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APPLICATION OF CEPSTRUM AND SPECTRUM HISTOGRAMS OF VIBRATION ENGINE BODY FOR SETTING UP THE CLEARANCE MODEL OF THE PISTON-CYLINDER ASSEMBLY FOR RBF NEURAL CLASSIFIER

WYKORZYSTANIE HISTOGRAMÓW WIDMA I CEPSTRUM DRGAŃ KORPUSU SILNIKA DO BUDOWY WZORCÓW LUZU W UKŁADZIE TŁOK-CYLINDER DLA KLASYFIKATORA NEURONOWEGO RBF*

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 1.1 dm³. 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 [1,7]. 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 [5]. According to the studies carried out, it is possible to utilise artificial neural networks for the evaluation of the clearance in piston-cylinder assembly.

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

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 1,1 dm³. Diagnozowanie silnika spalinowego metodami drganiowymi jest szczególnie utrudniona 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 [1,7]. 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 maskowania usterek mechanicznych przez adaptacyjne układy sterowania silnika [5]. Z przeprowadzonych badań wynika, że istnieje możliwość wykorzystania sztucznych sieci neuronowych do oceny luzu w układzie tłok-cylinder.

Słowa kluczowe: *diagnostyka, silniki spalinowe, sieci neuronowe.*

1. Introduction

For the improvement of the level of safety, the devices enabling current observation of vehicle movement parameters are becoming more and more important. The fast development of techniques influence on more and more widespread uses of such devices [10, 12].

Modern IC engine maintenance programmes incorporate various methods and techniques for early fault detection to maintain efficiency and high reliability [3, 5].

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 [8]. One of the methods for diagnostic data acquisition is to monitor the level of vibration generated by engine components.

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 [4, 9, 11, 13-16].

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 1.1 dm³. The tests

(*) Tekst artykułu w polskiej wersji językowej dostępny w elektronicznym wydaniu kwartalnika na stronie ***www.ein.org.pl*** 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 0-720º. The engine repair involved the replacement of worn pistons which reduced the clearance in the piston-cylinder assembly.

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 radial artificial neural networks.

2. Setting up the model by use the histogram of vibration spectrum

The analysis of time runs excluded the possibility to use them directly as the data for neural classifiers. Refer to figure 1 for examples of vibration signals recorded before and after the repair.

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.

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

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, everyone equals 500 Hz.

A histogram was prepared to enable the description of the character of spectrum changes for each sub-range. 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 procedure was shown in figure 3.

The histogram ranges assumed for further experiments are 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.

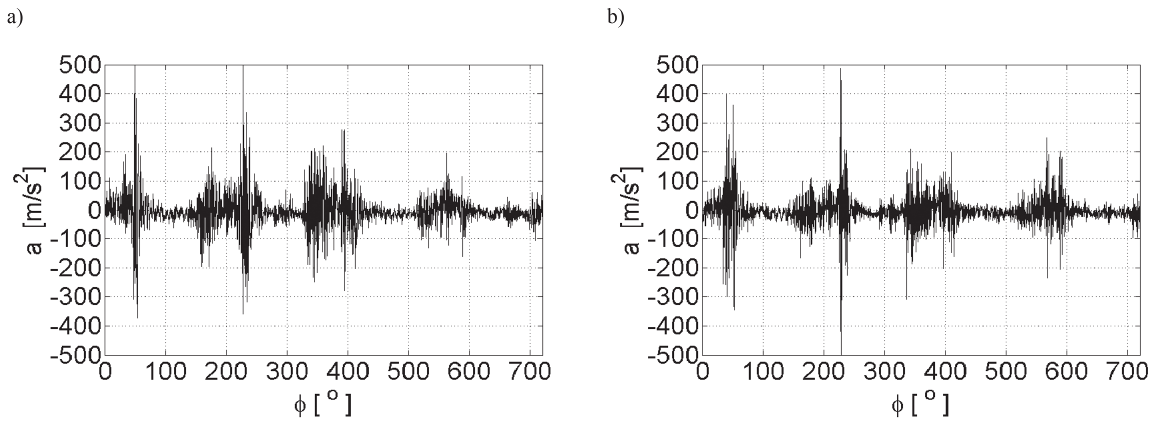

Fig. 1. Vibration acceleration runs recorded on the body before (a) and after (b) the engine repair

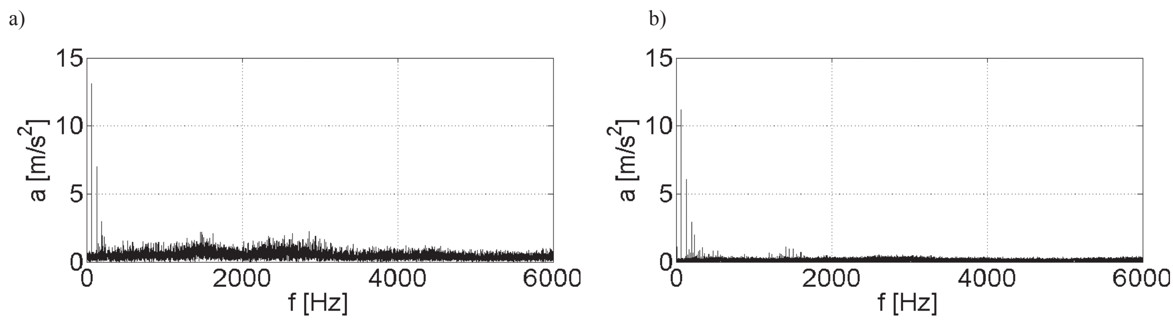

Fig. 2. Spectrum of vibration accelerations recorded o the body before (a) and after (b) the engine repair

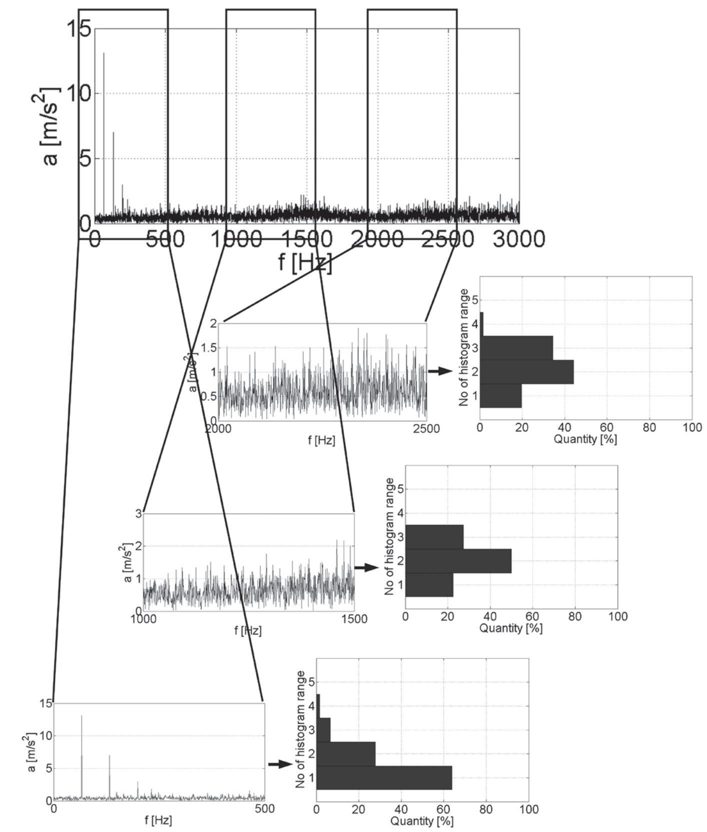

Fig. 3. Procedure of spectrum histograms determination

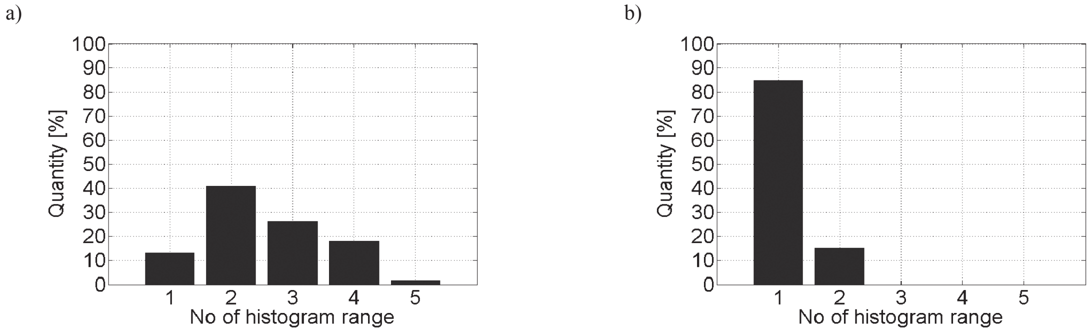

Fig. 4. Sample spectrum histogram of vibration accelerations recorded o the body before (a) and after (b) the engine repair

For all recorded time runs of the 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.

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

For the studies carried out, artificial neural networks of RBF type were utilised (Radial Basis Function). The radial 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 output neurons equals the number of classification categories. 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 [13, 15].

In the experiments carried out, the radial neural networks had the following structure:

- number of input neurons: 17,
- number of output neurons: 2,
- number of neurons in the hidden layer: 50.

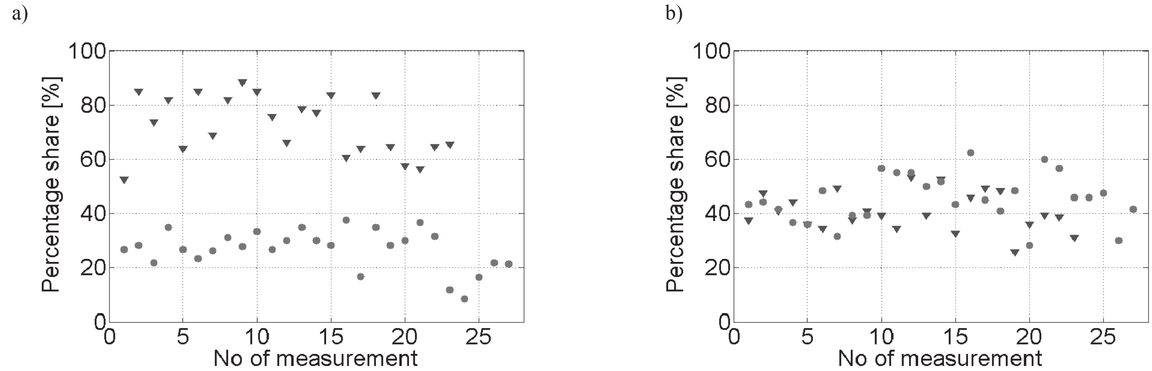

Fig. 5. Sample comparison between the spectrum sub-range and histogram range for the correct (a) and incorrect (b) separation of wear classes of the piston-cylinder assembly (Δ – engine prior to repair, • – engine after repair)

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 RBF type, the performance of the network for 86 various values of γ coefficient were checked.

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 2÷50000. For γ coefficient in the value range 0.0001÷2 significant increase of the classification error was noticeable.

3. Setting up the model by use the histogram of vibration cepstrum

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:

$$C(\tau) = \left| F\left(\log \left| F\left(x(t)\right)\right|^2 \right) \right|^2 \qquad (1)$$

Occurrence of noise, especially of periodic nature, is possible to be identified with that analysis [2]. It allows to separate the series components respectively to the pulse response of the system and the initiation [17]. 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 figure 6 for examples of cepstrum derived from the vibration signal for two different states of the engine.

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.

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.

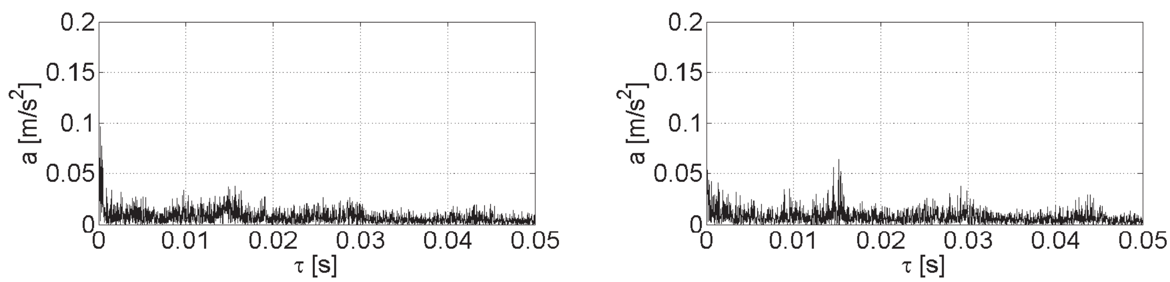

Fig. 6. Cepstrum of vibration accelerations recorded o the body before (a) and after (b) the engine repair

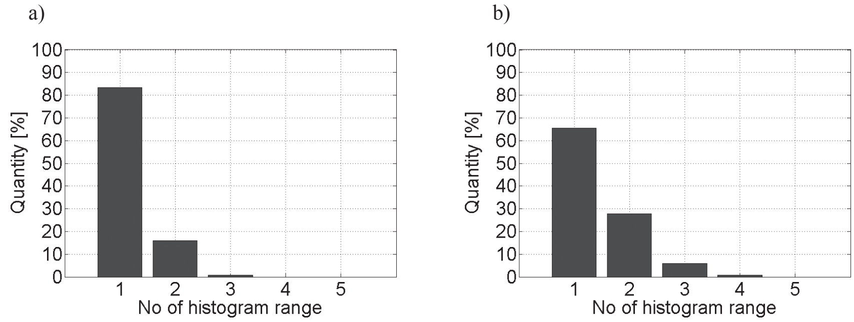

Fig. 7. Sample cepstrum histogram of vibration accelerations recorded o the body before (a) and after (b) the engine repair

Refer to figure 7 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 figure 8 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.

In the experiments carried out, the radial 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 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 RBF 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 9.

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 2÷50000. For γ coefficient in the value range 0.0001÷2 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 radial 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 and the spectrum 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 radial artificial neural networks.

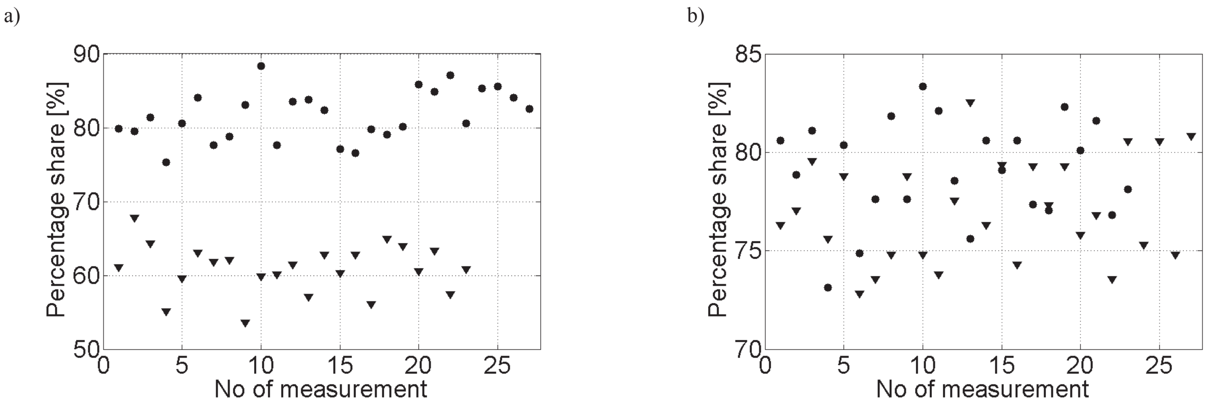

Fig. 8. Sample comparison between the cepstrum sub-range and histogram range for the correct (a) and incorrect (b) separation of wear classes of the piston-cylinder assembly (Δ – engine prior to repair, • – engine after repair)

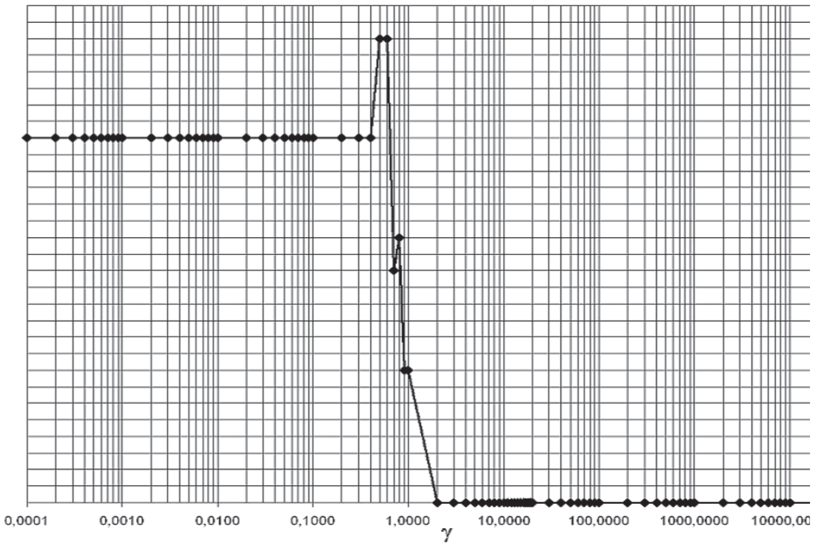

Fig. 9. The effect of the γ coefficient on the correctness of the RBF neural network classification (γ – the radial deviation of Gauss functions)

5. References

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