IC ENGINE VALVE FAULT DETECTION USING ENERGY DISTRIBUTION OF DIFFERENT RESOLUTION LEVELS OF DWT AS A INPUT DATA TO PNN CLASSIFIER

Henryk Madej, Piotr Czech

Silesian University of Technology, Faculty of Transport
Krasińskiego Street 8, 40-019 Katowice, Poland
tel.:+48 32 6034107, fax: +48 32 6034108
e-mail: henryk.madej@polsl.pl, piotr.czech@polsl.pl

Abstract

This article presents the attempt to detect the valve faults in the engine by using the vibroacoustic signal registered on the SI engine block. The object of the research was 4-cylinder 4-stroke with eight valves 1.3 l SI engine. The vibration energy cased by combustion process depends on the average rotation speed and the crankshaft position. Mechanical faults which are having an impact on combustion pressure and misfire cause temporary changes of the rotational speed and instantaneous energy spectral density. Form the research analyzed it shows that there is a possibility of using artificial neural networks to assess the condition of the valves in the combustion engines.

As part of the study, the descriptors calculated on the basis of the vibration acceleration signal registered on the engine block were proposed to serve as the source of information on the engine condition. The results have corroborated effectiveness of using the signal approximation and detail energy, acquired from the discrete wavelet decomposition, as the base for building models of engine operation.

The use of a probabilistic neural network with a correctly selected value of coefficient γ enables obtaining a faultless classification.

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

1. Introduction

The timing gear system is one of the principal, and precise in their operation, components of the combustion engine. Operational and breakdown wear of such components as the camshaft, pushers, valve springs and levers, as well as valves themselves, has a significant influence on the work of the engine, its performance and reliability. The timing gear system component subject to the highest load, both mechanical and thermal, is the exhaust valve. The valve head temperature reaches locally the value of 700-800°C, and in engines subject to the highest thermal load, it reaches 900°C. This happens as a result of the action of combustion gases, the temperature of which amounts to 900-1000°C, and their speed reaches a value of 600 m/s in the initial phase of opening the valve. The high temperature of the valve head results also from the lack of possibility of its cooling, which only takes place at the moment of contacting the valve-seat. The higher the rotational speed, the less heat will be taken by the head which has a direct contact with the coolant. The seat face of the valve and of the valve head wears out mostly as a result of exposure to streams of combustion gases. The wear of the exhaust valve is a consequence of joint action of repeated strokes during the valve closing, erosive influence of combustion gases with products of incomplete combustion and corrosive effect of flames [8, 14].

A particularly important issue in case of valves is to maintain, for as long as possible, their satisfactory tightness during periods of closure, for insufficient tightness of inlet valves causes a reduction of engine power and an increase of specific fuel consumption. Leakage of exhaust valves affects the engine power to a lesser degree, while the main problem here is a rapid increase of their wear intensity as a result of combustion gas blow-by, which very often leads to a complete damage of valve heads, caused by their burn-out.

Damage of this type results a reduction of effectiveness of action and durability of the catalyst, or its complete destruction. The symptoms of valve burn-out in its first stage can be effectively camouflaged by adaptive systems of control of the combustion engine operation [3, 5-7]. The modern control systems allow taking into account the differences which result from the scatter of parameters connected with tolerances in workmanship of a given engine, and with changes of characteristics caused by wear, which considerably hinders diagnosing of the engine. Detection of valve faults is also quite difficult in case of 6- and 8-cylinder engines. For this reason, it is justified to search for effective methods of processing vibroacoustic signals, which will allow detecting those faults in valves which cause leakage of a combustion chamber already in their initial stage.

2. Setting up the model for the local fatigue crack of an exhaust valve

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, 9-11, 13].

Data in the experiments carried out is derived from time runs of the vibration accelerations in the engine body. The object of tests was a 1.3 dm3 engine of a Ford Fiesta personal car. During tests, carried out on a Bosch FLA203 chassis test bench, acceleration of the head vibration and rotational speed of crankshaft were recorded. The frequency of sampling of vibration signals and rotational speed was 25 kHz. The tests were performed in conditions of a steady rotational speed and during starting. An inductive sensor, being part of engine tooling, was used to measure the instantaneous rotational speed of the crankshaft.

The main purpose of the study was to determine the effect of the simulated local fatigue crack of an exhaust valve of the first cylinder on the changing instantaneous rotational speed and head vibration.

In Fig. 1, an engine head with a damaged exhaust valve is presented.

Fig. 1. Simulated damage of exhaust valve

Measurement of compression pressure has shown that the simulated damage caused its decrease by ca. 20%.

The researches were made for 100% and 66% load engine. The signals were recorded for engine works on 3rd, 4th and 5th number of gear and steady speed: 60, 80, 90, 100, 110, 120 [km/h]. The series were made twice, for engine work without and with damage of exhaust valve. Finally, for each variant of load, speed, number of gear, and damage, 50 runs of accelerations of the engine body vibration was recorded. Everyone of run included 50 full operating cycles within the rotation angle of 0-720º.

Refer to Fig. 2 for examples of vibration signals recorded for engine without and with the simulated local fatigue crack of an exhaust valve.

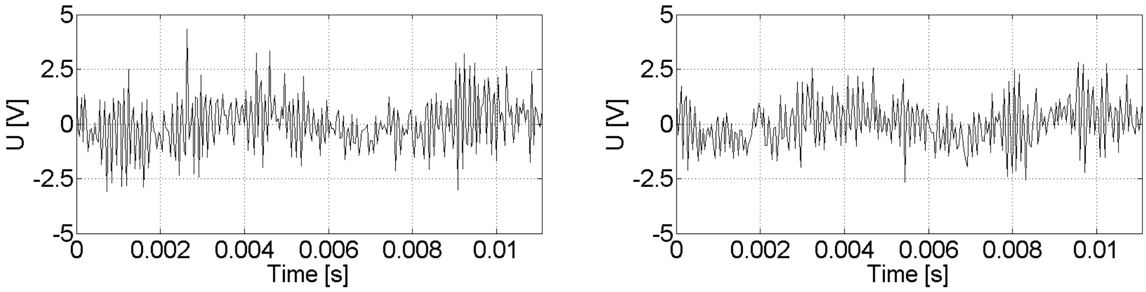

Fig. 2. Signal of head vibration accelerations without (a) and with the simulated local fatigue crack of an exhaust valve (b)

The analysis of time runs excluded the possibility to use them directly as the data for neural classifiers. The simulated local fatigue crack of an exhaust valve did not explicitly affect the character of changes in local measurements derived from the vibration signals [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.

A simultaneous analysis of the time and frequency related properties of signals by means of a wavelet transform is more and more frequently used in diagnosing combustion engines [9, 10, 12].

A wavelet analysis consists in signal decomposition and its presentation as a linear combination of the base functions known as wavelets. The features distinguishing this method of signal analysis from other methods are multilevel signal decomposition, variable resolution in time and frequency domains and the possibility of using base functions other than harmonic functions. In the literature, wavelet analysis is commonly presented in two variants: DWT (Discrete Wavelet Transform) and continuous CWT (Continuous Wavelet Transform).

The discrete wavelet transform (*DWT*) is derived from discretization of *CWT(a,b)*. The most common discretization is dyadic given by:

$$DWT(j,k)=\frac{1}{\sqrt{2^j}}\int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-2^j k}{2^j}\right)dt\,, \tag{1}$$

where a and b are replaced by 2^j and $2^j k$.

The original signal *x(t)* passes through two complementary filters and emerges as low frequency – approximations signals *A(t)*, and high frequency – details signals *D(t)*. The decomposition process can be iterated, with successive approximations being decomposed in turn, such that a signal can be broken down into many lower-resolution components.

The signal x(t) can be represented by:

$$x(t)=A_n(t)+\sum_{l=1}^{n} D_l(t)\,. \tag{2}$$

Wavelet algorithm can be implemented in two opposite directions – decomposition and reconstruction. In the decomposition direction, the discrete signal *x(t)* is convolved with low-pass filter *L* and a high-pass filter *H*, resulting in two vectors *cA1* and *cD1*. The elements of the vector *cA1* are called approximation coefficients, and the elements of vector *cD1* are called detailed coefficients.

As the signal decomposition level increases, the share of details decreases, the result of which is a situation where a reduced resolution is accompanied by a reduced content of details in the signal approximation.

The discrete wavelet transform enables decomposition and selective reconstruction (synthesis) of a signal within the whole range of analysis. It can be compared to signal filtration with a constant, relative band width.

In the conducted experiments, the signals of vibration accelerations underwent decomposition at one to ten levels. Next, the percent of approximations and details energy on levels were measured. The sum of approximations and details energy on levels equals 100% – this is energy of the original signal *x(t)*. The procedure is shown on Fig. 3.

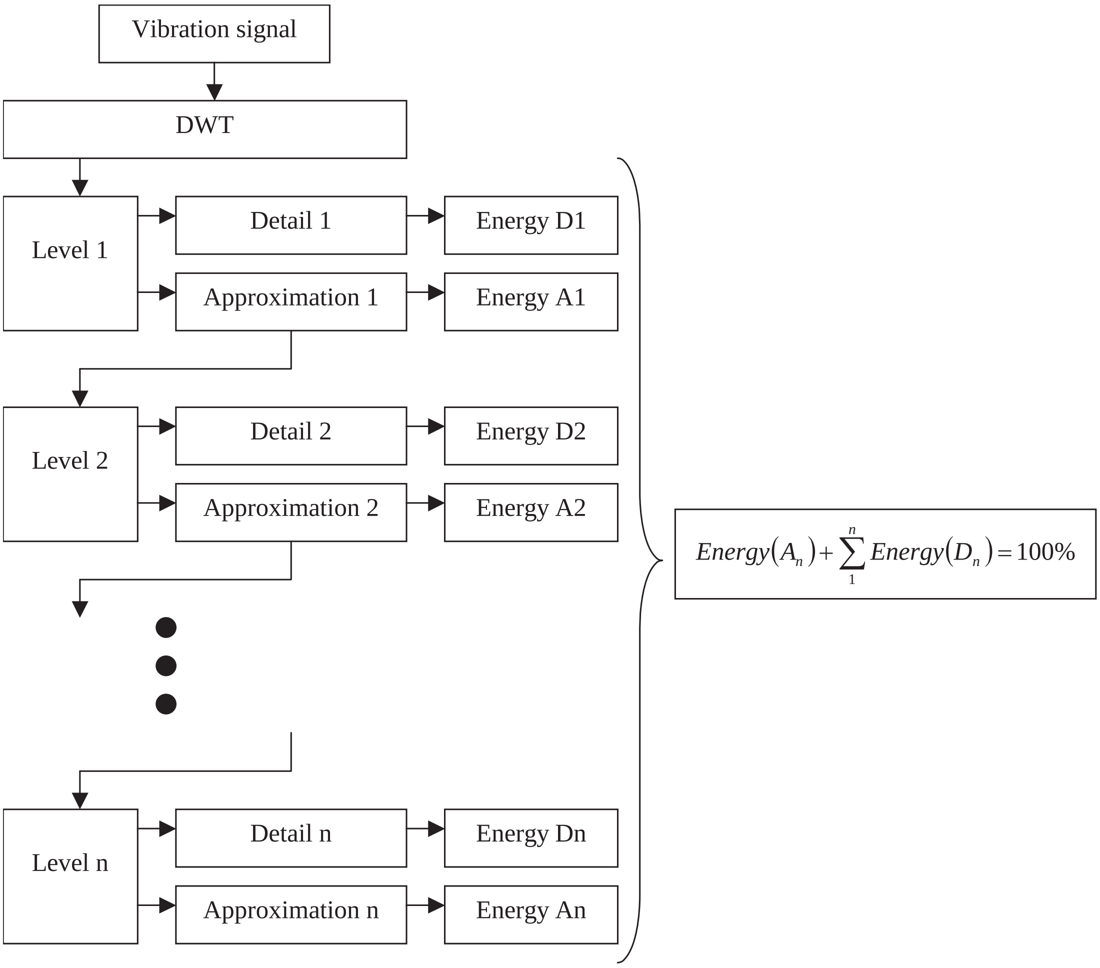

Fig. 3. Procedure of setting up

Nominated results, after conducting the proper process of standardizing and scaling where the input data for neural classifiers built based on probabilistic neural networks.

The exemplary results of energy percentage value contained in detail on second and fifth level decomposition was shown of Fig. 4 as for working engine both, with and without the fault of exhaust valve.

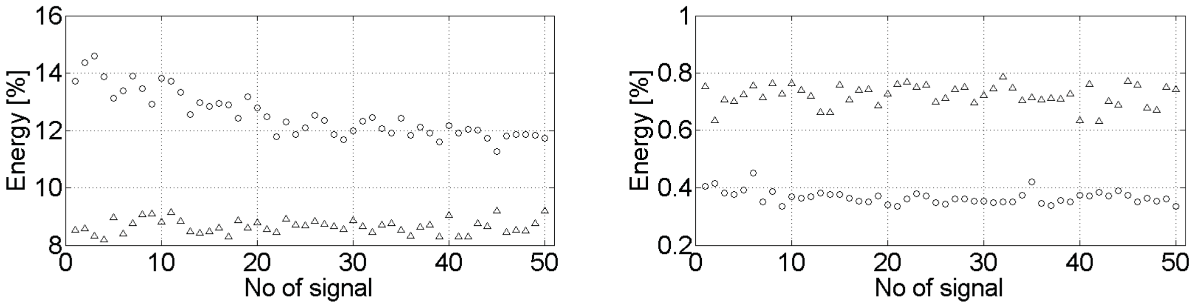

Fig. 4. Example of detail energy on 2nd (a) and 5th (b) level decomposition (• – efficient engine, Δ – engine with the simulated local fatigue crack of an exhaust valve)

3. Neural classifier for the local fatigue crack of an exhaust valve

For the studies carried out, artificial neural networks of PNN type were utilized (Probabilistic Neural Networks) [4, 13]. The probabilistic neural networks are used as the neural classifiers dividing the set of data into a determined number of output categories. They are of three-layer structure: input, hidden and output layer. 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 normalization ensuring summing up to one, they produce estimation of the probability of belonging to individual classes. While using such network type, proper smoothening coefficient γ should be selected. It represents the radial deviation of Gauss functions and is a measure of the range of neurons in the hidden layer. This value, when too low, causes the loss of knowledge generalizing property by the network, and, if too high, prevents the correct description of details. Similarly to the radial networks, the value of γ coefficient is determined experimentally. One the greatest advantages of PNN type networks is their high learning speed, whereas their complexity is the main drawback.

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.

In each conducted experiments the neural network had a task to classify registered vibrating signal to one of two classes adequate to capable engine and the engine with faulty exhaust valve.

In the first experiment there was examined the use of PNN neural networks for the engine working on certain gear and under the certain load, independently from the rotational speed. Neural classifiers contained: 2 neurons in the output layer, 50 neurons in the hidden layer and, depending on the amount of the levels of decomposition, from 2 to 11 neurons in the input layer.

Examples of results are shown in Fig. 5.

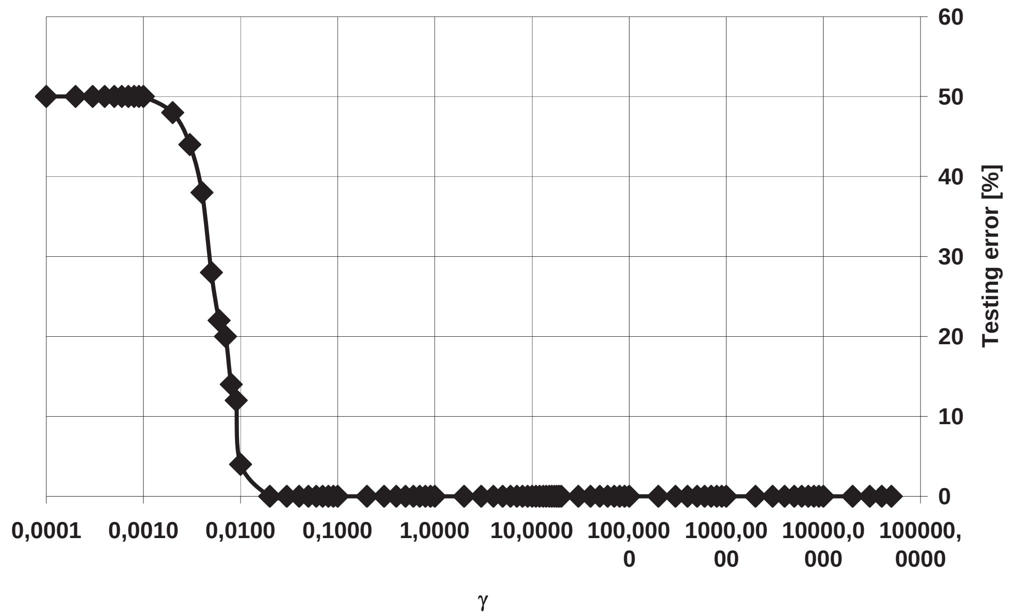

Fig. 5. The effect of the γ coefficient on the correctness of the PNN neural network classification – for engine work on 5^{th} gear and full load.

Seeing that for each from the analyzed conditions of working engine (number of gear, load) it was possible to built classifier providing faultless recognizing engine faults, there was conducted following experiment. In the experiment the task was to check if it's possible to recognize the faults of exhaust valve for the engine working on certain gear independently from the load.

The neural networks were built from: 2 neurons in the output layer, 100 neurons in the hidden layer and, depending on the amount of the levels of decomposition, from 2 to 11 neurons in the input layer.

Examples of results are shown in Fig. 6.

This experiment has gives the positive results as well.

In the following attempt it was decided to build classifier providing detection exhaust valve faults of the engine working on different gears with various loads and rotational speed.

Exploited in experiment PNN classifiers were built from: 2 neurons in the output layer, 300 neurons in the hidden layer and, depending on the amount of the levels of decomposition, from 2 to 11 neurons in the input layer.

The conducted experiment gave the positive results (Fig. 7).

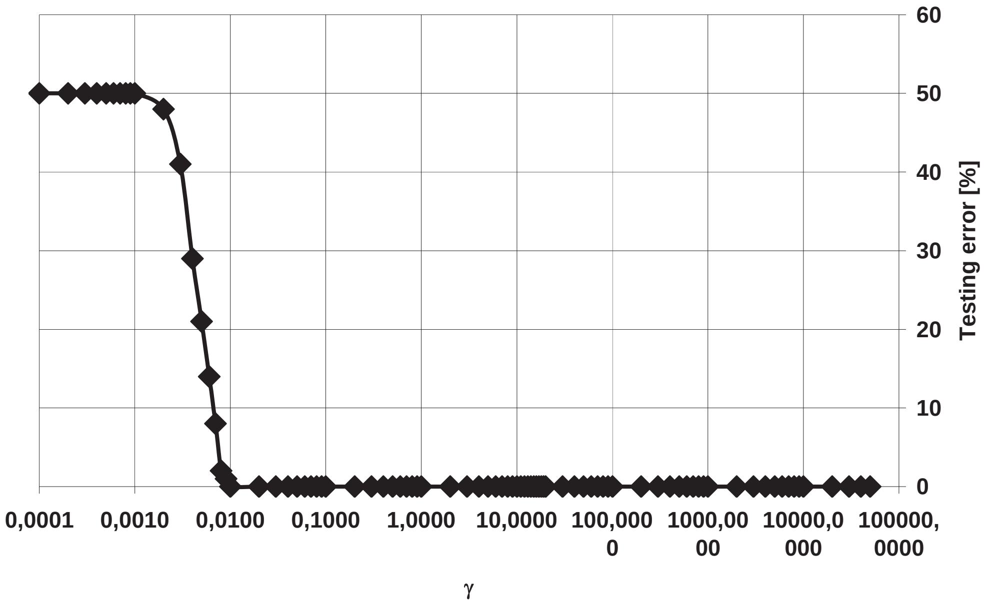

Fig. 6. The effect of the γ coefficient on the correctness of the PNN neural network classification – for engine work on 5th gear

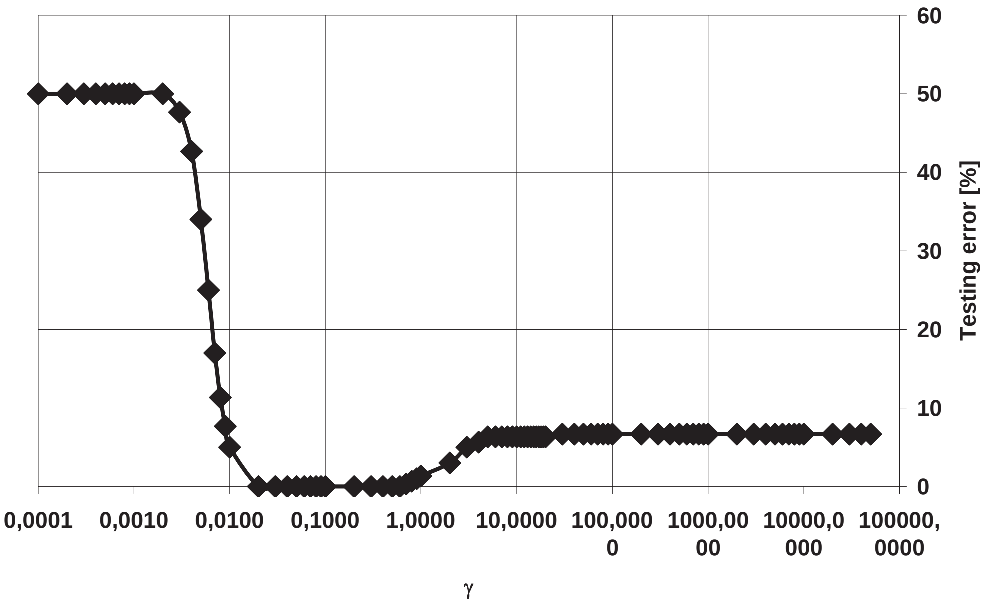

Fig. 7. The effect of the γ coefficient on the correctness of the PNN neural network classification

4. Summary

The studies have proven that it is possible to build a correctly working neuron classifier capable of recognizing different conditions of engine work, including those connected with damage of the local fatigue crack of an exhaust valve.

As part of the study, the descriptors calculated on the basis of the vibration acceleration signal registered on the engine block were proposed to serve as the source of information on the engine condition. The results have corroborated effectiveness of using the signal approximation and detail energy, acquired from the discrete wavelet decomposition, as the base for building models of engine operation.

The use of a probabilistic neural network with a correctly selected value of coefficient γ enables obtaining a faultless classification.

References

[1] Cempel, C., *Diagnostyka wibroakustyczna maszyn*, Państwowe Wydawnictwo Naukowe, Warszawa 1989.

[2] Czech, P., Łazarz, B., Wojnar, G., *Wykrywanie lokalnych uszkodzeń zębów kół przekładni z wykorzystaniem sztucznych sieci neuronowych i algorytmów genetycznych,* Wydawnictwo ITE, Radom 2007.

[3] Dąbrowski, Z., Madej, H., *Masking mechanical damages in the modern control systems of combustion engines,* Journal of KONES, Vol. 13, No. 3, 2006.

[4] Gately, E., *Sieci neuronowe. Prognozowanie finansowe i projektowanie systemów transakcyjnych,* WIG-Press, Warszawa 1999.

[5] Geveci, M., *An investigation of crankshaft oscillations for cylinder health diagnostics.* Mechanical Systems and Signal Processing, 19, 1107-1134, 2005.

[6] Heywood, J. B., *Internal combustion engines fundamentals*, McGraw Hill Inc 1988.

[7] Isermann, R., *Diagnosis methods for electronic controlled vehicles*, Vehicle System Dynamics, Vol. 36, No. 2-3.

[8] Janecki, J., Gołąbek, S., *Zużycie części i zespołów pojazdów samochodowych*, Wydawnictwo Komunikacji i Łączności, Warszawa 1984.

[9] Korbicz, J., Kościelny, J., Kowalczuk, Z., Cholewa, W. (praca zbiorowa), *Diagnostyka procesów, Modele, Metody sztucznej inteligencji, Zastosowania*, Wydawnictwa Naukowo-Techniczne, Warszawa 2002.

[10] Madej, H., Czech, P., *Diagnosing of disturbances in the fuel inflow to cylinders with the use of DWT analysis and PNN neural networks,* Scientific Problems of Machines Operation and Maintenance 3(155), Vol. 43, pp. 75-83, 2008.

[11] Osowski, S., *Sieci neuronowe do przetwarzania informacji,* Oficyna Wydawnicza Politechniki Warszawskiej, Warszawa 2000.

[12] Shirazi, F. A., Mahjoob, M. J., *Application of discrete wavelet transform (DWT) in combustion failure detection of IC engines,* Proceedings of the 5th International Symposium on imane and signal processing and analysis, 2007.

[13] Tadeusiewicz, R., Lula, P., *Wprowadzenie do sieci neuronowych,* StatSoft, Kraków 2001.

[14] Yang, W. X., *Establishment of the mathematical model for diagnosing the engine valve faults by genetic programming*, Journal of Sound and Vibration, 293, 213-226, 2006.