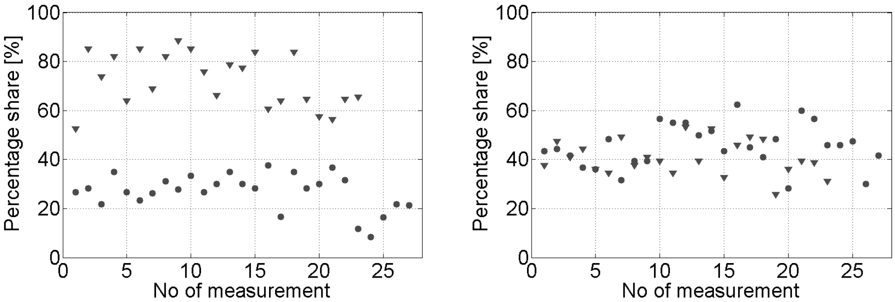

Fig. 5. Sample comparison between the spectrum sub-range and histogram range for the correct (a) and incorrect (b) separation of wear classes of the piston-cylinder assembly ("triangle" – engine prior to repair, "circle" – engine after repair)

Rys. 5. Przykładowe zestawienie podzakresu widma i zakresu histogramu dla poprawnego (a) i błędnego (b) odseparowania klas zużycia złożenia tłok–cylinder („trójkąt" – silnik przed naprawą, „koło" – silnik po naprawie)

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 [4,14]. 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 [14]. While using this network type, proper smoothening coefficient γ should be selected [4,14]. It represents the radial deviation of Gauss functions and is a measure of the range of neurons in the hidden layer [14]. This value, when too low, causes the loss of knowledge generalising property by the network, and, if too high, prevents correct description of details [2]. Similarly to the radial networks, the value of γ coefficient is determined experimentally [2,14]. One the greatest advantages of PNN type network is its high learning speed, whereas their complexity [14] is the main drawback.

In the experiments carried out, the probabilistic neural networks had the following structure (Figure 6):

– Number of input neurons: 17,
– Number of output neurons: 2, and
– Number of neurons in the hidden layer: 50.

The input data represented the percentage shares in selected subsequent spectrum 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.

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

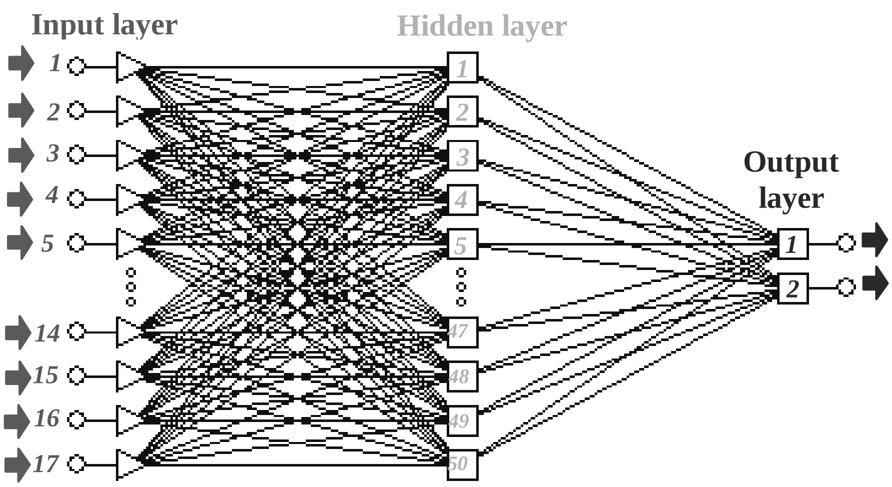

Fig. 6. Structure of neural networks
Rys. 6. Struktura sieci neuronowej

In the experiments aimed at the construction of a proper neural classifier of a 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 Figure 7.

With the experiments carried out, it was possible to set up a properly operating neural classifier. This result was obtained for γ coefficient value within the range 0.04-12. For γ coefficient in the value range 0.0001-0.02 and 15-50000 significant increase of the classification error was noticeable.

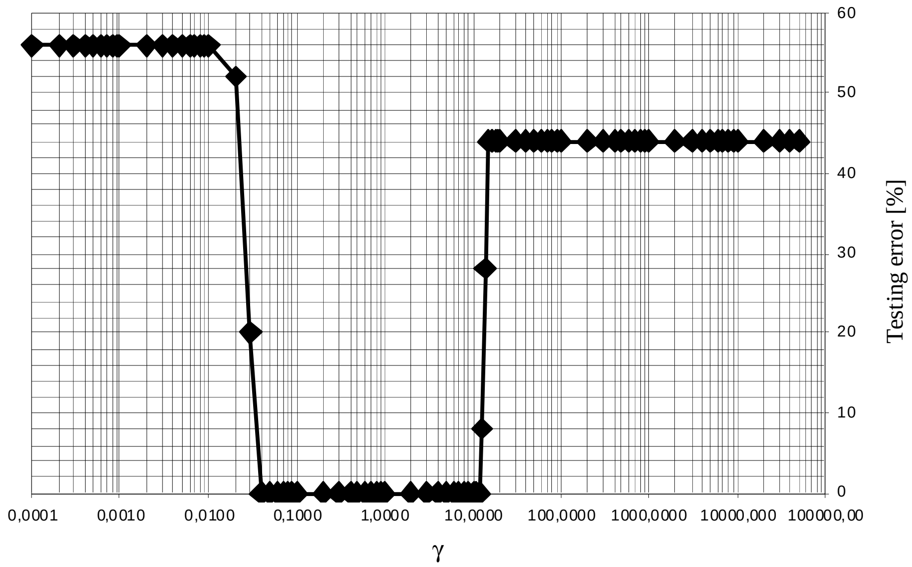

Fig. 7. The effect of the γ coefficient on the correctness of the PNN neural network classification
Rys. 7. Wpływ wartości współczynnika γ na poprawność klasyfikacji sieci neuronowej PNN

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 the proper method for pre-treatment of data intended for neural network training. The results obtained confirmed the usefulness of the spectrum histogram of the acceleration of the 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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Wykorzystanie histogramu widma drgań korpusu silnika do budowy wzorców luzu w układzie tłok–cylinder dla klasyfikatora neuronowego

S t r e s z c z e n i e

W artykule przedstawiono próbę oceny zużycia złożenia tłok–cylinder za pomocą sygnału drgań rejestrowanego na kadłubie silnika ZI. Obiektem badań był czterocylindrowy silnik spalinowy o pojemności 1,2 dm^3. Diagnozowanie silnika spalinowego metodami drganiowymi jest

szczególnie utrudnione ze względu na występowanie wielu źródeł drgań, co jest przyczyną wzajemnego zakłócania symptomów uszkodzeń. Diagnozowanie uszkodzeń silników metodami wibroakustycznymi jest trudne także ze względu na konieczność analizy sygnałów niestacjonarnych i impulsowych [5]. W procesie diagnozowania stosuje się różne sposoby selekcji sygnału użytecznego. Zmiany stanu technicznego silnika wywołane wczesnymi fazami jego zużycia są trudne do wykrycia ze względu na maskowanie usterek mechanicznych przez adaptacyjne układy sterowania silnika [3]. Z przeprowadzonych badań wynika, że istnieje możliwość wykorzystania sztucznych sieci neuronowych do oceny luzu w układzie tłok–cylinder.